A Work Project, presented as part of requirements for the Award of a Master Degree in International Finance from the NOVA – School of Business and Economics.

EMPIRICAL TESTS ON THE HUNGARIAN STOCK MARKET EFFICIENCY: ECONOMIC VALUE OF STOCK RETURN FORECASTS

VIRÁG CSUTHI 3304

A Project carried out on the Master in International Finance Program, under the supervision of:

André Castro Silva and Nucera Federico Calogero

MAY 2018

ABSTRACT

This paper focuses on the Hungarian stock market efficiency by applying a customized version of the recursive modeling approach and the switching portfolio strategy employed by Pesaran and Timmermann (1995). I investigate whether this modeling technique could have been more profitable comparing to a passive investment. I discover that the variables' predictive power and the economic value of the forecasts are liable to changes during the examined timeframe and the switching trading strategy cannot beat the market in the full sample. It provides approximately 1.5 times higher wealth, than the portfolios under the different model selection criterions. However, splitting the sample into two, the economic value of the forecasts becomes significant and the switching strategy can result economic profit.

Key words: stock return forecasts, Hungarian stock market, efficient market hypothesis, economic profit

INTRODUCTION

In this paper, I analyze the Hungarian stock market efficiency by simulating an investor's decision in real time. I examine, whether abnormal profits could be generated by trading with forecasts, based on publicly available information and a set of predictors. The representative investor is in possession of only historically available information and she faces model uncertainty regarding the choice of the forecasting variables, and the predictive model. Therefore, I assume, that the investor has a base set of candidate variables, which have been a priori considered to be relevant for forecasting, and each month she utilizes the model selection criteria to select the desired predictive model from all the possible combinations, when forecasting the next month's excess return. Further assuming that the investor has full confidence in her forecasts and she adopts these recursive forecasts into a trading strategy, in which she switches funds between the stock market index and bond, depending on whether the predicted excess returns are positive or negative. (17,20,22)

To evaluate whether excess stock returns are predictable to generate economic profit, I calculate the final wealth based on the portfolio decisions under the different model selection criterions and compare it to the wealth according to the passive investment, the buy-and-hold strategy. Since I simulate investors' portfolio decisions in real time, I need to consider one additional factor, the transaction costs. During the analysis I consider three possible scenarios: zero, low and high transaction cost. (17,23)

While there is an extensive literature and intense research on the predictability of stock returns of the US and UK stock market, other stock markets earned less academic attention. This is especially true for emerging markets, like Hungary. Because of the above mentioned and to enhance the personal motivation, I will evaluate in this paper my home country's stock market efficiency and focus on the Hungarian stock market index, the BUX index and consider an investor with strong home bias. (21)

I perform a whole sample analysis, and then deepen it with dividing the sample into two subsamples and performing the same examination for the sub periods. I have found that the economic profits gained from the forecasts are various across the different examined sample periods. If the investor had traded based on the switching portfolio strategy during the whole sample or the second sub-sample, she could have not gained economic profits. Moreover, the highest profit through these periods could have been exploited by investing in the market portfolio. However, applying this strategy for the first subsample, she could have earned substantial profit in excess of a passive investment. Considering the evaluation of market efficiency, let us take a look at the definition of Malkiel (1992): *"A capital market is said to be efficient if it fully and correctly reflects all relevant information in determining security prices. Formally, the market is said to be efficient with respect to some information set,* Ω_t*, if security prices would be unaffected by revealing that information to all participants. Moreover, efficiency with respect to an information set,* Ω_t*, implies that it is impossible to make economic profits by trading on the basis of* Ω_t*."* Given this, we can conclude that however there has been a period when the investor could have successfully outperformed the market and generated significant profit, by the end of the examined sample period the Hungarian stock market can be considered informationally efficient as the investor could not exploit the market with historically available information. (17,20,22)

METHODOLOGY

The switching portfolio strategy

I am observing an investor who believes in stock return predictability by means of a set of factors, but does not know the best underlying specification. Therefore, she chooses from the models, a priori believed to be able to forecast stock returns. Furthermore, I am contemplating an investor who is open-minded and has no strong beliefs in a specific model. She is likely to change the forecasting equation as time passes and her historical information enhances. I assume she has a logarithmic utility function, that she is willing to maximize over all investment periods with the decisions she makes at each single-period. In other words, instead of holding a specific portfolio during the whole investment period, she switches between a safe asset denominated in Hungarian Forint (HUF) and the Hungarian stock market index, the BUX index. (14,17,22)

At each point in time, *t*, the investor uses the information she possesses about a base set of observable k regressors, to forecast excess stock market returns in *t+1*. In case the predicted excess return of the BUX index is positive, her portfolio is totally invested in the stock market. If the excess returns are forecasted to be negative, she decides to allocate her wealth 100% in the safe asset, the Hungarian 1M T-bill. The investor performs the same exercise at *t+1* with an updated information set and perform a forecast for *t+2*. She repeats it until the end of the investment period, respectively. (14,17,22)

Recursive Forecasting Strategy and Model Selection Criteria

The investor's purpose with the switching portfolio is return and utility maximization throughout the concerned period. She has to maintain potential modelling and forecasting strategies, therefore, I do not suppose that the true data generating process (DGP) is fixed during the examined timeframe. To this end the investor executes a recursive modelling, according to which at each period t, she estimates a set of regression models spanned by all the possible permutations of *k* regressors. This results a total 2^k different models, estimated by the ordinary least squares (OLS) method. (14,15,17,22)

The investor is forecasting ER_{t+1}, the excess return at time *t+1*, by means of linear regressions

$$M_{t,i} : ER_{t+1} = \beta'_i X_{t,i} + \varepsilon_{t+1,i} \qquad i = 1,2,3, \dots, 2^k \qquad \text{(I)}$$

where $M_{t,i}$ indicates the *i*'th regression model and $X_{t,i}$ is a (k_i +1) x1 vector of regressors in the model for excess stock returns. It is obtained as a subset of the base set of regressors, X_t , which was decided a priori at the beginning of the period, and a vector of ones as intercept term. The parameters of each model, $\hat{\beta}_{t,i}$, are projected by the OLS technique. (14,17,22)

$$\hat{\beta}_{t,i} = (X'_{t,i}X_{t,i})'X'_{t,i}ER_{t+1} \tag{II}$$

There are a number of formal statistical model selection criterions suggested in the literature to support the investor in choosing the particular selection of $X_{t,i}$ to be used in forecasting ER_{t+1}. The representative investor applies the $\bar{R}^2$, the Akaike's Information Criteria (AIC) (Akaike (1974)) and the Schwarz's Bayesian Information Criterion (BIC) (Schwarz (1978)). These are likelihood-based criteria, that assist the investor to select the best model by assigning weights to the parsimony and fit of the models. The fit is evaluated by the log-likelihood function and its maximized value, and the parsimony is measured by the number of freely estimated coefficients. (1,17,19,22)

The AIC and BIC is derived by maximizing the information theoretic criterion and selects the model, which minimizes

$$AIC_i = \ln\left(\frac{ESS_i}{t}\right) + \frac{2 * k_i}{t} \tag{III}$$

$$BIC_i = \ln\left(\frac{ESS_i}{t}\right) + \frac{\ln(t) * k_i}{t} \tag{IV}$$

in which ESS_i is the sum of squared residuals and *t* denotes the size of the estimation window.

By using the adjusted R^2 , the investor picks the model that maximizes the criterion function

$$\bar{R}_i^2 = 1 - \frac{t-1}{t-k_i}\frac{ESS_i}{TSS_i} \tag{V}$$

in which TSS_i is total sum of squares. (11,17,22)

The investor applies the above described model selection criterions to linear regressions, and selects the model with the highest value for the criteria function to predict the next period's excess return. The BIC criterion has an important property. It will asymptotically select the true model under certain regulatory conditions, if the true model is included in the set of models from which the criteria select. This main property is not true for the AIC or the R^2 as the sample size increases without constraints. Nevertheless, both the AIC and the R^2 are able to yield the approximate model and the R^2 has a main advantage, that is has been substantially used in model evaluations by economists. (17)

BASE SET OF VARIABLES

When an investor tries to forecast stock returns, an important part of the process is to establish the base set of variables that she will include in the modelling. Since I attempt to undertake investor's decision is real time, she will only select factors that are accessible ex ante. (8,17,22)

During the 1980's several studies focused on the predictive power of valuation ratios, such as dividend yield or earning-price ratios. However, they received more weight and attention in the academic literature after Fama and French (1988) and Campbell and Shiller (1988). Fama and French (1988) for instance found, that the forecasting power of dividend yield increases with the return horizon. They provided a two-sided explanation for it. Firstly, the variance of expected returns grows faster than the return horizon, due to the high autocorrelation. Secondly, the discount-rate effect causes an attenuation in the growth of the variance of unexpected returns with the return horizon. Campbell and Shiller (1988) found that, if the stock is underpriced relative to its fundamental value, like dividend, returns tend to be high accordingly. Given her knowledge based on these academic literatures, the investor considers dividend yield and earning price ratio as variables with potential forecasting power. (4,5,12)

At around the same time, numerous studies signalized that short term interest rates also have predictive power and they are correlated with stock returns. Fama and French (1989) for example stressed out that short term interest rates are correlated with stock returns and they have a negative relationship. They found, that expected returns are lower when economic conditions are strong and higher when economic conditions are weak. Furthermore, Ang and Bekaert (2001) also shown that short term interest rates are robust predictors. They examined the predictability of stock returns with a present value model and found, that short term interest rates strongly and negatively predict excess stock returns. Furthermore, the negative relationship between inflation and stock returns has also been in the focus of the academic literature. Based on these the investor chooses short term interest rates and inflation as additional predictive factors. (2,13,22)

The relationship between exchange rates and stock returns has been a controversial topic in the literature. Cenedese, Payne, Sarno and Valente (2012) found, that the exchange rate movements are unrelated to differentials in country-level equity returns. Li and Huang (2008) also found that there is not a long-run equilibrium relationship between stock returns and exchange rates, however they found a strong evidence suggesting that there is a short-run unidirectional relationship from the nominal exchange rate to the stock returns. Furthermore, they suggested, that governments should be careful when implementing exchange rate policies hence they can affect stock returns in short-run. Considering these and the fact that, the Hungarian stock market index is denominated in Hungarian Forint (HUF), while the country is part of the European Union, the investor selects the EUR/HUF exchange into her benchmark set of variables. (5,6,16)

Seasonality effect has a long history in finance regarding stock returns. It has been examined by Clare, Psaradakis and Thomas (1995). They found that the UK stock market exhibits significant seasonality and stock returns tend to increase in January, April and in a smaller degree in December, and decrease in September. Nevertheless, the January effect has been employed most of the times in empirical finance, therefore the investor includes it in the set of variables, as a dummy, which each year takes value of unity in January and zero otherwise. (10,24)

There has been some interest in the academic literature in disserting the relationship between trading volume and the stock price in the future. Chordia and Swaminathan (2000) for instance pointed out the trading volume to be a significant determinant of the lead-lag patterns observed in stock returns. Transaction volume can be seen as an attractive indicator for forecasts, as an unusual trading volume might catch the attention, hence influence investment decisions and the future stock price. Therefore, the investor considers the change in the monthly transaction volume of the BUX index as a vital technical variable. (8,9,22,24)

Relying on her beliefs, knowledge of academic literature and publicly available information she decides to include the above described financial, macroeconomic and technical variables into her benchmark set of regressors, over which she is searching the suitable prediction model. This set contains the constant, which is always included in the model, and nine further variables, $X_t = \{Exret_{t-1}, TB_{t-1,} DY_{t-1}, EP_{t-1}, TB_{t-2}, Inf_{t-2}, EX_{t-2}, CV_{t-1}, J_t\}$. Taking this base set, the investor considers the prior month's excess return, $Exret_{t-1}$, the one month treasury bill rate, $TB_{t-1,}, TB_{t-2}$, the dividend yield, DY_{t-1} , earning-price ratio, EP_{t-1} , inflation, Inf_{t-2}, the EUR/HUF exchange rate, EX_{t-2}, change in volume, CV_{t-1}, and the January Dummy, J_t, as potential predictive factors. (17)

Another important factor in the regressor selection is the choice of the number of lags. Thus the investor is interested only in the most recent data, she is using lagged data for all the variables in the regression, except the January dummy. Taking into consideration, that macroeconomic data are published later than financial, the investor uses one-month lag for financial and two-month lag for macroeconomic indicators. Since financial literature often proposes that changes in interest rates have as a powerful effect on stock return, she involves not only the one-month lagged, but also the two-month lagged short term interest rates into her set. To resume, the benchmark set of regressors for forecasting excess returns on the Hungarian stock market index includes 1-lagged excess return, 1-lagged short term interest rate, 1-lagged dividend yield, 1-lagged earnings-price ratio, 1-lagged change in volume, 2-lagged short term interest rate, 2-lagged inflation, 2-lagged EUR/HUF exchange rate and the 0-lagged January dummy. (8,17,22,24)

DATA SOURCES

The above described indicators are measured monthly over the period 2008:01-2017:12. All the data is denoted in the local currency, the Hungarian Forint, have been extracted from Bloomberg and the calculations have been performed in Matlab and Excel. The dependent variable, the excess stock return of the BUX index has been calculated as $Exret_t = \left(\frac{P_t+D_t-P_{t-1}}{P_{t-1}}\right) - TB_{t-1}$, where P_t is the stock market index last price, D_t is the dividend and TB_{t-1} is the return earned by holding a one-month treasury bill between the period of *t-1* and *t*. (17,22)

The recursive model selection strategy is based on a sample period starting in 2008 January. 2008 was selected as the beginning of the assessment, hence it allows to evaluate the effect of the financial crisis for the efficiency of the Hungarian markets. Assuming that the investor is determined to trade at September 2009, she estimates $2^9 = 512$ variant models, by using historical data from the prior period 2008:01-2009:08 and the different combinations of the nine regressors. The suitable predictive model is elected with AIC, BIC or R^2 selection criteria and will be followed by a one-step-ahead forecast of the excess stock return in 2009:09. In order to forecast the excess return for 2009:10 the method is ingeminated over the period 2008:01-

2009:09 and so on. Apart from the fact, that it is demanding computationally, the described selection technique reproduces the examination process performed by an investor in real life. Furthermore, it seizures the ability of model switching in case of new and relevant empirical fact gained with the expanded sample size. (17,22)

EMPIRICAL RESULTS

Robustness of the variables

Given the high number of estimated models, I do not provide here all the details, but some demonstration of the predicted excess returns. Figure 1 represents the forecasted excess returns constructed by linear OLS regression and selected recursively under the different model selection criterions. The last graph shows the actual excess return's values.

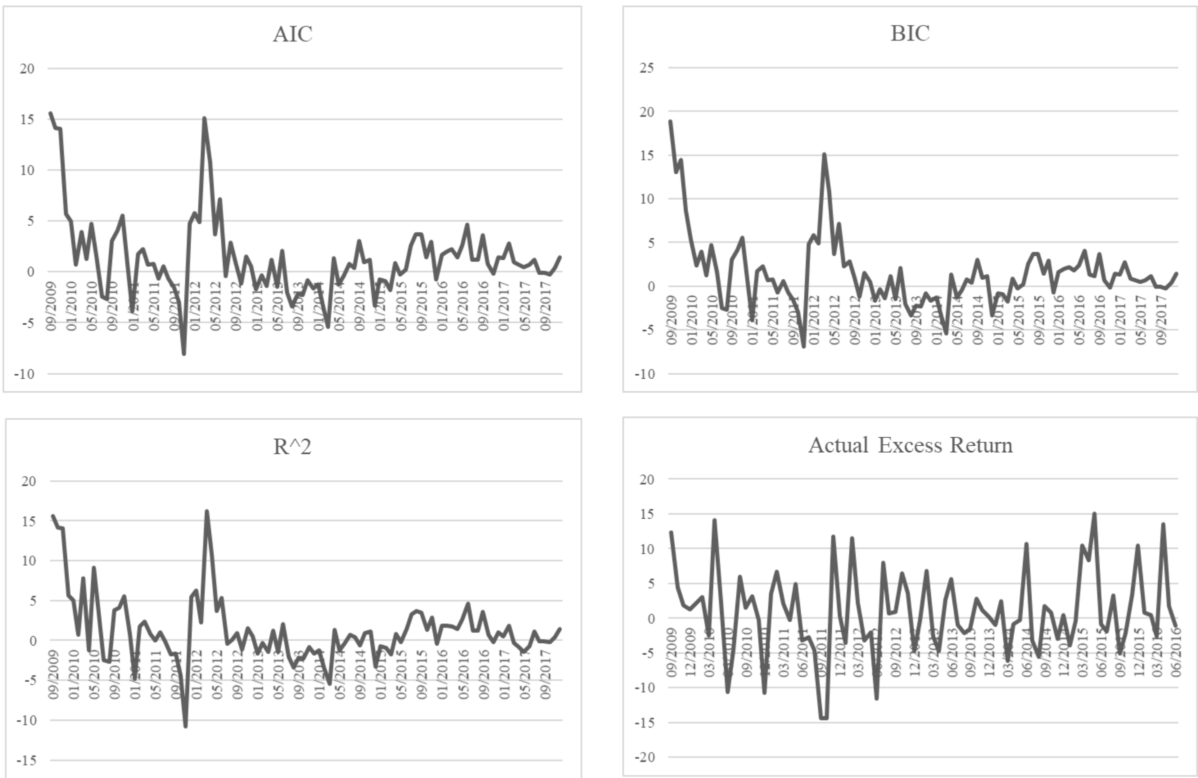

Figure 1: Recursive excess return forecasts under alternative model selection strategies for the period 2009:09-2017:12

It is notable, that the recursive forecasts are showing very parallel patterns. Representing a more volatile period in the first half of the sample period, and a more stable and less explosive phase from 2012 onwards. It can be seen as an effect of the financial crisis and the following sovereign debt crisis. Between 2002 and 2010, the government debt grew to a greater extent than in any other EU Member State. In 2011 the debt crisis was halted and a period of economic growth and the restoring process of the budget balance was parallel unfolded. The positive results of the restoration are not only reflected in the reduce of the Hungarian government debt ratio, but also in government securities yields and the trend of the recursively forecasted excess returns. The fact that the volatility of the prediction is more moderate than the actual values is not unforeseen. (3,17)

Table 1 further demonstrates the forecasted excess returns under the different model selection criterions.

	Nr of months with correct sign	**Nr of months with the same forecast**	**% of months with correct sign**	**% of months with the same forecast**
AIC	54	7	54%	7%
BIC	55	8	55%	8%
R^2	52	9	52%	9%

Table 1: Number and percentage of months when the forecasted excess stock return under the different model selection criterions were forecasted with the same sign or same rounded value as the actual excess return values

The period 2009:09-2017:12 encompasses 100 monthly excess stock return forecasts. Comparing the actual values to the forecasted ones under the three alternative model selection criterions, we can see similar preformation. Column 1 and 3 represent the number and the percentage of months when the forecasted and the actual excess stock return showed the same sign, both positive or negative value. Column 2 and 4 on the other hand indicate the number and the percentage of months when the rounded value of the forecasted and actual excess stock return was equal.

Table 2 represents the percentage of months, when the variable is included in the recursively selected model for all the factors in the benchmark base set. We can notice that the model selection criteria that selects the least regressors is the Schwarz, BIC. This is not surprising, since the BIC criteria assesses heavier penalty for inclusion, than the AIC or the R^2.

Whole Sample (2009:09-2017:12)									
	Exret (-1)	TB(-1)	DY(-1)	EP(-1)	TB(-2)	Inf(-2)	EX(-2)	CV(-1)	Y
AIC	0%	100%	99%	6%	100%	10%	98%	4%	6%
BIC	0%	100%	97%	2%	100%	1%	98%	0%	4%
R^2	13%	100%	99%	12%	100%	31%	98%	13%	9%

Table 2: Percentage of periods where a regressor us included in forecasting equations for the whole sample period 2009:09-2017:12

However, it is conspicuous that all three criteria have stable bias regarding four regressors. The one and two period lagged T-bill rates are included in the forecasting equation every month, the one-month lagged dividend yield and the EUR/HUF exchange rate also have a significantly high frequency selection.

An alternative way to show the robustness of the regressors' impact to the forecasts is to illustrate the time profile of their inclusion frequencies in the forecasting model. Figure 2 represents this time profile for the R^2 criteria by showing the months when the regressor is included in the forecasting equation with unity, and zero when excluded. In case a variable is chosen to be included on a consecutive basis, then it is feasible to deduce that the concerned regressor is momentous in stock return prediction. We can conclude that the one and two month lagged short term interest rates play a momentous role in generating the observed forecasts. As it is seen on Figure 2, from 2010 onwards the one-month lagged dividend yield is always selected. This fact is not striking, hence there is an extensive literature supporting the statistical significance of this variable in forecasting stock returns. Similar pattern emerges with respect to the two-month lagged exchange rate variable. Taking into consideration the R^2 criteria, the two-month lagged inflation is included in the equation periodically. Firstly, during the period of 2011-2012, after the higher than average rise in the food prices due to the EU regulations. Secondly, during the period of 2015-2017, which was associated with a rise in fuel and tobacco prices. (17)

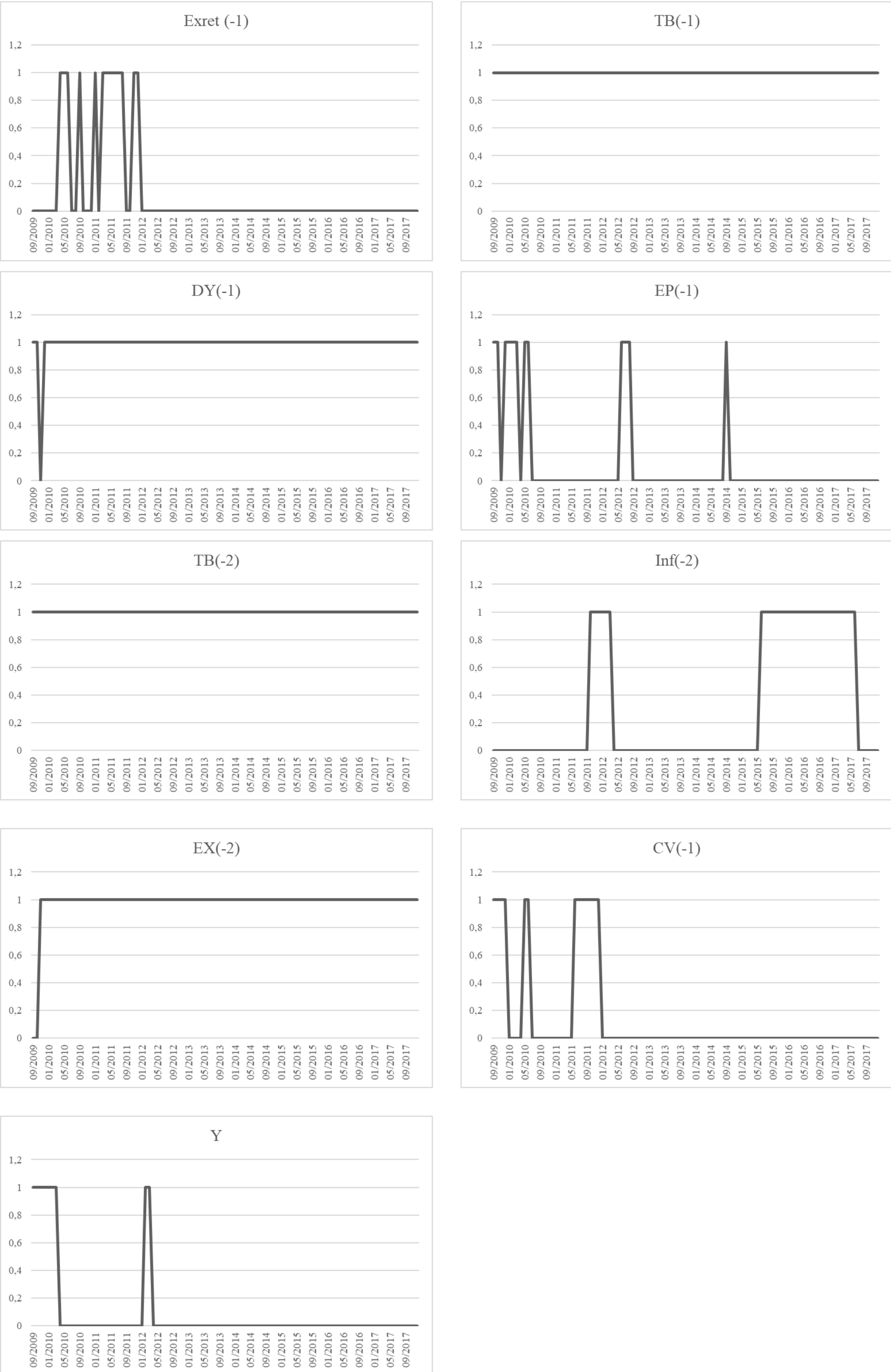

Figure 2:Inclusion frequency of the variables in the base set under the R^2 model selection criteria. 2009:09-2017:12
Note: The inclusion of the variables in the regression is depicted by unity and zero otherwise

However, considering the one-month lagged excess return, we can observe, that it was selected several times until 2012, but afterwards in the second part of the sample period the variable became insignificant. Moreover, the AIC and BIC criteria does not pick this regressor at all. Similar behavior emerges with respect to the one-month lagged change in volume variable, whose predictive power was concentrated for the first part of the sample. (17)

Economic Returns

To evaluate whether the recursive forecasts could have been employed to earn higher profit, than that gained by following a passive investment, the buy-and-hold strategy, I calculate the final wealth of the investor who fully switches her asset holdings between the stock market index and safe deposits in Hungary. Based on this strategy she holds the index when her forecast suggests that the index return will outperform the bond return, otherwise she holds the bond. It is important to point out, that short selling and leverage usage is not allowed for the sake of simplicity. (17,22)

By comparing a passive investment strategy with one based on frequent trading, transaction costs play an important role, as they can affect the final wealth obtained by the trading and with that the investment decision. I assume that there are three types of transaction costs: zero, low and high. Low and high transaction costs are considered as 0.1 and 0.5 percent of the final value of trading, and they are the same for stocks and bonds. Transaction costs occur when the investor switches between equity and bond holding. In case of the market and bond portfolio, they arise when the investment takes place at the beginning of the period, and only the dividends and interests are reinvested in the following months. Therefore, when computing the effect of transaction costs, the investor has to consider the number of switches. Figure 3 represents the frequency of changes between equity and bond holding under the different model selection criterions. It shows equity holdings with unity and bond holdings with zero. Under AIC she switches, and therefore exposed to transaction costs 65 times. Under BIC and R^2 this is 66 and 57 times respectively.

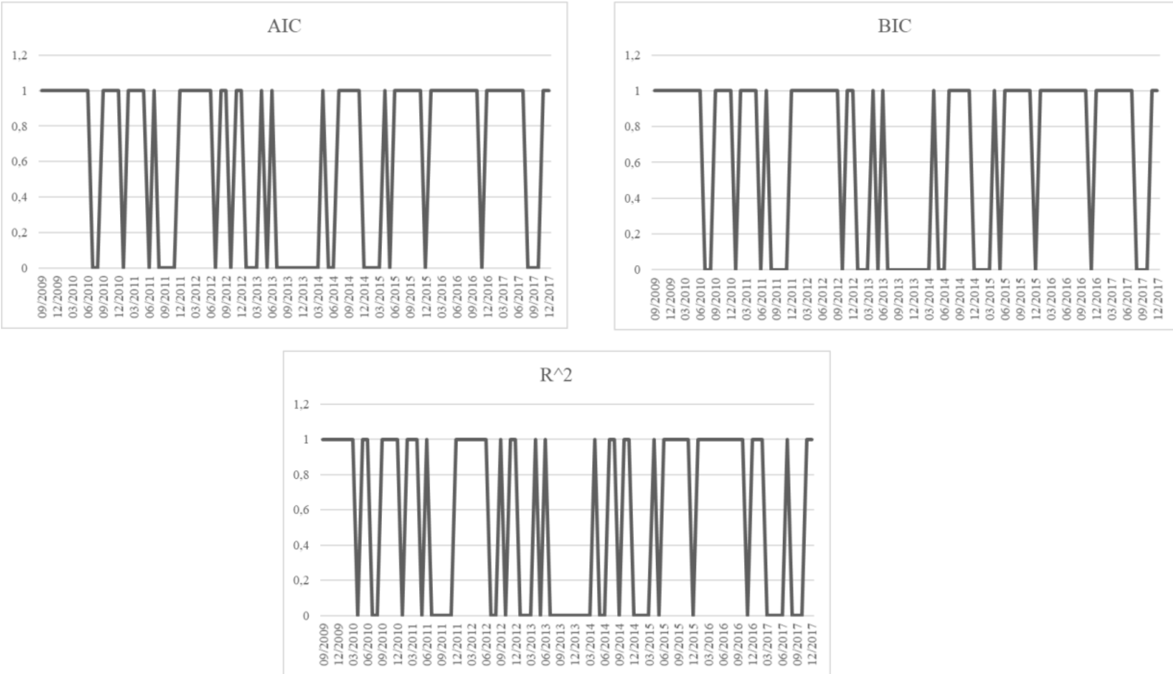

Figure 3: Frequency of the switches between the stock market index and the safe asset under different model selection criterions. Note: The investment in the stock market index is depicted by unity and zero otherwise.

Equation 6, 7 and 8 shows how these switches between the market portfolio and safe asset are represented in final wealth calculations under the AIC model selection criteria with zero, low and high transaction costs.

$$Final\ Wealth\ AIC - Zero\ TC = 100Ft * CumProd_{AIC} \tag{VI}$$

$$Final\ Wealth\ AIC - Low\ TC = 100Ft * CumProd_{AIC} * 0{,}999^{65} \tag{VII}$$

$$Final\ Wealth\ AIC - High\ TC = 100Ft * CumProd_{AIC} * 0{,}995^{65} \tag{VIII}$$

$CumProd_{AIC}$ is the cumulative product of the returns under the AIC model selection criteria, 100 Ft is the initial wealth of the investor, 0,999 and 0,995 represents the 0.1 and 0.5 percent transaction costs under the 65 occurring switches. In terms of the market and bond portfolio, the investor is obliged to these transaction costs only at the initial investment date. Therefore, in those cases the equations do not contain the power of 65 components respectively.

Table 3 reports the cumulative wealth measured in Hungarian Forint by the end of 2017 under the different investment strategies. Table 3 also represents the Sharpe ratio and the mean return for the differing portfolios. I assume that the investor has 100 Ft as an initial fund.

Under no transaction costs is the mean return on the BUX index 117.57 percent, which is almost two times higher than the mean returns on all the switching portfolios. Nonetheless, when considering the outputs of the switching portfolios under the different model selection criterions, the Schwarz criteria based portfolio outperforms the AIC and the R^2. They result mean returns of 72.33, 64.32 and 40.85 percent respectively. Differences in mean returns are represented in the final wealth as well. The end-of–period fund for the market portfolio is almost 1.5 times larger, than the end-of-period funds for all the switching portfolios.

Whole Sample (2009:09-2017:12)						
		Final Wealth (HUF)				
		Market Portfolio	Bonds	AIC	BIC	R^2
Transaction Costs	Zero	276.37 Ft	100.28 Ft	175.35 Ft	189.40 Ft	140.42 Ft
	Low	276.07 Ft	100.18 Ft	170.17 Ft	184.17 Ft	135.72 Ft
	High	274.96 Ft	99.78 Ft	150.87 Ft	164.60 Ft	118.41 Ft
	Mean Return	1.1757	0.0028	0.6432	0.7233	0.4095
	Sharpe Ratio	0.2096	-	0.1581	0.175	0.1081

Table 3: Performance measure for the BUX index switching portfolio relative to the Market portfolio and T-bills

By allowing low transaction costs, such as 0.1%, the final wealth of the investor is expected to reduce due to frequent rebalancing. This influence is even larger, when high transaction costs are presented (0.5%). In contrast, as it is visible on Table 3, transaction costs have a minimal effect on the market portfolio.

The results represented above are significantly different from the one that Pesaran and Timmerman (1995) found in their paper. They concluded that for the examined period, 1960-1992, the performance of the switching portfolios based on forecasts outperform the buy-and-hold investment strategy. The explanation behind this discrepancy in the results is multilateral.

First, the investigated time period for Pesaran and Timmerman is the era, when new empirical evidences question the weak form of Efficient Market Hypothesis, as they rely on the fact that past prices can generate abnormal returns. In contrast, the time period of this analysis is after the millennium, when abnormal profits are less frequent, almost disappeared. The second is a country specific explanation. The Hungarian Stock Exchange, the predecessor of today's Budapest Stock Exchange (BSE), was established in 1864 and operated as one of Europe's leading exchanges until it was disbanded in 1948. After the fall of communism, it was re-established in 1990 and its stock index was officially opened on the 5th of January 1995, with great prospective. However, the East Asian crisis, the Russian economic crisis, the global financial crisis and the related word marked processes led to the narrow band, in which the BUX was moving until 2015. The positive turnaround occurred after the crisis in 2015, when the index moved out of the narrow band and its volume started to grow. From the beginning of 2015 till the end of 2017, the BUX index increased a total of 137 percent, thus delivering outstanding performance not only in the region but also in global comparison. The above described evolution of the BUX index is well presented in Figure 4. (18)

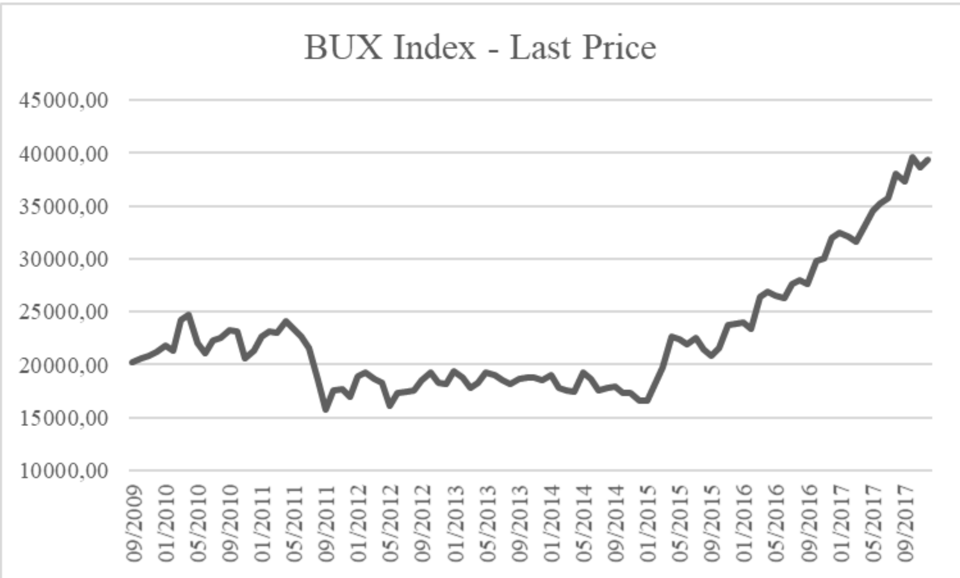

Figure 4: The evolution of the BUX index 2009:09-2017:12

SUB-SAMPLE ANALYSIS OF THE SWITCHING PORTFOLIO TRADING-STRATEGY

Robustness of the variables

Given the nature of the evolution of the Hungarian stock market index for the examined period, I perform the already described processes and analyze the performance of the switching portfolios over two sub-periods. First for the period 2008:01-2012:12 and thereafter for 2013:01-2017:12. As it was expected, the two periods result quite different outputs.

By exploring the robustness of the regressors contributing to the predictability of the BUX index, significant differences arise. Splitting the sample size into two, the technical indicators, as the change in volume or the January dummy, are included in the forecasting equation more frequently. Exchange rate two-period lagged tends to be included in the forecasting model during the first sub-sample almost every month, and less regularly during the second.

Sub-Sample (2008:11-2012:12)									
	Exret (-1)	TB(-1)	DY(-1)	EP(-1)	TB(-2)	Inf(-2)	EX(-2)	CV(-1)	Y
AIC	10%	100%	92%	32%	100%	16%	92%	24%	26%
BIC	10%	100%	88%	24%	100%	14%	92%	16%	22%
R^2	36%	100%	92%	42%	100%	26%	90%	38%	32%

Table 4: Percentage of periods where a regressor us included in forecasting equations for the sub-sample period 2008:11-2012:12

In contrast to the whole-sample evaluation, when the one-month lagged excess return was excluded in the forecasting models in most periods, by splitting the sample into two, it becomes selected more often.

Sub-Sample (2013:01-2017:12)									
	Exret (-1)	TB(-1)	DY(-1)	EP(-1)	TB(-2)	Inf(-2)	EX(-2)	CV(-1)	Y
AIC	18%	60%	84%	12%	26%	72%	30%	20%	16%
BIC	14%	46%	86%	10%	20%	46%	10%	14%	8%
R^2	28%	70%	88%	34%	58%	82%	40%	48%	14%

Table 5: Percentage of periods where a regressor us included in forecasting equations for the sub-sample period 2013:11-2017:12

The one and two month lagged interest rates show changes only in the second sub-period. This change is more eye-catcher in case of the two-month lagged interest rates, where there has been a significant decrease in the frequency of the inclusion. Another notable difference can be perceived in case of the two-month lagged inflation, which has been included in the forecasting models with a considerably higher frequency during the second sub-sample. This coincides with the above mentioned increase in fuel prices.

Economic Returns and Final Wealth

Computing the final wealth of the investor who is switching her portfolio holdings between stocks and bonds, the results of the two periods are contrary. I employ during these sub-sample evaluations the same assumptions as before, namely no short selling and leverage is allowed, transaction costs are the same for stocks and bonds and we distinguish three different types: zero, low and high. Furthermore, the considered investor has an initial investment fund of 100 Ft at the beginning of the trading period.

Table 6 shows the cumulative wealth measure in Hungarian Forint, the Sharpe Ratio and the mean return by the end of 2012 according to the different model selection criterions. The mean return of the passive investment strategy, the market portfolio is 53.9 percent, which is significantly lower than what an investor could have gained with the switching portfolios under the different model selection criterions. Among the three criterions, the Schwarz slightly outperforms the AIC and the R^2 , with 169.48 percent. The other two criteria result a mean return of 153.45 and 124.4 percent respectively.

With the scenario of zero transaction costs, the final wealth with switching portfolios under the three model selection criterions strongly outperforms the market portfolio. Investor can gain the highest final wealth and Sharpe ratio, by following the Schwarz, BIC, model selection criteria. The same conclusions can be drawn in case of the low (0.1%) and high (0.5%) transaction cost scenarios.

Sub-Sample (2008:11-2012:12)						
		Final Wealth (HUF)				
		Market Portfolio	Bonds	AIC	BIC	R^2
Transaction Costs	Zero	108.50 Ft	100.28 Ft	197.79 Ft	213.65 Ft	172.61 Ft
	Low	108.39 Ft	100.18 Ft	195.24 Ft	211.31 Ft	170.38 Ft
	High	107.95 Ft	99.78 Ft	185.32 Ft	202.18 Ft	161.72 Ft
	Mean Return	0.539	0.0056	1.5345	1.6948	1.244
	Sharpe Ratio	0.0622	-	0.2622	0.2864	0.2232

Table 6: Performance measure for the BUX index switching portfolio relative to the Market portfolio and T-bills

The fact, that the investor can earn abnormal profits and outperform the market portfolio by forecasting based on past prices and her own beliefs was expected considering the above described evolution of the BUX index.

By performing the same evaluation for the second sub-period, the results correspond more to the whole sample analysis. Table 7 shows the cumulative wealth measured in Hungarian Forint, the Sharpe ratio and the mean return by the end of 2017 according to the different model selection criterions.

Sub-Sample (2013:11-2017:12)						
		Final Wealth (HUF)				
		Market Portfolio	Bonds	AIC	BIC	R^2
Transaction Costs	Zero	230.72 Ft	100.04 Ft	135.69 Ft	147.82 Ft	142.83 Ft
	Low	230.49 Ft	99.94 Ft	133.00 Ft	145.48 Ft	139.72 Ft
	High	229.57 Ft	99.54 Ft	122.75 Ft	136.43 Ft	127.91 Ft
	Mean Return	1.7943	0.0008657	0.6685	0.8502	0.7943
	Sharpe Ratio	0.3736	-	0.1922	0.2274	0.2062

Table 7: Performance measure for the BUX index switching portfolio relative to the Market portfolio and T-bills

Taking in to consideration the outstanding performance and the significant increase in the BUX index during the second period, it is not surprising that the mean return of the market portfolio is substantially higher, than the mean return of all the considered switching portfolios. As in the previous period, among the different model selection criterions, the Schwarz results the best mean return with 85.02 percent. By following the AIC and the R^2 , the investor earns a mean return of 66.85 and 79.43 percent respectively.

The end-of-period wealth for the market portfolio is almost 2 times higher, than the funds for all the switching portfolios. This coincides with the whole sample examination.

CONCLUSION

In this paper, I assess the economic significance of predicting stock returns by simulating investor decision in real time. The concerned investor is maximizing her asset returns on the local Hungarian stock market index and the local risk free asset. She faces model uncertainty, therefore every month she is searching for the most suitable model for predicting excess stock returns. Assuming that she has full confidence in her forecasts, she is switching 100% of her funds between the stock market index and the risk free asset, based on the sign of the forecast. Looking at the inclusion frequency of the different variables in the forecasting equation during the whole sample and the two sub-sample examinations, we can clearly notice that changes in the underlying model for forecasting excess stock returns are necessary. This is especially relevant in case of the sub-period analyses.

The economic profit gained from the forecasts are various across the different sample periods. Therefore, whether the switching portfolios based on the forecasts under the three model selection criterions can outperform the market portfolio, depends on the time period when the investor wishes to trade. The results suggest that the period of 2008:11-2012:12 appears to be a timeframe with higher-than-normal predictability of excess returns on the BUX index. During this time, the investor could have gained a significant profit by following the switching trading strategy. However, this is not the case in terms of the whole sample 2009:09-2017:12 and the second sub-sample 2013:11-2017:12. During these periods there was no excess return that the investor could have earned from following the switching strategy and the recursively chosen forecasting model. Therefore we can conclude that for the former mentioned periods, the Hungarian stock market index can be considered informationally efficient. Moreover, the highest profit through these periods could have been gained by investing in the market portfolio.

These outputs and conclusions were drawn by taking into consideration a specific base set of regressors and model selection criterions. Changing the set of variables or the model selection criteria can cause different results. However, if we take a look at the evaluation of the Hungarian stock market index, the BUX index and its significant performance over the past years, it would not be surprising that even with those changes, the market would outperform the switching portfolio.

REFERENCES

1. Akaike, H. 1974. “A New Look at the Statistical Model Identification" IEEE Transactions on Automatic Control, 19, 716-723.
2. Ang, A. and Bekaert, G. 2001. “Stock Return Predictability: Is It There?" NBER Working Paper, w8207.
3. Baksay, G. and Palotai, D and Szalai, Á. 2015. “MNB: 2011 óta csökken az államadósság” Portfolio
4. Campbell, J. Y. and Shiller, R.J. 1988a, The dividend-price ratio and expectations of future dividends and discount factors, Review of Financial Studies 1, 195-228.
5. Campbell, J. Y. and Thompson, S.B. 2005. “Predicting the Equity Premium Out of Sample: Can Anything Beat the Historical Average?”
6. Cenedese, G. 2015. “The relationship between stock and currency returns” WEC
7. Cenedese, G. and Payne, R. and Sarno, L. and Valente, G. 2012. “What Do Stock Markets Tell Us About Exchange Rates?”
8. Charles, A. and Darné, O. and Kim, J. H. 2014. “International Stock Return Predictability: Evidence from New Statistical Test”
9. Chordia, T. and Swaminathan, B. 2000. “Trading Volume and Cross-autocorrelations in Stock Returns," Journal of Finance, 55, 913-935.
10. Clare, A.D., Psaradakis, Z. and Thomas, S.H. 1995. “An Analysis of Seasonality in the UK Equity Market” Economic Journal, 105, 398-409.
11. Dell’Aquila, R. and Ronchetti, E. 2004. “Stock and Bond Return Predictability: The Discrimination Power of Model Selection Criteria.”
12. Fama, E. F. and French, K.R. 1988. “Dividend Yields and Expected Stock Returns” Journal of Financial Economics, 22, 3-25.

13. Fama, E. F. and French, K.R. 1989, Business conditions and expected returns on stocks and bonds, Journal of Financial Economics 25, 23-49.
14. Favero, C.A. and Aiolfi M. 2002. “Model Uncertainty, Thick Modelling and the Predictability of Stock Returns.”
15. Giacomini, R. and White, H. 2006. “Tests of Conditional Predictive Ability”
16. Li, Y. and Huang, L. 2008. “On the Relationship between stock return and exchange rate: evidence on China”
17. Pesaran, M.H. and Timmermann, A. 1995. “Predictability of Stock Returns: Robustness and Economic Significance”. The Journal of Finance, Vol. L, No.4, September 1995: 1201-1228
18. Puzsár, J. 2014. "Ismétli magát a riasztó orosz történelem?". investor.hu
19. Schwarz, G. 1978. “Estimating the Dimension of a Model". Annals of Statistics, 6, 461-464.
20. Sollis, R. 2012. “Market Efficiency” in Empirical Finance for finance and banking, 143-183. Wex Sussex: John Wiley & Sons Ltd.
21. Thomakadis, A. 2016. “Do Combination Forecasts Outperform the Historical Average? Economic and Statistical Evidence” MPRA Paper No. 71589
22. Tian, J. 2005. “Economic Value of Stock Return Forecast: An Assessment on Market Efficiency and Forecasting Accuracy”
23. Timmermann, A. and Granger, C. W.J. 2004. “Efficient market hypothesis and forecasting”. International Journal of Forecasting, 20 (2004): 15-27.
24. Timmermann, A. and Pesaran, M. H. 1998. “A Recursive Modelling Approach to Predicting UK Stock Returns”