TECHNICAL ANALYSIS AND LIQUIDITY: THE CASE OF THE BUDAPEST STOCK EXCHANGE

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Abstract

Technical analysis is a popular technique among financial practitioners for supporting their investment decisions. In this thesis I examine two aspects of technical analysis using data for 26 stocks of the Budapest Stock Exchange from the period between 1997 and 2008. First, I analyze the profitability of moving average indicators with the methodology developed by Brock et al. (1992). My results suggest that for the majority of the stocks, technical trading rules can be useful in predicting future price movements. In the second part of the thesis I study the relationship between market liquidity and the timing of signals generated by the most successful trading rules. Using panel data methods I find that there is no strong link between liquidity and the timing of signals.

Table of Contents

1 Introduction

Technical analysis is a common term for a wide range of methods trying to predict future price-movements of financial assets using past information, usually the time series of past prices of the assets. Technical analysis has been very popular among financial practitioners as a tool for supporting their investment decisions. Numerous survey studies have shown that this form of investment analysis is widely used in various futures markets (Brorsen & Irwin, 1987), foreign exchange markets (Gehrig & Menkhoff, 2006), and stock markets (Sehgal & Gupta, 2005) around the world.

Despite the general acceptance of technical analysis among practitioners, academic research has been traditionally quite skeptical about it. According to Park and Irwin (2007), this skepticism was mainly due to two reasons. The first is the popularity of the efficient market hypothesis (Fama, 1970), which, even in its weakest form, implies that all the information carried by past price movements is already reflected in the current price, and thus cannot be used to achieve higher than average profits. The second reason for the original skepticism is the negative empirical findings in a number of early and widely cited studies about the profitability of technical analysis. In recent years, however, many studies have been published that seem to challenge the traditional opinion of academics. Some theoretical papers have shown that under certain circumstances technical analysis can provide valuable information (Treynor and Fergusson, 1985; Brown and Jennings 1989), and a great number of empirical studies have found technical analysis to be profitable on different markets over different time periods (e.g. Brock et al., 1992; Bessembinder & Chan, 1998).

Although substantial amount of literature is dealing with the profitability of technical techniques, so far no attempt has been made to analyze the relationship between liquidity and technical trading. Taking liquidity into account is really important when analyzing the performance of technical analysis. The result of technical analysis is always a trading strategy that provides buying and selling signals. The implementation of this strategy involves active trading on the market. Therefore, transaction costs have a substantial effect on the profitability of the trading strategy. Some studies have dealt with this issue by assuming a fixed amount of transaction costs throughout the period analyzed. However, the problem with this approach is that the liquidity of the market is not constant over time. If there is a significant relationship between liquidity of the market and the timing of the trades required by the technical trading strategy, it has severe implications regarding profitability. If, for example, the technical trading rules generate trading signals more often in times of low liquidity, than the profit opportunity suggested by previous empirical studies cannot be exploited. As soon as someone tries to implement the trading strategy, the prices start to move against him quickly (because of the low liquidity), and the profit opportunity disappears.

In this thesis I will analyze the link between liquidity and the performance of technical analysis. In order to analyze this relationship, I will use data from the Hungarian stock market, the Budapest Stock Exchange (BSE) from the period between 1997 and 2008. At the beginning of the analysis, two separate tasks have to be accomplished. After describing the data in chapter 2, I will start with examining the performance of technical analysis on the BSE over the sample period. I will evaluate the performance of certain moving average indicators using the methodology proposed by Brock et al. (1992). The assessment of the performance of technical analysis can be found in chapter 3. The second task is to measure the liquidity of assets traded on the BSE. In order to analyze how liquidity changed on the BSE over the sample period, I will calculate two liquidity measures proposed in previous empirical studies. The methodology and results of liquidity measurement are presented in chapter 4. After completing these two separate tasks, I will analyze the link between liquidity and technical analysis in chapter 5. Chapter 6 concludes the results of the research.

2 Data description

The empirical analysis of the thesis focuses on the Hungarian stock market, the Budapest Stock Exchange. I have chosen the period from July 1997 to December 2008 to study the relationship between technical analysis and liquidity. The start of the sample period was chosen to be this point, because of data availability. The BSE reports daily trading data in a well structured form for all the stocks listed, starting from July 1997.

When selecting stocks into the sample, I was focusing on papers listed in Category "A" on the BSE. The shares in Category "A" are more liquid in general and have a broader ownership structure than shares listed in Category "B". The reason for analyzing only relatively more liquid stocks is that technical analysis usually involves regular trading on the market. Thus, certain liquidity of a given stock is needed so that technical trading strategies can be implemented at all. In the case of Category "B" stocks, there are a lot of trading days without a single trade, and therefore testing how technical trading rules would perform is pointless for these shares. To be listed in category "A", the company has to meet certain criteria set by the stock exchange regarding capitalization of the stock, the ownership structure and corporate history of the company. As of May 2009, the listing requirements for stocks in category "A" can be seen in Appendix 1.

In the first step of building the database for the analysis, I collected which stocks were listed in Category "A" for every month of the sample period. At this point the sample contained 38 stocks. In the next step, those papers that did not have data for at least 1000 trading days were excluded from the sample. This means that all the remaining stocks have at least approximately four years of trading data. The final sample contains 26 stocks. Table 1[1] gives a summary about how long different stocks are presented in the sample.

[1] Table 1 can be found in Appendix 4.

I collected daily closing prices and trading volumes for the 26 stocks in the sample from the official web page of the BSE[2]. I also collected monthly capitalization data for all the stocks in the sample using Monthly Statistics published by the BSE in every month.

In the following chapter I will start presenting the empirical research I carried out. I start with analyzing the profitability of technical trading strategies on the BSE.

[2] The official web page of the BSE can be found at http://www.bet.hu

3 The performance of technical analysis

There exists a traditional skepticism in financial literature towards the usefulness of technical analysis. This skepticism has its roots in the popularity of the efficient market hypothesis. Fama (1970) provides the first comprehensive review on the literature about efficient markets. A market is called efficient when prices at any time fully reflect all available information. Market efficiency has three levels depending on what kind of information is reflected in market prices:

- Weak form of efficiency – all information that can be gathered by analyzing past prices of the asset is already reflected in the current price.
- Semi-strong form of efficiency – the current price reflects all publicly available information, including past prices and other statistics about the asset, announcements of annual earnings, stock splits, etc.
- Strong from of efficiency – the current price reflects all available information, including both public and private information.

The weak form of market efficiency plays an important role regarding technical analysis. If a market turns out to be at least weakly efficient, it is impossible to create stock picking strategies based on past prices that generate higher than average returns. Thus, if a market is weakly efficient, it implies that technical analysis is useless. According to Fama (1970), early empirical work on the weak form tests of the efficient market model is extensive, and "it seems fair to say that the results are strongly in support" (Fama, 1970, p. 414).

However, since the middle of the 80s a number of theoretical papers have been published showing that under certain conditions technical analysis can be useful in predicting future price movements of an asset[3]. In Treynor and Fergusson's model (1985) an agent receives information about a certain event and he has to decide if he wants to trade on the information. The problem of the investor is that he does not know whether the information is already reflected in the current price or not. If the investor receives the information before the majority of the market participants, he can exploit it by taking the appropriate position. Treynor and Fergusson (1985) show that using past prices, the investor is able to better estimate the probability that the information is not yet reflected in the price at the time when he receives it. Thus, in this model, past prices combined with other valuable information (knowing how the event will affect prices) can be helpful in achieving unusual profits. However, the authors also point out that in the model, non-price information creates the profit opportunity, past prices help only to exploit it.

Brown and Jennings (1989) propose a noisy rational expectations model in which agents trade in two periods. The authors argue that the noise coming from unobserved current supply of the risky asset makes it impossible for the current price to reveal all the private information. They show that, even in a rational-investor economy like this, the weighted average of the first and second period prices is a better information source than the second period price alone. In this model individuals would use technical analysis even though the second period price is set competitively by rational investors using all public information, including the price of the first period.

There is a large body of empirical literature on the profitability of technical analysis. Park and Irwin (2004, 2007) provide an extensive survey on this literature. They review 137 different studies published after 1960 that analyze the performance of technical analysis, and

[3] For detailed introduction on the theoretical background of technical analysis see (Park & Irwin, 2007, pp. 805-810) and (Brunnermeier, 2001, pp. 98-146)

conclude that among the 95 modern studies[4], 56 have supporting results for technical trading strategies, 20 studies obtain negative results, and there are 19 studies with mixed results. The authors also note that there seems to be an explosion in the literature in recent years. About half of the studies they review were published after 1995. As one of the reasons for this explosion, Park and Irwin (2007) identifies the publication of some very influential papers in the early 1990s. One of these studies is the paper written by Brock, Lakonishok and LeBaron (1992).

As Park and Irwin (2007, p. 795) claims:

"The study by Brock et al. is one of the most influential works on technical trading rules among modern studies. The influence can be traced to the finding of strongly consistent and positive results about the forecasting power of technical trading rules, the use of a long price history (90 years for the DJIA) and application for the first time of the model-based bootstrap method."

Brock et al. (1992) test 26 technical trading rules from two families of indicators, the so called moving average and trading range break indicators. The data series they use is the Dow Jones Industrial Average (DJIA) between 1897 and 1986. The authors find that returns generated under buy signals of the trading strategies are consistently higher than returns generated under selling signals. The main contribution of the paper is that the authors develop a test of significance for the trading rules using bootstrap methodology. The paper by Brock et al. (1992) has an important role for my thesis also, as I am going to apply the model-based bootstrap methodology introduced in it to analyze the performance of technical trading rules on the Budapest Stock Exchange.

The work of Brock et al. (1992) was followed by a great number of studies that applied the same methodology to various markets and various time periods[5]. Studies concentrating on developed stock markets (Hudson et al., 1996; Bessembinder & Chan, 1998; Day &Wang, 2002) have found significant profits, although these profits seem to diminish after transaction

[4] Studies published after 1988 are regard as modern studies by Park and Irwin (2007)
[5] Park and Irwin (2004) surveys 21 studies using the methodology of Brock et al. (1992).

costs taken into account and have declined over time. Many studies have applied the methodology of Brock et al. (1992) on emerging markets. Bessembinder and Chan (1995) have examined six different Asian stock markets between 1975 and 1990, and have found that technical analysis was successful in all the markets during the sample period. Ito (1999) has evaluated the profitability of technical trading rules on equity indices from different parts of the world (U.S., Japan, Canada, Indonesia, Mexico and Taiwan) between 1980 and 1996. He has found that technical trading strategies outperform the buy and hold strategy in all but the U.S. index. Markets in Latin America and Asia over the period from 1982 to 1995 have been examined by Ratner and Leal (1999). The authors have concluded that in all these emerging markets, trading rules presented forecasting ability throughout the period analyzed. Parisi and Vasquez (2000) were focusing on the Chilean stock market between 1987 and 1998. They have also found that the results provide a strong support for technical trading rules. Gunasekarage and Power (2001) also applied the methodology of Brock et al. (1992) on South Asian stock markets. They examined stock indices from Bangladesh, India, Pakistan, and Sri Lanka over the period from 1990 to 2000. Similarly to the previous studies on emerging markets, Gunasekarage and Power (2001) have found that their trading rules outperform the buy and hold strategy.

The general conclusion of the above studies is that trading rules seem to be profitable on emerging markets. No previous work, so far, has applied the model-based bootstrap methodology of Brock et al. (1992) to analyze the performance of technical analysis on the Hungarian, or any Central and Eastern European stock market. In this thesis, I make an attempt to fill this gap. Moreover, previous studies have tested the performance of technical analysis on market indices. By analyzing individual stocks, I hope to get a more complex picture of the profitability of technical trading rules. In the next section I continue by introducing the methodology of the analysis.

3.1 Methodology

Technical analysis is a common term for a large variety of techniques trying to forecast future price movements of an asset. Academic research usually focuses on techniques that can be expressed in mathematical form. These are called technical trading systems[6]. Trading systems based on moving averages are one of the most popular and most widely used indicators among practitioners (Park & Irwin, 2004, p. 18). These are the most extensively studied technical techniques in the academic literature. Brock et al. (1992) also use moving average type of indicators in their analysis.

I also chose to analyze technical trading strategies based on moving averages of closing prices. I will examine the most basic form of moving average rules which applies two moving averages of different lengths, a shorter moving average

$$SMA_t = \frac{\sum_{i=0}^{s-1} p_{t-i}}{s} \,,$$

and a longer moving average

$$LMA_t = \frac{\sum_{i=0}^{l-1} p_{t-i}}{l} \,.$$

In the above formulas p_t is the closing price of the asset on trading day t, while s and l are the lengths of the moving averages ($s < l$). A buy signal is generated when the shorter moving average is above the longer moving average, and a sell signal is generated in the opposite case, when the shorter moving average goes below the longer one.

$$signal_t = \begin{cases} 1 & if \quad SMA_{t-1} \geq LMA_{t-1} \\ 0 & if \quad SMA_{t-1} < LMA_{t-1} \end{cases}$$

There are a great number of different rules of this kind depending on the length of the moving averages applied. I will test 120 different trading rules using various combinations of short

[6] I will reffer to a particular technical trading system as trading strategy, trading rule, or indicator throughout the thesis.

and long moving averages (different combinations of s and l). The complete set of trading rules examined in the thesis is listed in Appendix 2.

When analyzing the performance of the technical trading rules I will follow the methodology proposed in the seminal paper by Brock et al. (1992). The measure of the performance of a given trading rule in the paper by Brock et al. (1992) is the difference between the conditional expectations of the daily returns based on the signals generated by the trading strategy. The daily returns are calculated as the log differences of the closing prices:

$$r_t = \ln(p_t) - \ln(p_{t-1}) .$$

The expected daily return conditional on buy signal is

$$\mu_b = E(r_t|signal_t = 1) ,$$

while the expected return conditional on a sell signal is

$$\mu_s = E(r_t|signal_t = 0) .$$

The conditional expectations will be estimated by the sample means, denoted by m_b and m_s. The performance measure can be calculated as the difference between these two conditional expectations. Brock et al. (1992) also calculate the conditional standard deviations of the returns in order to examine the risk of a given trading strategy

$$\sigma_b = (E[(r_t - \mu_b)^2|signal_t = 1])^{1/2} \;, and$$

$$\sigma_s = (E[(r_t - \mu_s)^2|signal_t = 0])^{1/2} .$$

The sample estimates of the conditional standard deviations will be denoted by s_b and s_s.

In order to assess the significance of the profitability of a trading strategy, Brock et al. (1992) develop a test based on a model-based bootstrap methodology. The main idea of the procedure is to compare the performance statistics (the difference between the conditional expected returns, $m_b - m_s$) generated by a technical trading rule on the original price series to the same statistics computed on a large number of simulated comparison price series. For generating the comparison series, Brock et al. (1992) use four different null models for the returns: random walk with a drift, AR(1), GARCH-M, and EGARCH.

The testing procedure is carried out as follows: first, the performance statistics is calculated using the original series. In the second step, the null model is fit to the original return series to obtain estimated parameters and residuals. Then a new series of residuals is generated by sampling with replacement from the standardized residuals of the original series. Using this series and the estimated parameters of the null model, a new return series can be created. With the help of this new return series, we can build up a simulated price series. Then the technical trading rule can be applied to the comparison price series and the performance measure can be calculated. Repeating this process a large number of times gives a good approximation for the distribution of the performance measure under the null model. The simulated p-value for the null-hypothesis that the profitability of the rule can be explained by the given null model is obtained as the portion of the generated comparison series for which the profitability measure is greater than that of the original series. I will use 500 replications of the original return series in the test procedure.

Depending on the type of the null model applied during the testing procedure, different particularities of the return series can be taken into account in the testing procedure. If, for example, we would like to take into account the autocorrelation in the returns, an autoregressive model can be used, and if we would like to control for the changing volatility of the return series, an ARCH type of null model can be applied. I will use three different null models when applying the model-based bootstrap in analyzing the profitability of technical analysis. These three models are the random walk with a drift, the AR(1), and the GARCH(1,1)-M processes.

The random walk with a drift model was not simulated by fitting a model to the original return series. Instead, as suggested by Brock et al. (1992), the bootstrap return series were generated by randomly drawing from the original returns with replacement. Te return series created this way have the same unconditional distribution as the original returns; however, the returns are independent by construction.

The second null model I used during the testing procedure is the AR(1) model

$$r_t = \alpha + \rho r_{t-1} + \varepsilon_t \ , \quad |\rho| < 1 \ .$$

Moving average strategies might generate higher than average returns if the underlying stock's returns are positively serially correlated. After positive (negative) return days the moving average strategy is more likely to give a buy (sell) signal, and because of the positive autocorrelation in the returns, it is more likely that on the next trading day the return will be positive (negative) again. It is easy to imagine that moving average rules produce “abnormal” returns by exploiting the positive serial correlation. If an AR(1) model is used as null model during the test procedure, the bootstrap return series will have the same first order autocorrelation as the original series. If the high return generated by a trading rule is due to the autocorrelation in the returns, the technical trading rule applied to the comparison price series should also generate high returns. As a consequence the proportion of the 500 replications in which the performance statistics is greater than that of the original series will be higher. Thus, the simulated p-value of the test will be high, giving support to the null hypothesis that the profitability of the trading rule can be explained by the underlying null model.

The third null model I will use is the GARCH(1,1)-M model[7]

$$r_t = \theta + \lambda \sigma_t^2 + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

[7] The representation is fromulated following the EViews 5 User's Guide.

This model assumes that the conditional variance of the returns is changing and that the expected return on the asset is related to the expected asset risk. It might happen that technical trading strategies work because they can somehow predict changes in the volatility of the asset and these changes in volatility are priced in the returns. With the help of the GARCH-M as a null model in the bootstrap, this possibility can be taken into account during the testing procedure.

The following section will discuss the results I got when I applied the previously outlined methodology in order to assess the profitability of technical analysis on the Budapest Stock Exchange.

3.2 Results

In order to be able to apply the bootstrap method of Brock et al. (1992), first I had to fit the null models to the 26 return series and obtain the estimated coefficients and residuals. The estimated coefficients are reported in Table 2 for the AR(1) model and in Table 3[8] for the GARCH(1,1)-M model. In the case of the AR(1) model, it can be seen from Table 2 that there are stocks with significant positive first order autocorrelation, and there are also stocks with significant negative serial correlation. For the GARCH(1,1)-M model the coefficients in the variance equation are significant for all the stocks indicating the presence of changing volatility.

Table 4[9] gives a general summary about the overall performance of the 120 technical trading rules tested on the 26 different stocks of the BSE. The first column of Table 4 shows the difference between the conditional expected daily returns ($m_b - m_s$) averaged across all the 120 moving average rules. The first thing to note here is that except three cases, all the

[8] Table 2 and Table 3 can be found in Appendix 4.
[9] Table 4 can be found in Appendix 4.

values are positive. This means that for most of the stocks, the trading rules, on average generated higher returns under buy signal than under sell signal. A value of 0.001 indicates that on average the daily buy return is 0.1 percent higher than the expected daily sell return. This is around 25 percent on a yearly basis, which is a considerable difference.

The second column of Table 4 presents the number of the trading strategies (from the total of 120) for which the difference between the expected conditional returns is positive ($m_b - m_s > 0$). There are only two stocks where this value is below 60, meaning that for the vast majority of the stocks, more than half of the trading rules generated higher returns under buy signals than under sell signals. For most of the stocks, the number of indicators that produced higher buy returns is over 90, indicating that for these stocks the overall profitability of the moving average indicator is quite convincing. However, so far I have not talked about the significance of these results.

Columns 3 to 5 summarize the results of the model-based bootstrap tests developed by Brock et al. (1992). The columns show the number of trading rules, where the simulated p-value is smaller than 0.05. This can be interpreted as for these rules the hypotheses that the difference between the expected conditional returns is generated by the given null model is rejected. The value 0 indicates that none of the 120 rules tested can generate so high difference in the expected conditional returns that cannot be explained by the null model. A value of 60, on the other hand, suggests that the profitability of half of the trading rules is so high that it cannot be explained by the given null model.

Column 3 corresponds to the random walk, column 4 to the AR(1), and column 5 to the GARCH(1,1)-M model. The first observation to make here, is that the lowest numbers usually appear in the column of the GARCH(1,1)-M model. This suggests that the changing volatility of a given stock plays an important role in the profitability of the moving average rules. There are four stocks which have their lowest values in the column corresponding to the AR(1) model. These are exactly the same stocks which have significantly positive ρ coefficient in the AR(1) model. This result confirms that moving average indicators can be more successful if there is a positive first order autocorrelation in the returns of the stock.

A general conclusion can be that moving average rules perform differently on different markets. There are nine stocks, where none of the analyzed trading rules could generate such a difference in expected returns that cannot be explained by at least one of the null models[10]. On the other hand there are stocks for which the profitability of more than half of the moving average strategies cannot be explained by any of the null models.

The last column of Table 4 provides some insight into the riskiness of the trading strategies. It shows the number of trading rules where the conditional standard deviation under sell signal is higher than under buy signal. It can be concluded that in the vast majority of the cases, the trading rules are able to select those periods when the market is less volatile.

In chapter 5, I will continue the analysis using results from the best performing trading rule for each stock. Therefore, I briefly summarize the performance of the best strategies with the help of Table 5[11]. By best strategy I mean the one that generated the highest $m_b - m_s$ statistic throughout the period for each of the stocks examined. The first column of Table 5 shows the difference between the expected conditional returns ($m_b - m_s$). All of the differences are positive and have a considerably large magnitude. Column 2 to column 4 present the p-values simulated with the model-based bootstrap methodology. For most of the stocks all three tests reject at 5% level that the difference of the expected conditional returns generated by the best performing trading rule can be explained by the particular null model. There are nine stocks, the same ones that I mentioned earlier, where the profitability of the best rule does not seem to be significant at 5% level according to at least one of the null

[10] These stocks include the BCHEM, DEMASZ, FOTEX, IEB, LINAMAR, MTELEKOM, RICHTER, ZKERAMIA and ZWACK.

[11] Table 5can be found in Appendix 4.

models. The conditional standard deviations of the returns are presented in the last two columns of Table 5. For all the stocks, the best performing trading rule have less volatile returns under buy signal than under sell signal.

After analyzing the profitability of moving average indicators on different stocks of the Budapest Stock Exchange, it can be concluded that picture is mixed, but mainly supports the usefulness of technical analysis. There are stocks where large proportion of the trading rules tested seems to produce higher than average returns, and this profitability cannot be explained by any of the popular null models. For the majority of the stocks there are at least some trading strategies that proved to be significantly profitable during the period analyzed. However, there are also some stocks, where even the most successful moving average rule cannot generate significantly higher returns under buy signal than under sell signal. It would be interesting to analyze what factors determine these differences between the stocks. However, having only 26 stocks in the sample, this task does not seem to be a feasible exercise. This analysis probably could be implemented by examining a larger sample of stocks on a bigger stock market.

There is another important factor that has to be taken into account when analyzing the profitability of technical analysis, the effect of transaction costs. Technical analysis requires regular trading on the market. If trading signals are generated when market liquidity is low, transaction costs can be so high (in form of higher bid-ask spread or larger price impact of the trade) that the profit opportunity indicated in this chapter cannot be exploited. I will try to examine this issue by analyzing the relationship between the liquidity of the market and the timing of the signals generated by the trading strategies. In order to be able to analyze this relationship, first I have to measure liquidity on the BSE over the sample period. This part of the research is presented in the next chapter.

4 Liquidity on the Budapest Stock Exchange

In this chapter I will make an attempt to measure the liquidity of assets traded on the Budapest Stock Exchange. Liquidity is a broad concept, because it covers a number of transactional properties of a capital market. Kyle (1985, p. 1316) identifies these properties as "tightness" – the cost of turning around a market position over a short period of time, "depth" – the size of an order flow that changes the market price by a given amount, and "resiliency" – the speed with which prices recover from a random shock.

In an ideal empirical research, measures of liquidity should be calculated using high-frequency data sets that contain transaction level data. However, in many cases high-frequency data sets are not available, or are costly. This is especially true for emerging markets. To overcome this problem, a number of measures have been proposed in the literature that use low-frequency data, that is daily price and volume series, to estimate liquidity. The obvious advantage of these measures is that, because of data availability, they make it possible to study liquidity over long periods of time and over various markets. On the other hand, the disadvantage of them is that they estimate transaction costs less precisely than measures using high-frequency data. That is why measures using only daily price and volume data are frequently referred to as proxies for liquidity.

Liquidity proxies are of special importance for my research. Similarly to other emerging markets, it is hard to obtain transaction level data from the BSE[12]. Therefore, I will use daily return and volume data during my analysis. According to Goyenko et al. (2009) there are two big groups of low-frequency liquidity measures. The first group involves so called spread measures. They try to estimate the average bid-ask spread that an investor faces on a given

[12] The Budapest Stock Exchange calculates a highy frequency liquditiy measure, the Budapest Liquiditiy measure introduced by Kutas & Végh (2005). However, the values of the measure are available only from March 2008, and are not freely accessible.

market. The second group includes the so called price impact measures. Price impact measures try to estimate the effect of a trade with a given size on the market price.

Numerous studies have proposed methods for measuring market liquidity using low-frequency data sets. Roll (1984), Hasbrouck (2004), and Lesmond et al. (1999) develop spread proxies, while Amihud (2002) and Pastor & Stambaugh (2003) introduce different price impact measures. These measures have been derived using different ideas and assumptions about the market. Some important questions arise: how these liquidity measures perform compared to each other? Which proxy should be used in an empirical research?

Goyenko et al. (2009) compare various spread and price impact proxies[13] with liquidity benchmarks calculated from transaction level data sets. They use US data from the period between 1993 and 2005 to carry out the analysis. The general conclusion of the article is that liquidity measures based on daily data provide good estimations of high-frequency transaction cost benchmarks. In most of the cases the correlations between the proxies and their respective benchmarks are high. Goyenko et al. test twelve different spread measures and find that there are three proxies that consistently dominate the remaining nine in performance. The measure developed by Lesmond et al. (1999) is one of these three proxies[14]. Within the price impact measures, Amihud's (2002) measure seems to be the best proxy[15]. One caveat of the paper is that the authors solely focus on US stock markets, thus the results cannot be generalized directly to international markets.

Lesmond (2005) addresses the question, how different liquidity measures perform in emerging markets. The analysis covers 23 emerging markets including Hungary. The author's approach is similar to the one applied by Goyenko et al. (2009), namely that the liquidity proxies are compared to a benchmark in order to determine their efficacy in estimating the underlying liquidity. Lesmond (2005) compares four different liquidity measures, turnover,

[13] Both liquidity measures used in this thesis are included in their analysis.
[14] I will use the measure introduced by Lesmond et al. (1999) as a spread proxy in my analysis.
[15] I will use Amihud's (2002) measure as a price impact measure.

Amihud's (2002) measure, Roll's (1984) measure, and the measure by Lesmond et al. (1999) with a high-frequency benchmark. The author concludes that the LOT measure is the best in capturing within-country liquidity and the measures proposed by Amihud (2002) and Roll (1984) are also valid proxies for liquidity.

It can be concluded that measuring liquidity using daily return and volume data is probably not the best solution. However, if transaction level data sets are not available, these low-frequency liquidity measures provide a reasonable alternative.

4.1 Methodology

In order to measure the liquidity of the stocks in my sample, I will use two liquidity measures proposed in previous studies. As a spread measure, I will use the liquidity proxy introduced in the paper by Lesmond et al. (1999), and as a price impact measure, I will calculate the measure suggested by Amihud (2002).

The starting point of the spread measure of Lesmond et al. (1999) (hereafter, LOT measure) is the incidence of days with zero return. The basic idea behind the LOT measure is that if the value of new information on a given day does not exceed the cost of trading, then the marginal investor will not trade, which will result zero return for the given trading day. The transaction cost can be interpreted as a threshold that has to be exceeded before the return of the asset will reflect new information. Lesmond et al. (1999) propose a latent variable model that describes the above idea:

$$r_{j,t}^{*} = \beta_j \cdot rm_t + \varepsilon_{j,t} \ , and$$

$$r_{j,t} = \begin{cases} r_{j,t}^{*} - \alpha_{1,j} & if \ \ r_{j,t}^{*} < \alpha_{1,j} \ \ and \ \ \alpha_{1,j} < 0 \\ 0 & if \ \ \alpha_{1,j} \le r_{j,t}^{*} \le \alpha_{2,j} \\ r_{j,t}^{*} - \alpha_{2,j} & if \ \ r_{j,t}^{*} > \alpha_{2,j} \ \ and \ \ \alpha_{2,j} > 0 \end{cases} ,$$

where $r^*_{j,t}$ is the true, unobservable return of asset j on day t, $r_{j,t}$ is the observed daily return, rm_t is the observed market return, α_1 is the threshold for trades on negative information, and α_2 is the threshold for trades on positive information.

The marginal trader will weigh the cost of trading against expected gains, and if the expected gains do not exceed the transaction costs, he will not trade. In this case, the observed return is zero. If the expected gains are higher than the transaction cost, the marginal trader will decide to trade on the information and the true return will be observable. Given some distributional assumption about the error term, α_1 and α_2 can be estimated by maximum likelihood[16]. The LOT measure of proportional round-trip transaction costs for asset j will be

$$LOT_j = \hat{\alpha}_{2,j} - \hat{\alpha}_{1,j} \ .$$

I will estimate the LOT measure for each of the assets in my sample at monthly frequency. The LOT spread measure for asset j in month m will be denoted by $LOT_{j,m}$.

Amihud (2002) uses a different approach to define a price impact measure for a given asset. He defines a daily liquidity measure as the ratio of the daily absolute return to the trading volume on that day. The liquidity of asset j in month m is simply calculated as the average of the daily liquidities in the given month

$$Amihud_{j,m} = \frac{1}{T}\sum_{t=1}^{T}\frac{|r_{j,t}|}{vol_{j,t}} \ ,$$

(hereafter, Amihud measure) where T is the number of trading days during the month, $r_{j,t}$ is the daily return of asset j, and $vol_{j,t}$ is the respective daily volume. This ratio can be interpreted as the daily price impact of one unit of trading volume. It shows the magnitude of the price change that can be attributed to a trade worth one unit of the volume, which in this case is 1 HUF. This concept defines liquidity as the response of the price to order flow.

[16] The loglikelihood function of the ML estimation can be found in Lesmond et al (1999, p. 1122). They assume that the error term is normally distributed.

Before continuing the analysis, I made two adjustments to the Amihud measure. First, I multiplied all its values by 1000000. The reason for this is that in their original form, price impact measures show the effect of one unit of trading volume, which is 1 HUF in the case of the BSE. As a consequence, the values of the measures were extremely small. The rescaling produces more convenient magnitudes. After the multiplication, the Amihud measure can be interpreted as the effect of a trade worth 1000000 HUF.

The second adjustment of the measure is suggested by Pastor and Stambaugh (2003). The authors argue that as the relative size of a 1 million HUF trade varies across time, it is reasonable to construct a price impact measure so that it takes into account this variation. They suggest to scale the series by a factor $(capital_t/capital_1)$, where $capital_t$ is the total capitalization of the stocks in the sample at the end of month $t-1$.

There is one more thing to note here. Both liquidity measures indicate less liquid months with higher values. That is why sometimes they are referred to as measures of illiquidity rather than measures of liquidity.

4.2 Results

In order to assess the liquidity of the Budapest Stock Exchange between 1997 and 2008 I calculated the two measures introduced in the previous section (LOT measure and Amihud measure) for every asset $j = 1 \dots 26$ in every month $m = 1 \dots 138$ when the asset appeared in the sample.

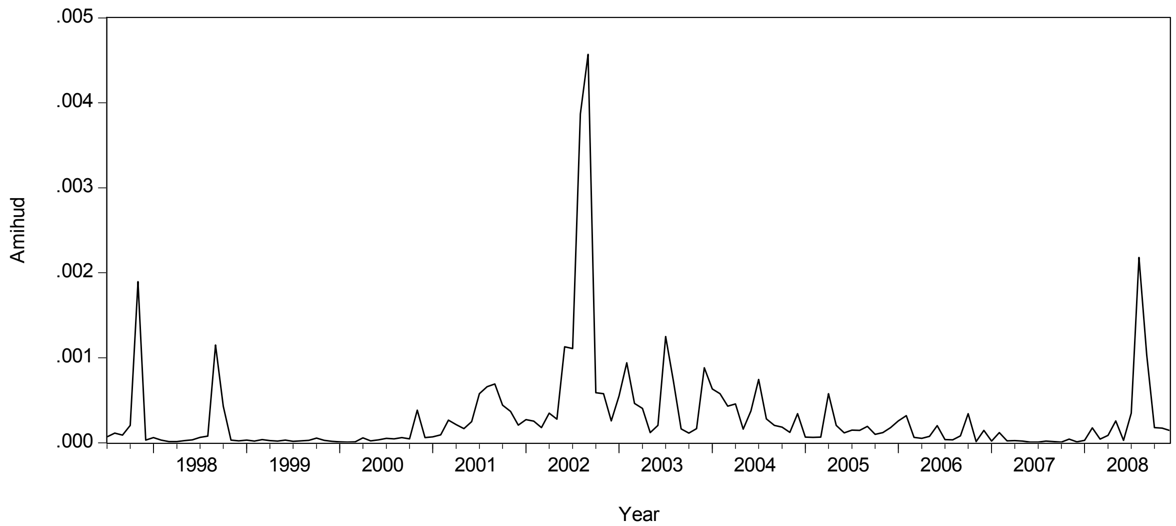
Table 6[17] presents cross-sectional statistics about the calculated liquidity measures. The average value for the Amihud measure ranges from 0.0000045 to 0.0238. This means that in the case of the most liquid stock in the sample, a trade worth one million HUF would have induced a 0.00045 percent price change on average during the sample period. This does not

[17] Table 6 can be found in Appendix 4.

look like a big effect, but there are only a few stocks on the Hungarian stock market with such a relatively high liquidity level. The most illiquid stock in the sample has an average Amihud value of 0.0238, meaning that in the market of this stock, a trade worth one million HUF would have induced a 2.38 percent price change on average, which is a quite considerable effect. If we consider the maximum values of the Amihud measure, we can find values like 0.52. This suggests that for some stock, in its most illiquid month, a one million HUF trade would have changed the price by roughly 52 %. These large values imply that there are stocks in the sample with which it was nearly impossible to trade in some months during the period analyzed. Table 6 presents the same statistics about the LOT measure. On the market of the most liquid stock investors were facing an average bid-ask spread of 0.56 %. The largest average bid-ask spread throughout the period was 2.98 % according to the LOT measure.

Figure 1 plots the market liquidity of the BSE throughout the sample period. The market liquidity is calculated in every month as the capitalization weighted average of the individual stock liquidities.

Figure 1 – Market liquidity measured by the Amihud measure



The figure illustrates an important feature of market liquidity when measured by price impact measures. This is the occasional large drops in liquidity, which is associated with large upward spikes in the Amihud measure. Pastor and Stambaugh (2003) observe similar drops when analyzing the liquidity of US markets. The first big spike in October 1997 corresponds to the height of the Asian financial crisis. The second spike in September 1998 can be associated with the Russian debt crisis and the collapse of the LTCM (Pastor & Stambaugh, 2003, p. 653). The biggest drop in liquidity during the sample period was in the third quarter of 2002, when stock markets around the world experienced serious drops. Until 2002 that was the worst quarter for stock markets since 1987. The most recent spike corresponds to the beginning of the current crisis.

Figure 2 – Market liquidity measured by the LOT measure

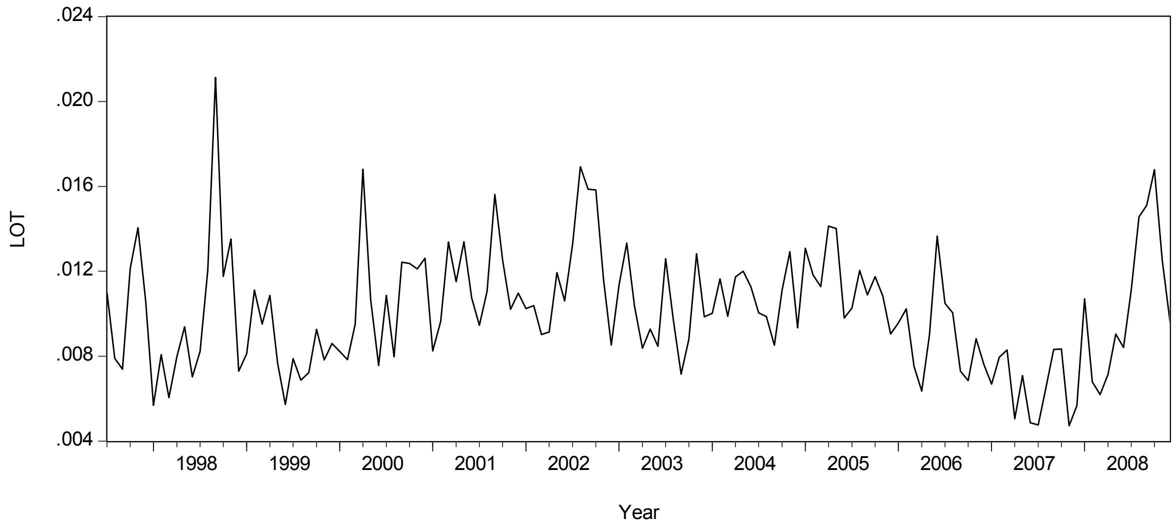


Figure 2 plots the market liquidity when measured with the capitalization weighted average of the individual LOT measures. The changes in the measured bid-ask spread does not show such big drops in liquidity as in the case of the price impact measure. However bigger upward spikes can be observed at the same places as with the previous measure. The correlation between the two measures of market liquidity is 0.498. The two measures are also positively related on individual level. The correlation between them across all observations is 0.254.

After analyzing both the performance of technical analysis and market liquidity on the BSE, I can continue by examining the relationship between them.

5 Relationship between technical analysis and liquidity

The last part of the thesis focuses on the relationship between liquidity and the performance of technical analysis. Following the signals of a technical trading strategy involves active trading on the market. This means that there are liquidity costs connected to every technical trading rule. These liquidity costs occur in the form of various fees, bid-ask spread or as the price impact of the trade. Some of the previous empirical studies have attempted to adjust for transaction costs when analyzing the profitability of technical trading strategies. The adjustment is usually done by assuming fixed amount of transaction costs throughout the period analyzed and deducting it whenever a trade occurs (e.g. Hudson et al., 1996; Ito, 1999; Day & Wang, 2002), or by calculating break-even transaction costs[18] and comparing them to actual transaction costs (e.g. Bessembinder & Chan, 1995; Bessembinder & Chan, 1998). With this approach one can easily adjust for the cross-sectional liquidity differences between stocks by simply calculating separate liquidity costs for each of the stocks analyzed.

However, the possible problem with above approaches is that they do not account for the fact that liquidity is varying over time. The time variability of liquidity is an important aspect regarding the profitability of technical trading rules, because if it turns out that these rules generally produce more trading signals in times of low liquidity, it has severe implications on profitability. Low liquidity, in the form of a higher bid-ask spread or a larger price impact of the trades, can substantially lower the profits that can be obtained by technical analysis.

In this chapter I will make an attempt to analyze the relationship between the liquidity of a stock and the trading activity required by the technical analysis. The main question

[18] Break-even transaction cost is defined as the transaction cost that would totally eliminate the profit generated by the trading rule.

throughout the chapter is whether trading rules generate more trading signals in times when market liquidity is lower than usual. If this is the case, the profit opportunities found in chapter 3 may not be exploitable.

5.1 Data and methodology

In order to analyze the relationship between the liquidity of the market and the timing of the trading signals generated by the technical rule, I will rely on the results of chapter 3 and chapter 4, as the data used in the analysis comes from these chapters.

The data is structured as panel data. The cross-sectional units are the 26 stocks in the sample ($i = 1 \dots 26$), while the time dimension consists of 138 consecutive months between July 1997 and December 2008 ($t = 1 \dots 138$). This would mean a total of 3588 observations. However, as described in chapter 2, not all the stocks are present in the sample throughout the whole period, so the panel dataset will be unbalanced with a total number of 2688 observations.

The dependent variable will be the number of trading signals generated in each month by the best performing trading rule for each of the stocks. These are the trading rules that are summarized in Table 5. I chose to use the best performing rules in the analysis because I am interested in whether the rules that seem to work well produce more or less signals in low liquidity months. The dependent variable is calculated for stock i in month m simply as the number of signal changes (from buy to sell or from sell to buy) during the month. The variable will be denoted as $Signal_{it}$.

The variable of main interest is the measure of illiquidity. I will use both measures introduced in chapter 4. The measure introduced by Amihud (2002) will be denoted by $Amihud_{it}$ and the measure developed by Lesmond et al. (1999) will be denoted by LOT_{it}. In some of the specifications I will use dummy variables that indicate months with extremely low or extremely high liquidity for each stock. I will use these dummy variables to assess how the trading rules behave in months with extreme liquidity or illiquidity. $Illiq10_{it}$ for example will take value 1 for stock i in 10 percent of the months, when the value of the liquidity measure is the highest for stock i. So $Illiq10_{it}$ is a dummy for the 10 percent most illiquid months for each of the stocks. $Liq10_{it}$ will be the dummy for the 10 percent most liquid months for each of the stocks. I will also use the variables $Illiq5_{it}$, $Liq5_{it}$, $Illiq20_{it}$, and $Liq20_{it}$ that are defined similarly.

I will use two other variables in the regressions. The first measures the average daily return on stock i in month m, and is denoted by Ret_{it}.The second is the standard deviation of the daily returns during the month and is denoted by Sd_{it}. It is important control for these variables, because drops in liquidity are usually associated with market downturns and high volatility.

Some cross-sectional descriptive statistics of the liquidity measures have already been summarized in Table 6. Cross-sectional descriptive statistics of other variables are shown in Table 7[19]. It can be observed that the averages of the dependent variable ($Signal_{it}$) are quite different. This reflects the fact that for different stocks, different kind of trading rules had the best performance. For some of the stocks, the best trading rule generated trading signals often, and for other stocks the best strategy generated signals less frequently. Figures 1 and 2 have already presented the monthly (capitalization weighted) averages of the liquidity measures. Figures 3 to 5[20] present the monthly (simple) averages of the other variables. None of the variables seem to contain trend or seasonality. When the variables are plotted for the individual stocks, similar pictures arise.

[19] Table 7 can be found in Appendix 4.
[20] Figures 3 to 5 can be found in Appendix 3.

In order to uncover the relationship between liquidity and the number of signals generated by the technical trading rules, I will estimate the following model:

$$Signal_{it} = \beta_0 + \beta_1 \cdot Liquidity_{it} + \beta_2 \cdot Ret_{it} + \beta_3 \cdot Sd_{it} + a_i + \varepsilon_{it} \quad ,$$

where $Liquidity_{it}$ denotes the liquidity measure used in the particular specification. In specifications where the liquidity measures appear in their original form (not the dummies indicating extreme liquidity months), I will use the logarithmic transformation of the measures. This transformation is suggested by Amihud (2002) in the paper where he introduced the Amihud measure, and tested the effect over time of market illiquidity on expected stock return.

The a_i term in the above model corresponds to the cross-sectional heterogeneity. I will estimate the model with cross-sectional fixed effects in order to account for factors that determine the cross-sectional differences between the numbers of signals generated. These, for example, include factors that determine what type of rule provides the best performance for a particular stock.

There is one more possible problem that I have to take into account during the estimation, the problem of simultaneity. The problem of simultaneity might arise if market participants really use these technical rules, or at least similar strategies. In this case if a trading signal is generated, it will induce trading, which will affect the liquidity, the average return and the volatility of the given month. I try to overcome this problem by using instrumental variables. I will try to instrument the variables $\log(Amihud_{it})$, Ret_{it}, and Sd_{it} by their counterparts calculated from the Dow Jones Industrial Average (DJIA) index for the same period. The variable $AmihudDJIA_t$ is the Amihud measure calculated from the DJIA in month t. The variable $RetDJIA_t$ is the average daily return of the DJIA during month t, and $SdDJIA_t$ denotes the standard deviation of the daily returns in month t. All the cross-sectional units ($i = 1 \ldots 26$) are instrumented with the same series calculated from the DJIA.

5.2 Results

Table 8[21] presents the coefficient estimates for the different specifications of the model introduced in the previous section. In the first regression (column 1) the variable $\log(Amihud_{it})$ is used as the measure of liquidity. The coefficient is positive suggesting that less liquid months (higher Amihud value) are associated with more trading signals. The coefficient is statistically significant at 5% significance level. However, the magnitude of the coefficient is very small. It suggests that a hundred percent increase in the value of the Amihud measure is associated with 0.035 more trading signals during the month. Although the value of the Amihud measure increases to a large extent in times of very low liquidity, the economic significance of this effect is still negligible.

In the second regression illiquidity is measured with the spread measure (LOT). The coefficient on $\log(LOT_{it})$ is positive again, implying that more trading signals are generated in months with less liquidity, however the coefficient is not statistically nor economically significant. Since only the Amihud measure had statistically significant coefficient, I use only this measure in the rest of the specifications.

In regressions 3 to 5 the extreme liquidity and illiquidity dummies are used. In column 3 the effect of the 5 percent most extreme months is considered. It can be concluded that in the most illiquid months 0.1 more trading signal is produced by the trading strategies than in months with usual liquidity. The coefficient is statistically significant and the effect is a little bit higher than in the previous specifications considering that across all stock the average signal per month is around 1.2. It can be also concluded from this regression that in the most liquid months, on average, 0.24 less signal is produced. In columns 4 and 5 we can see that the effect of the extreme month dummies becomes less and less significant if more and more months are taken into account.

[21] Table 8 can be found in Appendix 4.

The last column shows the result of the regression where the simultaneity problem is trying to be handled. The variables are the same as in the first column, but the instrumental variable estimation is used. The size of the coefficient is similar to that in column 1, but the coefficient becomes statistically insignificant.

In sum it can be concluded that I have not found a strong relationship between illiquidity and the number of trading signals generated by the technical trading strategies. In some of the specifications there is a statistically significant positive relationship, but the magnitudes of the effects are negligible and if the simultaneity problem is taken into account, even the statistical significance is disappearing.

6 Conclusion

In this thesis I have concentrated on two issues. In the first part, I have examined the performance of technical analysis on the Hungarian stock market. I have tested 120 different moving average indicators on 26 different stocks of the Budapest Stock Exchange (BSE) over the period from 1997 to 2008. In the second part of the thesis, I have analyzed whether the liquidity of the market can be an obstacle in exploiting the profit opportunities provided by technical analysis.

When analyzing the profitability of moving average rules on the BSE, I used the model-based bootstrap methodology proposed by the widely cited study of Brock et al. (1992). In line with previous empirical research on other emerging markets, I have found that for most of the stocks, technical trading strategies provide profit opportunities that cannot be explained by any of the popular null models of asset returns (random walk with a drift, AR(1), GARCH(1,1)-M). Moreover, by examining individual stocks, I was able to point out that the performance of technical analysis varies over different stocks. There were stocks in my sample for which large proportion of the trading rules tested have proved to be profitable. On the other hand, there were nine stocks in the sample, for which none of the moving average indicators were significantly profitable during the period analyzed. A possible extension of this part of the thesis would be to assess the factors determining how successful technical analysis is on the market of a particular stock.

After analyzing the performance of technical analysis, I continued by examining whether the time variation of market liquidity can be a problem in exploiting the profit opportunities provided by technical trading strategies. For measuring liquidity, I used two liquidity proxies proposed in previous literature, one developed by Amihud (2002) and the other by Lesmond et al. (1999). I used panel data of the same 26 stocks over the 138 months of the sample period to study the relationship between market liquidity and the timing of trades generated by the most successful trading strategies. My results indicate that there is no strong link between the timing of the trades and the changes in liquidity. In some specifications I have found statistically significant positive relationship between illiquidity of the market and the number of trades required by technical trading rules. However, the magnitude of the effect is economically negligible and when the problem of simultaneity is handled, even the statistical significance is disappearing.

My results suggest that adjusting the profitability of technical analysis with constant transaction costs over the period analyzed, which is a common practice in the empirical literature, is not a bad solution.

Appendices

Appendix 1 Listing requirements for equities in category "A"

6.3 Further Listing Requirements for Equities Category "A"

6.3.1 The value of security series to be listed may not be below HUF two billion five hundred million (2,500,000,000) in terms of market value.

6.3.2 Minimum Free Float
At the time of listing the security series, the requirements for the minimum free float are:

6.3.2.1 A minimum of 25% of the securities in the series to be listed shall constitute the free float.

6.3.2.2 To meet the required Free Float minimum – in case the ration falls short of 25% - the market value of freely floating securities shall be at least HUF two (2) billion.

6.3.2.3 If the security series does not meet the requirements listed in sub section 6.3.2.1 and 6.3.2.2 than the security series shall be held by at least five hundred (500) investors with ownership evidenced at the time of listing.

6.3.3 The series to be listed shall be held by at least one hundred (100) investors, with evidence of ownership available.

6.3.3.1 The requirement related to the number of shareholders need not be examined for Issuers that apply for listing securities that are already listed at a regulated market and are found to pass the category tests performed using the trading data of that market.

6.3.4 The Issuer of the securities (taking its legal predecessor into consideration as well) shall have three full business years, certified by an auditor.

Source: Regulations of the Budapest Stock Exchange for listing, continued trading and disclosure - Effective date: 01 May, 2009; http://www.bse.hu/data/cms61385/ListingReg_010509_tiszta_v1.1.pdf; downloaded: 15 May, 2009.

Appendix 2 Moving average rules examined during the analysis

#	SMA	LMA	#	SMA	LMA	#	SMA	LMA	#	SMA	LMA
1	1	5	31	10	20	61	20	80	91	40	125
2	1	10	32	10	25	62	20	90	92	40	150
3	1	15	33	10	30	63	20	100	93	50	60
4	1	20	34	10	40	64	20	125	94	50	70
5	1	25	35	10	50	65	20	150	95	50	80
6	1	30	36	10	60	66	25	30	96	50	90
7	1	40	37	10	70	67	25	40	97	50	100
8	1	50	38	10	80	68	25	50	98	50	125
9	1	60	39	10	90	69	25	60	99	50	150
10	1	70	40	10	100	70	25	70	100	60	70
11	1	80	41	10	125	71	25	80	101	60	80
12	1	90	42	10	150	72	25	90	102	60	90
13	1	100	43	15	20	73	25	100	103	60	100
14	1	125	44	15	25	74	25	125	104	60	125
15	1	150	45	15	30	75	25	150	105	60	150
16	5	10	46	15	40	76	30	40	106	70	80
17	5	15	47	15	50	77	30	50	107	70	90
18	5	20	48	15	60	78	30	60	108	70	100
19	5	25	49	15	70	79	30	70	109	70	125
20	5	30	50	15	80	80	30	80	110	70	150
21	5	40	51	15	90	81	30	90	111	80	90
22	5	50	52	15	100	82	30	100	112	80	100
23	5	60	53	15	125	83	30	125	113	80	125
24	5	70	54	15	150	84	30	150	114	80	150
25	5	80	55	20	25	85	40	50	115	90	100
26	5	90	56	20	30	86	40	60	116	90	125
27	5	100	57	20	40	87	40	70	117	90	150
28	5	125	58	20	50	88	40	80	118	100	125
29	5	150	59	20	60	89	40	90	119	100	150
30	10	15	60	20	70	90	40	100	120	125	150

Appendix 3 Figures

Figure 3 – Monthly averages of variable *Signal*

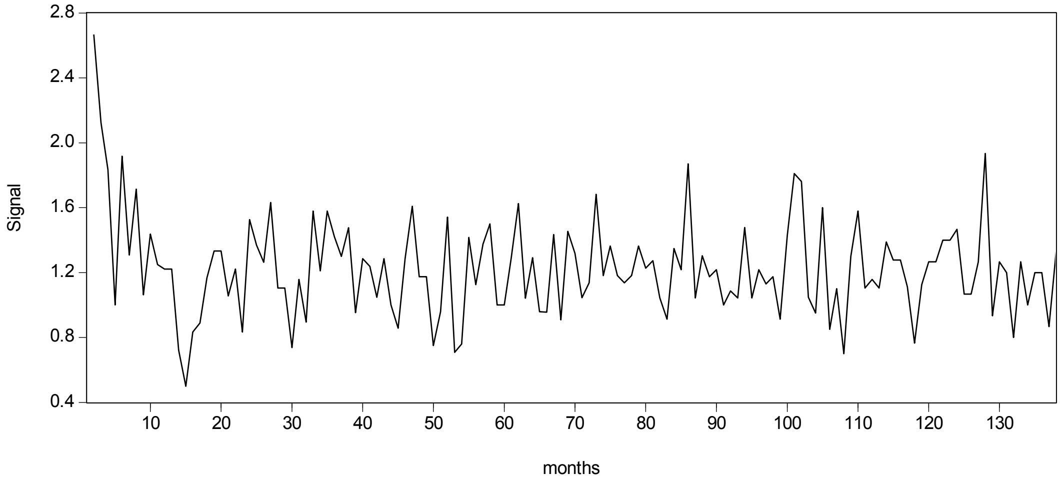


Figure 4 – Monthly averages of variable *Ret*

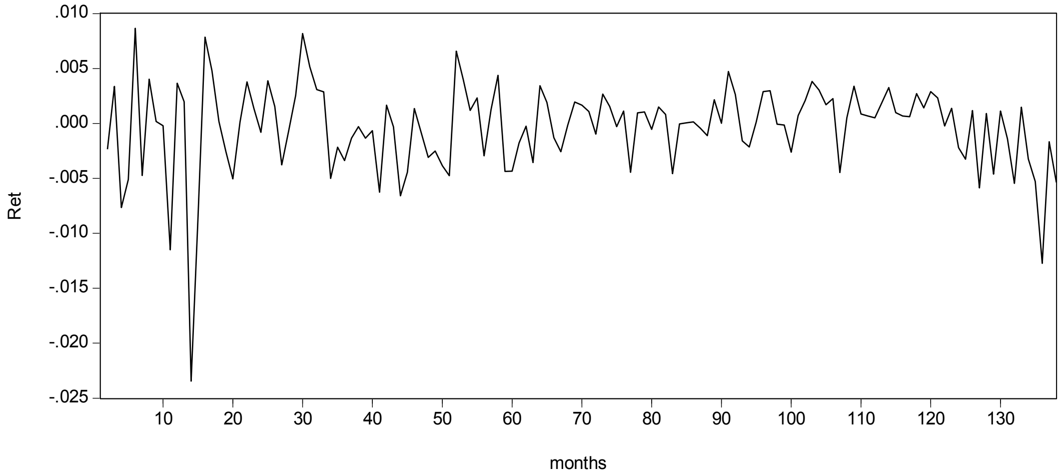
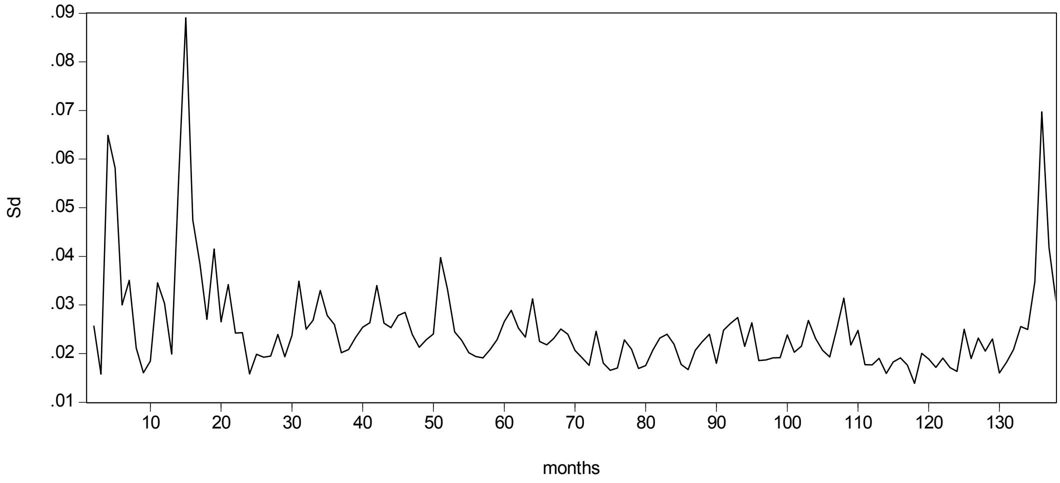


Figure 5 – Monthly averages of variable *Sd*



Appendix 4 Tables

Table 1 – Stocks in the sample

	starting date	end date	trading days	trading months
ANTENNA	02/04/2001	15/02/2006	1222	58
BCHEM	01/07/1997	29/03/2007	2438	116
DANUBIUS	01/07/1997	31/12/2008	2873	138
DEMASZ	01/04/1998	30/11/2006	2173	104
EGIS	01/07/1997	31/12/2008	2873	138
EXBUS	01/03/2000	30/09/2005	1399	67
FHB	01/12/2003	31/12/2008	1275	61
FOTEX	01/07/1997	31/12/2008	2873	138
GLOBUS	02/04/2001	21/08/2006	1351	64
GRABO	01/07/1997	28/12/2001	1119	53
GRAPHI	16/05/2000	14/06/2007	1774	84
HUMET	02/04/2001	31/12/2008	1937	93
IEB	01/07/1997	17/05/2007	2470	118
LINAMAR	02/04/2001	31/12/2008	1937	92
MOL	01/07/1997	31/12/2008	2873	138
MTELEKOM	14/11/1997	31/12/2008	2778	133
OTP	01/07/1997	31/12/2008	2873	138
PANNERGY	01/07/1997	31/12/2008	2873	138
PICK	01/07/1997	29/11/2002	1349	64
PRIMAGAZ	01/07/1997	31/01/2003	1390	67
RABA	17/12/1997	31/12/2008	2755	132
RICHTER	01/07/1997	31/12/2008	2873	138
SYNERGON	05/05/1999	31/12/2008	2418	115
TVK	01/07/1997	31/12/2008	2873	138
ZKERAMIA	01/07/1997	30/09/2005	2063	97
ZWACK	01/07/1997	31/12/2008	2873	138

Table 2 – Estimated coefficients for the AR(1) models

	α	(t-stat)	ρ	(t-stat)
ANTENNA	0.00038	(0.59)	-0.024	(-0.84)
BCHEM	0.00027	(0.5)	-0.005	(-0.27)
DANUBIUS	-0.00009	(-0.2)	-0.142	(-7.66)
DEMASZ	-0.00003	(-0.06)	-0.030	(-1.42)
EGIS	-0.00006	(-0.12)	0.007	(0.4)
EXBUS	-0.00263	(-3.82)	-0.046	(-1.72)
FHB	0.00044	(0.6)	-0.041	(-1.46)
FOTEX	0.00018	(0.29)	-0.003	(-0.14)
GLOBUS	-0.00015	(-0.2)	-0.151	(-5.6)
GRABO	-0.00171	(-1.36)	-0.155	(-5.23)
GRAPHI	-0.00062	(-0.93)	-0.079	(-3.33)
HUMET	-0.00195	(-1.61)	0.075	(3.31)
IEB	-0.00006	(-0.1)	-0.084	(-4.2)
LINAMAR	0.00014	(0.22)	-0.189	(-8.39)
MOL	0.00028	(0.63)	0.065	(3.51)
MTELEKOM	-0.00012	(-0.31)	0.013	(0.69)
OTP	0.00056	(1.12)	0.065	(3.51)
PANNERGY	-0.00033	(-0.65)	0.003	(0.18)
PICK	-0.00083	(-0.93)	0.014	(0.51)
PRIMAGAZ	-0.00129	(-1.19)	-0.116	(-4.34)
RABA	-0.00059	(-1.19)	0.018	(0.95)
RICHTER	0.00016	(0.32)	0.077	(4.14)
SYNERGON	-0.00068	(-1.14)	0.093	(4.57)
TVK	-0.00012	(-0.23)	-0.043	(-2.31)
ZKERAMIA	-0.00055	(-0.86)	-0.035	(-1.61)
ZWACK	0.00043	(1.03)	-0.151	(-8.19)

The estimation was implemented using Eviews6.

Table 3 – Estimated coefficients for the GARCH(1,1)-M model

	θ	t-stat	λ	t-stat	ω	t-stat	α	t-stat	β	t-stat
ANTENNA	0.0004	(0.52)	-0.44	(-0.2)	6.0E-05	(11.83)	0.24	(11.81)	0.67	(31.32)
BCHEM	-0.0005	(-0.95)	1.09	(1.1)	8.5E-06	(10.43)	0.14	(29.77)	0.88	(305.87)
DANUBIUS	-0.0004	(-0.59)	1.22	(0.95)	4.1E-05	(10.22)	0.13	(12.06)	0.81	(62.23)
DEMASZ	0.0011	(1.68)	-1.83	(-0.98)	2.4E-05	(11.87)	0.17	(15.98)	0.79	(95.99)
EGIS	0.0003	(0.33)	0.40	(0.33)	3.5E-05	(10.34)	0.13	(20.12)	0.83	(92.53)
EXBUS	-0.0030	(-1.98)	1.22	(0.49)	7.2E-05	(5.71)	0.14	(7.28)	0.75	(25.01)
FHB	0.0012	(1.24)	-0.30	(-0.19)	4.6E-05	(5.96)	0.15	(10.31)	0.79	(35.25)
FOTEX	-0.0008	(-1.01)	1.50	(1.7)	4.5E-05	(15.21)	0.13	(17.78)	0.84	(167.16)
GLOBUS	-0.0024	(-1.63)	3.32	(1.68)	8.1E-05	(10.52)	0.12	(8.59)	0.78	(43.75)
GRABO	-0.0015	(-1.47)	0.45	(0.52)	1.4E-04	(11.2)	0.33	(14.07)	0.60	(30.16)
GRAPHI	-0.0015	(-0.52)	1.39	(0.38)	3.0E-04	(8.39)	0.09	(6)	0.54	(9.78)
HUMET	-0.0033	(-2.36)	0.33	(0.53)	4.6E-04	(12.48)	0.31	(11.46)	0.52	(18.19)
IEB	-0.0025	(-1.52)	2.52	(1.48)	6.0E-04	(14.33)	0.15	(9.43)	0.20	(3.68)
LINAMAR	0.0024	(2.16)	-2.60	(-1.64)	3.2E-06	(4.63)	0.02	(12.43)	0.97	(449.1)
MOL	0.0007	(1.13)	0.36	(0.29)	2.7E-05	(8.9)	0.14	(22.21)	0.81	(76.24)
MTELEKOM	-0.0008	(-1.09)	2.51	(1.42)	2.0E-05	(8.91)	0.10	(10.58)	0.85	(71.94)
OTP	0.0010	(1.71)	0.40	(0.38)	2.5E-05	(9.19)	0.14	(16.88)	0.83	(84.79)
PANNERGY	0.0004	(0.62)	-0.42	(-0.39)	4.9E-05	(12.38)	0.15	(14.35)	0.79	(74.82)
PICK	-0.0012	(-0.97)	1.28	(0.79)	6.7E-05	(16.51)	0.17	(17.58)	0.79	(99.01)
PRIMAGAZ	-0.0040	(-1.07)	1.87	(0.8)	8.3E-04	(7.9)	0.14	(6.25)	0.37	(4.59)
RABA	-0.0012	(-1.74)	1.95	(1.43)	6.1E-05	(11.73)	0.16	(12.49)	0.75	(43.9)
RICHTER	0.0003	(0.46)	0.68	(0.61)	1.9E-05	(8.82)	0.10	(19.02)	0.87	(137.85)
SYNERGON	-0.0007	(-0.87)	0.66	(0.56)	2.0E-05	(8.61)	0.07	(15.39)	0.90	(162.42)
TVK	0.0003	(0.61)	0.38	(0.41)	1.8E-05	(11.11)	0.13	(25.03)	0.86	(174.08)
ZKERAMIA	0.0003	(0.48)	-0.59	(-0.64)	2.9E-05	(13.5)	0.21	(16.09)	0.78	(74.11)
ZWACK	0.0002	(0.58)	0.43	(0.47)	2.6E-05	(22.39)	0.19	(22.5)	0.77	(114.33)

The estimation was implemented using EViews6.

Table 4 – Summary of the performance of all trading rules

		# of rules from the 120, where				
	m_b-m_s	m_b-m_s>0	0.05>p_1	0.05>p_2	0.05>p_3	s_b<s_s
ANTENNA	-0.00023	47	7	7	6	113
BCHEM	0.00025	74	9	10	0	120
DANUBIUS	0.00024	96	1	1	1	120
DEMASZ	0.00002	68	0	0	0	118
EGIS	0.00168	114	71	70	67	120
EXBUS	0.00154	103	31	34	23	119
FHB	0.00251	116	77	87	67	120
FOTEX	0.00212	120	73	74	0	83
GLOBUS	0.00068	99	4	14	1	120
GRABO	0.00309	118	30	54	27	120
GRAPHI	0.00157	118	28	44	35	74
HUMET	0.00152	102	7	4	3	93
IEB	0.00027	96	0	0	0	77
LINAMAR	0.00074	99	28	53	0	120
MOL	0.00027	75	12	5	11	120
MTELEKOM	-0.00002	58	0	0	0	118
OTP	0.00015	67	4	3	4	120
PANNERGY	0.00152	120	51	51	50	120
PICK	0.00123	107	9	9	1	119
PRIMAGAZ	0.00108	82	11	27	6	87
RABA	0.00143	116	42	41	43	120
RICHTER	0.00026	86	1	0	1	120
SYNERGON	0.00264	120	89	80	84	109
TVK	0.00103	102	35	38	22	120
ZKERAMIA	0.00079	110	5	8	0	120
ZWACK	-0.00009	74	0	0	0	115

p_1, p_2 and p_3 denote the simulated p-values from the model-based bootstrap procedure with the null model of the random walk (p_1), the AR(1) (p_2), and the GARCH(1,1)- M (p_3).

Table 5 – Summary of the performance of the best performing rule

	m_b-m_s	p_1	p_2	p_3	s_b	s_s
ANTENNA	0.00289	0.014 **	0.008 ***	0.026 **	0.0220	0.0223
BCHEM	0.00319	0.002 ***	0.002 ***	0.256	0.0208	0.0296
DANUBIUS	0.00186	0.038 **	0.018 **	0.034 **	0.0228	0.0290
DEMASZ	0.00122	0.090 *	0.076 *	0.212	0.0191	0.0225
EGIS	0.00313	0.000 ***	0.004 ***	0.006 ***	0.0226	0.0312
EXBUS	0.00353	0.008 ***	0.010 **	0.014 **	0.0183	0.0266
FHB	0.00378	0.004 ***	0.000 ***	0.018 **	0.0202	0.0313
FOTEX	0.00434	0.000 ***	0.000 ***	0.052 *	0.0331	0.0335
GLOBUS	0.00319	0.022 **	0.010 **	0.026 **	0.0227	0.0317
GRABO	0.00594	0.020 **	0.008 ***	0.026 **	0.0262	0.0477
GRAPHI	0.00340	0.008 ***	0.002 ***	0.010 **	0.0282	0.0290
HUMET	0.00472	0.020 **	0.032 **	0.036 **	0.0507	0.0519
IEB	0.00169	0.076 *	0.062 *	0.058 *	0.0280	0.0327
LINAMAR	0.00311	0.006 ***	0.002 ***	0.078 *	0.0216	0.0336
MOL	0.00231	0.004 ***	0.034 **	0.002 ***	0.0214	0.0261
MTELEKOM	0.00115	0.078 *	0.100	0.072 *	0.0188	0.0231
OTP	0.00255	0.000 ***	0.008 ***	0.006 ***	0.0226	0.0315
PANNERGY	0.00288	0.002 ***	0.004 ***	0.004 ***	0.0227	0.0296
PICK	0.00366	0.016 **	0.018 **	0.048 **	0.0300	0.0351
PRIMAGAZ	0.00460	0.016 **	0.002 ***	0.022 **	0.0410	0.0415
RABA	0.00247	0.010 **	0.014 **	0.014 **	0.0219	0.0290
RICHTER	0.00189	0.020 **	0.132	0.028 **	0.0237	0.0292
SYNERGON	0.00523	0.000 ***	0.002 ***	0.000 ***	0.0296	0.0297
TVK	0.00301	0.002 ***	0.002 ***	0.018 **	0.0253	0.0307
ZKERAMIA	0.00273	0.014 **	0.012 **	0.072 *	0.0250	0.0329
ZWACK	0.00115	0.072 *	0.050 *	0.080 *	0.0182	0.0268

p_1, p_2 and p_3 denote the simulated p-values from the model-based bootstrap procedure with the null model of the random walk (p_1), the AR(1) (p_2), and the GARCH(1,1)- M (p_3). If the simulated p-value is smaller than 0.1, 0.05, and 0.01, it is denoted by *, **, and *** respectively.

Table 6 – Cross sectional statistics of liquidity measures

		Amihud		LOT	
	obs	mean	max	mean	max
ANTENNA	58	0.0009	0.0081	0.0119	0.0343
BCHEM	116	0.0011	0.0312	0.0109	0.0412
DANUBIUS	138	0.0074	0.4353	0.0164	0.0512
DEMASZ	104	0.0010	0.0106	0.0119	0.0443
EGIS	138	0.0001	0.0012	0.0115	0.0899
EXBUS	67	0.0084	0.2815	0.0187	0.0598
FHB	61	0.0004	0.0094	0.0116	0.0422
FOTEX	138	0.0043	0.1664	0.0195	0.1463
GLOBUS	64	0.0109	0.1188	0.0281	0.1172
GRABO	53	0.0022	0.0229	0.0172	0.0715
GRAPHI	84	0.0087	0.4444	0.0146	0.0678
HUMET	93	0.0238	0.5222	0.0267	0.0795
IEB	118	0.0105	0.1531	0.0248	0.1535
LINAMAR	92	0.0117	0.3274	0.0298	0.1430
MOL	138	4.5E-06	8.4E-05	0.0065	0.0535
MTELEKOM	133	4.6E-06	2.1E-05	0.0070	0.0294
OTP	138	7.1E-06	9.4E-05	0.0056	0.0325
PANNERGY	138	0.0027	0.0749	0.0148	0.0592
PICK	64	0.0035	0.0568	0.0211	0.1266
PRIMAGAZ	67	0.0124	0.2068	0.0252	0.1049
RABA	132	0.0005	0.0034	0.0137	0.0602
RICHTER	138	1.5E-05	0.0005	0.0079	0.0277
SYNERGON	115	0.0006	0.0063	0.0149	0.0882
TVK	138	0.0011	0.0328	0.0137	0.0513
ZKERAMIA	97	0.0039	0.1148	0.0172	0.1056
ZWACK	138	0.0068	0.4138	0.0204	0.1794

Table 7 – Cross-sectional descriptive statistics of variables

	Signal		Ret		Sd	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
ANTENNA	1.35	1.03	0.00034	0.0047	0.020	0.010
BCHEM	0.19	0.40	0.00028	0.0059	0.023	0.013
DANUBIUS	0.45	0.72	-0.00010	0.0042	0.024	0.012
DEMASZ	0.82	0.81	0.00012	0.0045	0.019	0.009
EGIS	0.44	0.72	-0.00004	0.0063	0.024	0.013
EXBUS	0.16	0.57	-0.00266	0.0048	0.024	0.009
FHB	0.12	0.33	-0.00010	0.0046	0.024	0.012
FOTEX	1.22	1.12	0.00011	0.0087	0.029	0.016
GLOBUS	0.22	0.49	-0.00009	0.0049	0.025	0.012
GRABO	0.17	0.43	-0.00190	0.0090	0.032	0.028
GRAPHI	0.55	0.71	-0.00047	0.0066	0.024	0.014
HUMET	1.52	1.23	-0.00215	0.0103	0.047	0.025
IEB	0.34	0.59	-0.00016	0.0073	0.025	0.018
LINAMAR	0.07	0.26	0.00005	0.0041	0.025	0.013
MOL	5.32	2.08	0.00024	0.0051	0.021	0.011
MTELEKOM	1.52	1.76	-0.00025	0.0048	0.020	0.008
OTP	0.82	0.84	0.00056	0.0055	0.023	0.013
PANNERGY	0.25	0.66	-0.00035	0.0060	0.024	0.012
PICK	1.53	1.11	-0.00092	0.0075	0.027	0.019
PRIMAGAZ	1.11	0.84	-0.00126	0.0083	0.035	0.022
RABA	0.36	0.69	-0.00054	0.0052	0.023	0.012
RICHTER	5.27	1.93	0.00011	0.0058	0.023	0.013
SYNERGON	2.15	1.20	-0.00075	0.0079	0.026	0.013
TVK	0.70	0.90	-0.00020	0.0057	0.025	0.015
ZKERAMIA	1.07	0.82	-0.00076	0.0071	0.024	0.016
ZWACK	0.42	0.63	0.00032	0.0032	0.018	0.013
All	*1.21*	*1.81*	*-0.00029*	*0.0062*	*0.025*	*0.015*

Table 8 – Estimation results for the *Signal* regressions

Dependent var.:	Signal					
log(Amihud)	0.0346					0.0305
	(0.029)					(0.602)
log(LOT)		0.0003				
		(0.265)				
Illiq5 (Amihud)			0.1080			
			(0.013)			
Liq5 (Amihud)			-0.2471			
			(0.029)			
Illiq10 (Amihud)				0.0393		
				(0.090)		
Liq10 (Amihud)				-0.1538		
				(0.030)		
Illiq20 (Amihud)					0.0085	
					(0.870)	
Liq20 (Amihud)					-0.1253	
					(0.090)	
Ret	8.2496	7.5211	8.1347	8.1714	8.1049	10.9536
	(0.057)	(0.059)	(0.047)	(0.047)	(0.057)	(0.338)
Sd	-7.3585	-6.6339	-7.1909	-7.0223	-6.9430	-7.9911
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.074)
Intercept	1.7008	1.3781	1.3967	1.3970	1.4104	1.6812
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)
cross-section FE	yes	yes	yes	yes	yes	yes
IV-s used	no	no	no	no	no	yes
R^2	0.669	0.668	0.669	0.668	0.668	0.669
Obs.	2688	2688	2688	2688	2688	2688

The p-values are calculated using White period method of EViews that is robust to arbitrary serial correlation and time-varying variances in the disturbances.

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