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Emerging Markets Queries in Finance and Business

An intraday analysis of the market efficiency-liquidity relationship: the case of BVB stock exchange

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Abstract

This article has the aim of investigating the relationship between market efficiency and liquidity on an emerging market, the Romanian financial market. Since there are very few studies that address this issue and even fewer studies conducted in developing countries, such an analysis is auspicious. Its complexity is given by the fact that the above link is studied through the use of panel data, a panel of processed intraday observations. Although the article's random effects regression uses inverse indicators of efficiency and liquidity, the result still provides a positive relationship between these two factors reaching the same conclusion as the one of CRS (2008) - market liquidity has a positive impact on informational efficiency, the increase of liquidity leading to greater efficiency.

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Keywords: financial market, market liquidity, profitability.

1. Introduction

Various theoretical arguments and empirical evidence suggest that market liquidity is closely linked to financial market efficiency. Given the important role that these two concepts occupy in the economic literature, the link between them has been and continues to be a hot topic. Therefore, it is quite normal to ask ourselves the

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question Do liquidity fluctuations have something in common with the variations of the degree of market efficiency?

Liquidity and trading activity are important features of financial markets, being especially debated by market microstructure researchers. Although market microstructure is sometimes perceived as an isolated Finance sub domain, Avanidhar Subrahmanyam (2009) shows that its variables are relevant in almost all financial domains. Specifically, market liquidity has profound implications for risk assessment, on strong non- arbitrage theorems and on market efficiency.

There are many theories that relate to the process of price formation and the role of information. In 1976, Garman describes how market prices are formed based on the nature of the order flow and on supply and demand imbalances. Kyle (1985) analyses the informational effect by examining how an informed investor is acting strategically in order to maximize the value of his private information. Kyle's theory is further discussed and enriched by Admatha and Pfleiderer (1988), Foster and Viswanathan (1990) and Seppi (1990) who tackle the strategic effects of trading also from the perspective of uninformed investors.

Researching the market microstructure, O'Hara explores the process of price formation by studying how information is incorporated in security prices "as microstructure research is conducted on financial markets, this aspect increases our ability to understand both returns and the process through which markets become efficient "(O'Hara, 1997, p.1). Consequently, market microstructure focuses on informational efficiency (the extent to which market prices correctly and quickly reflect new information over shorter periods of time).

Recent studies of order flow and returns' predictability expand their analysis making connections with liquidity and market efficiency. However, previous studies tackle the connection between the two concepts from another perspective. They examine the relationship between liquidity and profitability through liquidity premium, offered during a transaction of illiquid instruments. Pastor and Stambaugh (2003) argue the cross-sectional relationship between securities' returns and liquidity risks.

By further highlighting only recent studies that focus on the above relationship, it is mandatory to start with the surprising works of Cushing & Madhavan (2000) or Tarun Chordia, Richard Roll & Avanidhar Subrahmanyam (2005) who explain that returns are predictable based on previous order flows and to some extent based on past returns when taking into consideration short term horizons.

Their results contradict the classical theory, formulated in the review made by Fama (1970) through the efficient market hypothesis (EMH): an efficient financial market is "one in which prices always fully reflect the available information". Thus, the securities underpin all the information that led to their formation and allow investors to take optimal financial decisions (in an efficient capital market no title is undervalued or overvalued). Consequently, in this type of market is it impossible to predict future returns as past events have been already taken into account. Only new information can lead to new levels of equilibrium. The same Fama determines the classical taxonomy of information: the weak form EMH efficiency, the semi-strong form and the strong form. In the case of the weak-form efficiency the security's price immediately reflects all specifying information contained in the past history of that title's prices, the semi-strong form efficiency reflects immediately all the available public information whereas the strong-form efficiency reflects immediately all the available information, whether public or private. Nevertheless, out of the three forms mentioned, the weak-form is the most analysed, at the opposite being the strong form as private information is usually hard to be identified.

Three years later, Chordia et. al (2008) extend their analysis and show how the relationship between profitability and flow predictability varies over time and along different liquidity regimes. Noteworthy is the fact that these scholars are among the first to examine the predictability of returns in connection with liquidity interpreting the results from the market efficiency's perspective. Using intraday data, they point out the fact that a market considered to be efficient throughout a day is not necessarily efficient at a particular time of that day-market participants need time to incorporate new information published in their trading strategies.

Chordia et al. (2008) analyzed a sample of the largest and most transacted 193 companies listed on the NYSE, observed daily from 1993 to 2002. Their research outlines two main hypotheses on how short term liquidity can be associated with market efficiency.

The first hypothesis tackles the situation in which market makers are unable to absorb the impact of price pressures as a consequence of the imbalances between buy-sell orders. Those who are able to detect the temporary price deviations from their fundamental values may apply arbitrage which can speed up the convergence of prices to their fundamental values. The high degree of liquidity facilitates arbitrage profits that will cause low predictability of return and a high degree of market efficiency. In this case, liquidity is positively associated with financial market efficiency (a "+" relationship between the two variables).

However, there is a second hypothesis, a situation in which market makers don't use the information comprised in the order flow and thus the predictability of returns is immediately eliminated. The current situation creates an incentive for outside agencies to gather information about the flows. By trading and gathering information the so-called adverse selection is created. While liquidity decreases, the market will become more efficient because prices will incorporate more information (Barberis et. al, 1998). Such high efficiency may be associated with low liquidity (a "-" relationship between the two variables).

The above hypotheses have also been tested by using a much larger sample, the new findings supporting the initial results. Therefore, Chung and Hrazdil (2010) used a sample consisting of 4,222 companies traded on the NYSE during the period 1993-2004. They confirm the relationship between liquidity and market efficiency in both large companies and in the case of smaller and less traded firms.

Their study covers two methodologies: their first methodology corresponds to the CRS methodology used to extract and estimate the degree of market efficiency whereas the second one examines the predictability of returns from the firm's perspective and not from the portfolio's perspective as in the case of CRS.

By applying these methodologies Chung and Hrazdil (2010) confirm the findings of both CRS and those made by their predecessors: public information about future returns is contained in past flows (Subrahmanyam, 2008) and it takes some time for the prices to reflect the new information (Hillmer and Yu, 1979, Chan et al. Chordia et al 1996. 2005).

This article contributes to the existing literature by studying the relationship between market efficiency and liquidity with the aid of panel data quantifying the variables by using different and more accurate methods.

2. The data

The purpose of this article is to test the link between financial market efficiency, liquidity and market volatility by analyzing the most liquid 13 companies listed on the BSE : SIF1, FIC2, SIF3, SIF4, SIF 5, AZO, BIO, BRK, BSE, SNP, TLV, BRD, TEL. The research was conducted by observing intraday data recorded during each day of 2011, each trading session taking place during the interval 10.00 – 17.00.

The originality of this study lies in the fact that the relationship between liquidity and market efficiency is studied on intraday data, the observations being arranged and tested using panel data.

Historically, the choice of sampling frequency was determined by the data availability. At first, monthly returns were used. As time passed, daily data became available. In recent years lower costs of recording and data storage have given access to high frequency data, usually data collected at a frequency of less than 24 hours (intraday data or high frequency data) on major financial markets.

There are few studies using intraday data- processing this type of data requires intensive labor and in most cases the data are not available. However, Andersen, Bollerslev, Diebold & Labys (2000) and Andreou & Ghysels (2001) have used intraday data in their market microstructure analysis in order to diminish the possible contamination with market frictions (infrequent trading, bid -ask bounce).

The relationship between variables is modeled using panel data (longitudinal or cross-sectional time-series data). This choice is superior to cross-sectional data or time series (taken independently) in terms of variability and complexity. The advantages of using panel data are highlighted by Baltaghi (2001) "Panel data give more informative data, more variability, less co linearity among the variables, more degrees of freedom and more efficiency."

Panel models are very attractive as they approach the heterogeneity aspect and offer an analysis of fixed and / or random effects.

3. Panel's methodology

In order to investigate the empirical relationship between the degree of informational efficiency, liquidity and volatility, panel data is used. Such data indicate that variables are represented by both cross-sectional and time series variables. Also the presence of fixed effects and / or random is suggested.

A pooled OLS model cannot capture certain factors (e.g. cultural factors), some cross-sectional differences (differences related to the dependent variable) or variables that change over time but not between entities, fact that offers us all the economic arguments needed to test both of the two effects.

Panel models analyse group effects (individual specific effects), time effects or both. These effects are either fixed or random. A fixed / random one-way model only includes a set of dummy variables (either assigning a dummy for each individual or a dummy for each time period), whereas a fixed / random two-way model considers two sets of dummy variables (the assignment of a dummy for each individual and a dummy for each time period).

In this article only the one-way fixed model (on the individual) and one-way random model (also on the individual) were tested.

Based on the definition of Kennedy (2008) the fixed effects model examines the relationship between the dependent variable and the independent entity (country, person, company etc.), each entity having individual characteristics that may / may not influence the independent variables. Because the individual specific effect, does not vary over time it is considered as being part of the intercept-it can correlate with other variables. By estimating a LSDV regression (Least Squares Dummy variable) or the WITHIN estimation, the effect of the time invariable characteristics is eliminated examining the net effect of the regressors.

$$y_{it} = \beta_{1it} + \beta_{2it}x_{2it} + \ldots + \beta_{kit}x_{kit} + u_{it} = \beta_{1it} + x_{it}^{'}\beta_{it} + v_{it} \qquad (1)$$

μ_i : fixed or random effect specific to an individual (group) or period of time, which is not included in the regression; $v_{it} \approx IID(0,\sigma^2)$

Unlike the previous model, in the random effects model the variance between entities is considered to be random and uncorrelated with the regressors included in the model "the key difference between fixed and random effects is the correlation, or non-correlation of the model's unobserved individual effect with the model's regressors and not the stochastic or non-stochastic characteristic of these effects" (Greene, 2008).

The random effects model assumes the non-correlation of the individual effect (heterogeneity) with the regressors, the effect being a component of the error term. Consequently, this model is also called the error component model. The intercepts and regressors' slopes are constant, the difference between the entities (or periods) existing only in their specific individual errors and not in the intercepts. The estimation is performed by GLS (Generalized Least Squares) in the case in which the covariance structure of an individual is known or by FGLS methods (feasible generalized Least Squares) and EGLS methods (Estimated Generalized Least Squares), used to estimate the variance-covariance matrix of the entire V, when the covariance structure of an individual is unknown.

$$y_{it} = \beta_{1it} + \beta_{2it}x_{2it} + \ldots + \beta_{kit}x_{kit} + u_{it} = \beta_{1it} + x_{it}^{'}\beta_{it} + v_{it} \tag{2}$$

$$\mu_i : random\ effect \qquad v_{it} \approx IID(0, \sigma_v^2)$$

The period analyzed in this article was divided into intervals of two weeks, a period considered long enough to get good estimates and short enough to capture the dynamics of efficiency and liquidity.

Using fixed and random effects (FE and RE) on group (individual characteristics) the independent variables were analyzed:

- Efficiency (IE): percentage of windows for which the RW hypothesis was rejected
- Liquidity (IL): effective spread
- Volatility(VOL): standard deviation of returns

$$\begin{aligned} IE_{it} &= (\alpha + \mu_i) + \beta_1 IL_{it} + \beta_2 VOL_{it} + v_{it} \quad one-way\,FE \\ IE_{it} &= \alpha + \beta_1 IL_{it} + \beta_2 VOL_{it} + (\mu_i + v_{it}) \quad one-way RE \\ i &= 1,\ldots,n \qquad t = 1,\ldots,T \end{aligned} \tag{3}$$

4. Variable's description and their computation methods

4.1. Efficiency

It is crucially important to understand the fact that in this article market efficiency is quantified by taking into account the relative efficiency and not absolute efficiency. Therefore, RW III method will be analysed, the tests applied in this case being those that study linear correlations, portmanteau tests or variance ratio tests.

Also this article applies the Auto. Q test (Automatic Portmanteau Test, Escanciano and Lobato -2009) in R software by using the rolling windows approach (rolling Auto Q). For each of the 26 periods (year 2011 is divided in 26 periods, a period consisting of 2 weeks) this method has been applied. By successively using the rolling Auto.Q method, the first day's effect has been removed. Due to this translation, each successive application removes one return from the last window making it insignificant. By eliminating these frictions a fair presentation of the degree of efficiency is given.

A window is considered significant if the test rejects the null hypothesis (RW3 - returns are not serially correlated), the random walk hypothesis at the chosen threshold of 5%. Thus this method provides a reverse indication of the degree of efficiency.

By using the obtained probabilities the percentage of inefficiency is computed for each period:

$$Inef = \frac{N^*}{N} * 100 \tag{4}$$

where N * - the number of windows of a sub-period for which p <0.05 and N - the total number of windows of a sub-period.

Because this percentage is limited to the range [0, 1] a logistic transformation was applied to obtain a continuous variable along the range $[-\infty, +\infty]$:

$$\xi = \log\left(\frac{Inef}{1 - Inef}\right) \tag{5}$$

4.2. Liquidity

A liquid market is the market in which large trading volumes can be immediately and quickly executed with minimal effects on prices. It is interesting to learn that liquidity has two types of dimensions, static (tightness, depth and breadth) and dynamic (resiliency and immediacy). However, is necessary to specify the fact that this article underlines only the tightness dimension of liquidity referring to the direct transaction costs without expanding the analysis towards the indirect transaction costs measured by the price impact. Thus, higher the costs lower the liquidity.

There are many methods by which the transaction cost can be computed. Nevertheless, Roll' measure (1894) is the only one that adds the market efficiency variable in calculating transaction costs by proposing a new measurement called the Effective bid-ask spread. Being an implicit cost, the bid-ask spread is paid by those who demand liquidity (those who want to buy at the best ask order or sell at the best bid order), and represents a liquidity cost. However, at the same time the bid-ask spread aims to compensate those who provide liquidity and the market makers. Consequently, the spread becomes a direct measure of the cost of trading being an indirect liquidity measure- higher the costs lower the liquidity will be and conversely.

$$\text{Effective spread} = 2\,|\ln(P_k) - \ln(M_k)| \tag{6}$$

P_k the price of transaction k

$$M_k = \frac{ASK + BID}{2} \tag{7}$$

In the data section of this article the main reasons for which the use of intraday data is superior were presented. Nevertheless, it has to be also highlighted the importance of intraday data in the context of liquidity: this type of data processing allows a true measure of liquidity, a benchmark that captures the true costs of trading. Therefore, this article offers a liquidity benchmark and not a liquidity proxy.

4.3. Volatility

It represents a measure of the annualized standard deviation, or the statistical variation from the average -a daily percentage change in the price of an asset. In other words, volatility represents the uncertainty given by historical price movements along a fixed period of time.

$$\hat{\sigma} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}[R_i - E(R_i)]^2} \tag{8}$$

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{9}$$

where P_t - the price level of the index at t

Given that we have 26 periods of time, 26 volatility values, effective spreads and 26 market inneficiency values are calculated for each of the 13 titles.

5. Empirical Results

As stated before, by using a balanced panel data which has the characteristics of a macro-panel fixed and random effects (FE and RE) on group (individual characteristics) of the independent variables were tested by the analysis of the following models:

- one-way model with fixed effects

$$IE_{it} = (\alpha + \mu_i) + \beta_1 IL_{it} + \beta_2 VOL_{it} + v_{it} \tag{10}$$

- one-way model with random effects

$$IE_{it} = \alpha + \beta_1 IL_{it} + \beta_2 VOL_{it} + (\mu_i + v_{it}) \tag{11}$$

$i = 1, \dots, n$
$t = 1, \dots, T$,

where IE_{it} is an inverse measure of the degree of informational efficiency for the title i during t, IL_{it} being also also an inverse measure of the liquidity of the i asset in the same range, VOL_{it} a control variable which measures the volatility; μ_i : a fixed or random effect specific to an individual (or group) or a period of time (in our case we talk about a fixed effect / random specific to a group since we analyse the one-way fixed effects and way random effects on the individual).

By using the within estimator in model the following results are obtained:

Table 1. Fixed effects within regression

IE	Coeficient	t statistic	Prob>|t|
IL	0.0616671	0.13	0.894
VOL	28.60905	1.01	0.311
Cons	-1.072182	-7.09	0.000
F Test	F(12, 323) =	3.64	Prob > F= 0.0000

Since the probability associated with the F test from the last line of the above regression rejects the null hypothesis (H_0: the 12 dummy parameters of the LSDV1 model are 0) at the chosen 5% threshold, there is evidence of the existence of individual effects. The OLS estimator is biased and inconsistent favoring the accuracy of the within model.

$$IE\,[number\,,t] = xb + u[number] + e[number\,,t] \tag{12}$$

Since χ^2 probability associated with the test has a value less than 5% (Prob> chi2 = 0) the null hypothesis (LM's null hypothesis: the error variance components specific to the individual or time are 0 ($H_0 : \sigma_\mu^2 = 0$) is rejected indicating the presence of random effects, the OLS estimator being biased and inconsistent.

Estimated results are included in the following table:

Table 2. Breusch and Pagan Lagrangian multiplier test for random effects

	Var	sd = sqrt(var)
IE	1.36151	1.166838
E	1.172441	1.082793
u	.094087	.306736

Test: var(u) = 0
chi2(1) = 19.47
Prob > chi2 = 0.0000

We can thus speak of the existence of both effects in the analysed panel data. In order to choose the best model a robustness method was used along with the Hausman estimator, method suggested by Wooldridge (2002) and performed by the xtoverid command applied in STATA software. This test examines whether the individual effects are uncorrelated with the other regressors in the model. If these effects are correlated, the random effects model does not support the Gauss-Markov model's hypothesis of and thus is no longer a BLUE model (Best Linear unbiased Estimate). Using the random effects model as a means to find the variables' estimators and to establish the relationships between these, the following results were obtained:

Table 3. GLS regression with random effects

IE	Coeficient	t statistic	Prob>|t|
IL	0.2979657	2.37	0.018
VOL	53.51788	2.27	0.023
Cons	-1.213179	-6.56	0.000
Wald Test	Wald $\chi^2(2)$ =	60.69	Prob > χ^2= 0.0000

A robust GLS estimation method was applied in STATA software by using the xtreg command together with the robust argument.

For a threshold of 5%, it can be stated the fact that all the regressors are significant. The probability associated with the coefficients is less than 5% (IL=0.018, VOL=0.023 and constant=0) thus rejecting the null hypothesis (each coefficient differs from 0) and accepting the fact that illiquidity and volatility have a significant influence on the dependent variable (the degree of market efficiency).These results are sustained by the overall quality of the model, quality suggested by the Wald test's rejection of the null hypothesis (p = 0 <5%). Thus, all model coefficients are different from 0.The economic literature argues that many of the emerging financial markets and even the developed ones are inefficient. Poor trading (infrequent and irregular), fewer financial assets with significant capitalization are important reasons for which serious deviations from efficiency characterize these markets. Regarding the 13 securities listed on the Bucharest Stock Exchange, there is a direct link between inefficiency and illiquidity given by the positive sign of the IL estimator (0.29), a relationship which gives liquidity the status of a main determinant of stability and efficiency. The above findings also support the first hypothesis proposed by Chordia et al. (2008), presented in the introductory chapter, the one underpinning the economic literature. Therefore, the positive relationship between the two variables can be explained by the fact that poor transactions trigger illiquidity which diminishes arbitrage opportunities and so serious deviations from the random walk hypothesis are triggered.Taking into account the control variable, it should be stated the fact that the volatility's coefficient is also positive (53.51) but here we are talking about VOL which is a direct measure of volatility, therefore it can be concluded that volatility affects indirectly the efficiency.

6. Conclusions

Given the important role that liquidity and market efficiency plays in the economic literature, the link between them has been and continues to be a hot topic. This article focuses on delivering an accurate study by taking into consideration the recent studies on market microstructure by which the predictability of returns is analyzed in connection with liquidity the results being interpreted from market efficiency's perspective. Consequently, the empirical research of the 13 most liquid securities traded on Bucharest Stock Exchange test the link between the relative efficiency and liquidity, a bond processed on intraday data on Romania's emerging market. This result is obtained by econometrically modeling the collected data. Being arranged in a panel, these observations help at constructing variables (using a true measure of liquidity, an efficiency proxy and a control variable), at applying a series of tests through which the random effects model is found appropriate and then applied. Consequently, the regression in which the individual effects are part of the error term shows a direct and significant relationship between efficiency and liquidity hence supporting CRS's (2008) prime hypothesis also in the context of the Romanian financial market, an emerging market: market liquidity has a positive impact on informational efficiency, the increase of liquidity leading to greater efficiency.

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