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# Liquidity, information and market efficiency: an intraday approach on a frontier stock market

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## Abstract

The positive impact of liquidity on market efficiency has been confirmed on the Bucharest Stock Exchange using high-frequency data. Stock market efficiency is significantly higher during informational periods and lower in non-informational periods. Liquidity improves the price discovery process regardless of the informational environment.

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## 1. Introduction

High liquidity stimulates arbitrage operations resulting in an increase of the market efficiency degree on stock markets. In most cases, the relationship liquidity-efficiency is studied on low frequency data because it is difficult to obtain market microstructure data. A common practice in literature is identifying the best low frequency measure for liquidity starting from microstructure variables such as effective spread or realized spread. The few existing studies using intraday data were carried out on the American Market and confirm that liquidity has a positive impact on incorporating information into prices. Using a sample of American companies, Chordia *et al.* (2008) were the first to highlight the positive relationship between liquidity and market efficiency, measured by return predictability. This result was confirmed by Chung and Hrazdil (2010) on a larger sample on the NYSE. They also found that the relationship is stronger in informational periods.

Despite the investors' increasing interest in emerging markets, the relationship between liquidity and market efficiency has never been investigated on Central and Eastern Europe stock markets, in a market microstructure approach. This article contributes to the existing literature by highlighting the findings regarding the liquidity – efficiency relationship on a frontier stock market, respectively the Bucharest Stock Exchange (BSE). In contrast to previous studies, we use the percentage of rolling windows for which the null hypothesis of no return correlation is rejected, a measure[1] of efficiency that captures the dynamics of market efficiency. Applying a test in rolling windows diminishes the "first day effect"[2].

## 2. Data and methodology

*Data used*

Low liquidity, frequent quotation interruptions and data unavailability caused difficulties in constructing our sample. We selected ten of the most liquid companies listed on the BSE, observed between 20 December 2010 and 28 June 2013. Available data includes all intraday tick data, namely price, volume and bid/ask quotes, supplied by SSIF Broker SA. This is one of the leading brokerage companies on the BSE.

*Methodology*

The analysed period was divided into 66 two-week periods. For every company, we calculated measures for market efficiency, liquidity and adverse selection every fortnight. We also introduced two control variables, total number of trades (*TNT*) and average trade size (*ATS*). *TNT* is the total number of trades that occurred over the two week period and *ATS* represents the average trading volume (in local currency – RON) of the firm measured across all days over a fortnight. A logarithmic transformation has been applied to the control variables. Several econometric models were used to investigate the relationship between efficiency and the mentioned variables.

We applied the Automatic Portmanteau test proposed by Escanciano and Lobato (2009), in a rolling window approach for all time periods. The length of every window was set to 100 intraday quotations[3]. The test, which takes heteroskedasticity into account, can be expressed as follows:

$$AQ = T \sum_{i=1}^{\tilde{p}} \tilde{\rho}_i^2$$

[1] This measure of efficiency was introduced by Lim (2007).
[2] See Todea and Zoicas-Ienciu (2008) for details.
[3] According to Timmerman (2008) the length of the window should be as small as possible in order to capture the dynamics of the predictability in time, yet large enough to have high performance of the test.

where $\tilde{\rho}_i^2 = \hat{\gamma}_i^2/\hat{\tau}_i^2$, $\hat{\gamma}_i^2$ and $\hat{\tau}_i^2$ are the sample autocovariance of returns and squared returns, respectively. The optimal lag $\tilde{p}$ is obtained by a compromise between Akaike's and the Bayesian information criteria. The $AQ$ statistic asymptotically follows the $\chi^2(1)$ distribution.

The market efficiency indicator is the proportion of the windows in which the null hypothesis of no return correlation is rejected at a 5% level of significance. The higher the proportion in a sub-period is, the greater the deviation from market efficiency. This inverse measure of market efficiency (hereafter referred to as *Inefficiency*) takes values between 0 and 1.

We use the effective spread $Illiq = 2 \cdot |ln(P_t) - ln(M_t)|$, as an inverse measure for liquidity, where $P_t$ is the transaction price and $M_t$ is the midpoint of the bid-ask spread. The narrower the spread is, the more liquid the market will be. Identifying informational periods is important in order to analyse the associated degree of market efficiency and the impact of liquidity on the efficiency in such periods. On the American market, Chung and Hrazdil (2010) showed that efficiency is lower during informational periods, their results being consistent with the under-reaction hypothesis. Moreover, the liquidity has a stronger positive effect on efficiency in these periods. Using the same method, we constructed a dummy variable, denoted *HAS*, which takes a value of 1 in informational periods and 0 otherwise. The high adverse selection component of the bid-ask spread is the result of new information on the market. We use the models proposed by Lin et al. (1995) and Huang and Stoll (1995) to estimate the adverse selection. Those are $\Delta M_{t+1} = \lambda(z_t) + e_{t+1}$, and $\Delta M_{t+1} = \alpha\left(\frac{S_t}{2} \cdot Q_t\right) + v_{t+1}$ respectively, where: $\Delta M_{t+1} = M_{t+1} - M_t$,; $z_t = P_t - M_t$, where $P_t$ represents the transaction price at time t; $S_t$ is the BID-ASK spread at time t and $Q_t$ is the transaction type (1 if the transaction was a buy and -1 if it was a sell – see the Lee and Ready (1991) algorithm). The variable HAS takes the value 1 if both coefficients $\lambda$ and $\alpha$ are significant at least at 10%, both being above the median of the respective measure calculated based on the entire analysed period, and 0 otherwise. To analyse what happens in non-informational periods, we also constructed another variable, NHAS which takes a value of 1 for non-informational periods and 0 otherwise.

**Table I. Descriptive statistics and correlation matrix of regression variables**

| **Panel A: Descriptive statistics** | | | | | |
|---|---|---|---|---|---|
| | **Min** | **Max** | **Mean** | **Median** | **Std. Dev.** |
| **Inefficiency** | 0.0000 | 1.0000 | 0.2712 | 0.2325 | 0.2081 |
| **Illiquidity** | 0.0004 | 26.6975 | 0.3894 | 0.0059 | 2.0742 |
| **HAS** | 0.0000 | 1.0000 | 0.5667 | 1.0000 | 0.4959 |
| **TNT** | 1.5911 | 5.1512 | 3.8847 | 4.0106 | 0.5974 |
| **ATS** | 1.8751 | 4.5883 | 3.5364 | 3.6542 | 0.5468 |

| **Panel B: Correlation matrix** | | | | |
|---|---|---|---|---|
| | **Inefficiency** | **Illiq** | **HAS** | **TNT** |
| **Illiq** | 0.0771 | | | |
| **HAS** | -0.1410 | -0.1626 | | |
| **TNT** | 0.0192 | -0.4296 | 0.1088 | |
| **ATS** | -0.0932 | -0.0925 | 0.1109 | 0.2419 |

Table I provides descriptive statistics and the correlation matrix of all regression variables. The endogenous variable, *Inefficiency*, is bounded to the interval [0,1]. Therefore, we use the "Fractional probit" model proposed by Papke and Wooldridge (2008) estimated via pooled quasi-maximum likelihood (QMLE) and generalized estimating equations (GEE). Such a model would look like this:

$$Inefficiency_{it} = \alpha + \gamma_1 Illiq_{it} + \gamma_2 TNT_{it} + \gamma_3 ATS_{it} + \delta_1 Illiq_i + \delta_2 TNT_i + \delta_3 ATS_i + \varepsilon_{it}$$

where $Illiq_i, TNT_i$ and $ATS_i$ are time averages of their corresponding variables for every firm, and they are introduced to control for the unobserved heterogeneity.[4]

The correlation matrix (Table I – Panel B) generally indicates a weak dependence between the variables. The matrix shows a direct correlation between *Inefficiency* and *Illiq*, therefore, a direct relationship between market efficiency and liquidity.

## 3. Empirical results

When interpreting the results from Table II, we must take into account the fact that *Inefficiency* and *Illiq* are inverse measures. Panel A estimates indicate a direct and significant association between efficiency and liquidity. High levels of liquidity stimulate arbitrage operations, resulting in an increase in market efficiency degree.

**Table II. Regression results**

| **Model:** | **Fractional Probit** | | | |
|---|---|---|---|---|
| **Estimation method:** | **GLM** | | **GEE** | |
| **Panel A: Efficiency - Liquidity relationship** | | | | |
| Illiq | 0.0346*** | (19.05) | 0.0347*** | (18.38) |
| TNT | 0.0962 | (0.67) | 0.0861 | (0.61) |
| ATS | -0.7551*** | (-4.35) | -0.7533*** | (-4.32) |
| **Panel B: Efficiency - Informational periods** | | | | |
| HAS | -0.1893*** | (-3.80) | -0.1866*** | (-3.82) |
| TNT | 0.1463 | (1.03) | 0.1367 | (0.97) |
| ATS | -0.7662*** | (-4.46) | -0.7631*** | (-4.41) |
| **Panel C: Efficiency - Non-informational periods** | | | | |
| NHAS | 0.1893*** | (3.80) | 0.1866*** | (3.82) |
| TNT | 0.1463 | (1.03) | 0.1367 | (0.97) |
| ATS | -0.7662*** | (-4.46) | -0.7631*** | (-4.41) |
| **Panel D: Efficiency - Informational periods – Liquidity** | | | | |
| HAS | -0.1911*** | (-3.83) | -0.1893*** | (-3.84) |
| HAS*Illiq | 0.0259*** | (3.61) | 0.0262*** | (3.55) |
| TNT | 0.1430 | (0.98) | 0.1324 | (0.92) |
| ATS | -0.7671*** | (-4.51) | -0.7643*** | (-4.46) |
| **Panel E: Efficiency - Non-informational periods – Liquidity** | | | | |
| NHAS | 0.1715*** | (3.31) | 0.1690*** | (3.31) |
| NHAS*Illiq | 0.0264*** | (10.90) | 0.0267*** | (11.19) |
| TNT | 0.1301 | (0.89) | 0.1198 | (0.83) |
| ATS | -0.7615*** | (-4.44) | -0.7585*** | (-4.39) |

Significant at * - 10%, ** - 5%, *** - 1%; the intercept and time averaged variables estimations are not reported.

[4] See Papke and Wooldridge (2008) for details.

Regardless of the estimation method used, from the two control variables, only ATS influences the efficiency directly and significantly. This could be explained by the actions of the informed traders. They trade large portfolios of stocks when they acquire new information, leading to an increase in the efficiency degree. On the contrary, when there is no new information on the market, the noise traders, who trade small portfolios, induce correlations in the return series, leading to inefficiency implicitly.

The same argument sustains the fact that the estimates of the *HAS and NHAS* variables in Panels B and C respectively, indicate that stock market efficiency is significantly higher during the informational periods and lower in non-informational periods. During informational periods, information is faster incorporated in prices, leading to increases in market efficiency.

In Panel D and E we investigated how liquidity affects efficiency during periods with various levels of information. The significant *HAS*Illiq* coefficients show that higher liquidity in informational periods have a positive effect on efficiency. The high liquidity reduces the effect of asymmetric information on stock market efficiency and it improves the price discovery process. Despite the fact that the market has a lower degree of efficiency during non-informational periods, Panel E reveals that liquidity has a positive impact on efficiency. In these periods, when the market is liquid, arbitrage operations are stimulated, thus eliminating or diminishing some imbalances with a positive effect on market efficiency.

## 4. Conclusions

This study confirms the direct relationship between efficiency and liquidity on the BSE and the investors' prompt reaction to new information. Liquidity improves the price discovery process regardless of the informational environment. Therefore, ensuring an increased liquidity should be a continuous concern of regulatory authorities of this market. Decreasing trading fees, listing new companies on the BSE and assuring a predictable legislative framework could lead to a more dynamic trade activity with a positive impact on market efficiency.

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