MOMENTUM STRATEGIES IN THE
UKRAINIAN STOCK MARKET:
IMPLICATIONS FOR EFFICIENCY

by

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A thesis submitted in partial fulfillment of
the requirements for the degree of

MA in Financial Economics

Kyiv School of Economics

2013

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Abstract

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In this study the weak form of efficient market hypothesis is examined by finding abnormal returns for momentum trading strategies on the Ukrainian stock market. We use simple momentum, Sharpe ratio and Rachev ratio to determine momentum for a short term prospective. For this purpose data from 2009 to 2013 for the Ukrainian stock market is used.

In contrast to studies devoted to developed markets most part of the strategies give significant abnormal return. The pass of portfolio returns is modeled by ARMA-GARCH process. Forecast is done using Monte-Carlo simulations. Based on the STARR ratio we have chosen the best trading strategy simulation and found that it over performs the market for 0,6% a day on average. Therefore, the efficient market hypothesis is rejected for Ukrainian Stock market.

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Chapter 1

INTRODUCTION

All over the world stock markets are widely used to attract or invest capital by companies or investors respectively. But stock markets' volumes differ dramatically in different countries. Developed stock markets (like NYSE, NASDAQ, Tokyo Stock Exchange, London Stock Exchange etc.) attract the main part of capital on stock markets all over the world. One of the wide-spread opinions for the fact is that these markets are more efficient than the other ones. On the one hand, this fact explanation investors an opportunity to expect fair, based on the asset value, return in the long run. On the other hand, due to this explanation firms expect a fair market pricing of their assets.

The recent 2008 crisis and posterior recession forced investors to consider alternative venues for their capital. In particular, developing markets were given an opportunity to attract significant capital resources to inject into the local economies. The focus of this research is on the rapidly developing Ukrainian stock market, whose volume of trades increased sharply during last years. The system of online trading introduced recently attracts private investors into trading on stock market. But have these innovations made Ukrainian stock market efficient enough to be a valuable instrument for international investors to make short term and long term investments into the Ukrainian economy? This is the main question studied in this research.

Most modern asset pricing theories assume that the efficient market hypothesis holds. The efficient market hypothesis claims that the market prices contain all available information and instantly react to all changes. However, there is a strong evidence of systematic asset mispricing during last decades. According to Daniel et al. (1998), the most frequent anomalies are market reaction to the earnings surprises, overreaction of prices to news, high volatility of asset prices relative to fundamentals and price bubbles. In order to explain these anomalies De Bondt and Thaler (1995) state that "the most robust finding in the psychology of judgment is that people are overconfident". Supporting this finding, Daniel et al. (1998) and Grinblatt et al. (1995) described three main well-known investors' psychological biases: overconfidence about the private information, biased self-attribution and herding behavior. These biases can affect stock market dramatically. For example, herding behavior is one of the factors of price bubbles formation. Therefore, it is very important to test market efficiency for Ukrainian stock market with respect to these biases.

One of the main properties of efficient markets is that on a risk-adjusted basis investor cannot make systematic profits over a long period of time. There are many trading strategies used by investors, traders and portfolio managers all over the world attempting to beat the market systematically. According to Griffin et al.(2005), Chan et al.(1999) and Jegadeesh et al.(1999), momentum strategies are one of the most frequently used now. The essence of momentum strategies lies in the fact that investors tend to overvalue stocks that went up during last trading period, and undervalue stocks, that went down (Graham and Dodd, 1962). The main assumption behind these strategies is about the continuance of existing market trends. That is, when the price of an asset increases, a momentum investor believes in future appreciation and vice versa – if the price of an asset significantly depreciates a momentum investor follows the market and sells (or short-sells) additional amount of the asset to gain from the trend.

De Long et al.(1990) emphasize that the main advantage of momentum-based models is their consistency with empirical results about market anomalies – correlation of assets returns, price bubbles and overreaction of prices to news. Therefore, these strategies are the best candidates to find market anomalies and psychological biases described earlier.

The same momentum strategy can give dramatically different results for different markets. Research papers published all over the world cover all developed markets (Jegadeesh and Titman, 1993; Vandell and Parrino, 1986; Rouwenhorst, 1998 and others) and many emerging ones (for example, Chui, Titman and Wei, 2000). However, there were no studies on momentum strategies devoted to the Ukrainian stock market. The main reasons for this were poor data quality, low trading volumes, bad investment climate all of which made these market less attractive for both researchers and investors than other emerging markets. However, nowadays trading conditions and available history are sufficient to determine profitability of momentum strategies on these markets. Therefore, testing momentum strategies for Ukraine is now a feasible and timely research question.

In this study three different momentum strategies, proposed by Biglova el al (2004), will be analyzed in order to figure out systematic abnormal returns. Criteria for each strategy have their own adjustment to risk and, therefore, deal in different way with main psychological biases present in financial markets. The first strategy does not take into account risk at all, but is very simple for understanding and calculation and therefore is very appealing to investors. The second one adjusts returns to the volatility (variance) of the past performance and is also relatively simple for implementation. The last criterion deals with value at risk and expected tail losses. It much better reflects the risk of the underlying asset but is tough for understanding and calculation and therefore is more likely to be used only by professional traders and portfolio managers.

In order to cover both short-term and mid-term investors' behavior, other factors that should be taken into account are formation and holding periods for the portfolio. Following Chan, Hameed and Tong (1999), Jegadeesh and Titman (1993, 1999) and Michaelly et al.(1995), in this study one week, one-month and 3-month periods will be used.

In case of observing systematic abnormal returns from any of the strategies, its returns' autocorrelation will be tested. As stock return distributions commonly have fat tales, based on the results of autocorrelation test, ARMA-GARCH model of appropriate lag is constructed as it is proposed by Biglova et al. (2004).

The data that will be used is taken from the Ukrainian Exchange. As the last 2008 world crisis significantly affected Ukrainian economy and led to structural changes in it, the daily data for a 4-year period (beginning from early 2009) will be used.

This study has the following structure. The literature review gives the intuition of momentum profits relation to market efficiency, describes methods of trading, markets for implementation of momentum strategies, time dimensions for trading and predictability of portfolio returns. The methodology section explains how the stability of returns generated by different momentum strategies is tested. Data description section describes collected data and explains data modifications made. Empirical results section goes through all steps of calculations – from portfolio returns formation to the best strategy determination. Conclusions are devoted to main findings of this study and describe prospects for further research.

Chapter 2

LITERATURE REWIEV

In this study momentum strategies are used to determine whether Ukrainian stock market is efficient. We start from the intuition behind profitable trading strategies. The second part introduces and explains differences between momentum strategies. The next part explains modeling the array of portfolio returns for each momentum strategy over the history path. Based on these models prediction for following period is simulated. Independence performance ratio is used to obtain the best strategy between simulated ones. The last part is devoted to the data discussion.

Jensen (1978) explains the essence of the efficient market theory in the following statement: "A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t". We will focus on a weak form market efficiency, in which "the information set θ_t is taken to be solely the information contained in the past price history of the market as of time t" (Jensen, 1978). Therefore, one of the ways to test the weak form of the efficient market hypothesis for Ukrainian stock market is to investigate whether there exists a profitable trading strategy that consistently over-performs the market.

In order to determine such trading strategy lets revise psychological biases that force the stock market to over/under react. Daniel et al. (1998) and Grinblatt et al. (1995) claim three main well-known investors' psychological biases:

1. Overconfidence about the private information,

2. Biased self-attribution,

3. Herding behavior.

Under the first bias authors point to two main issues. First of all, they claim that experts are more overconfident than others in their judgment of the market situation (Griffin and Tversky, 1992). The second issue is based on the fact that overconfidence for mechanical tasks like arithmetic calculations (for example, valuation of future cash flows) is less visible than for diffuse tasks like making diagnoses of illnesses.

The second bias claims that investors' confidence is a function of investment outcomes. From the psychological point of view, people tend to credit themselves for past success, but blame others in case of failure. The well-known phrase pointed by Langer and Ross (1975) describes the essence for this bias – "Heads I win, tails it's a chance". Concerning herding behavior Grinblatt et al. (1995) claimed that in the case of significant movements of stock price investors tend to move with the market, i.e. "join a herd". Based on these three biases we can say that investors are more likely to close loss position when price begins moving in the loss direction (due to biased self-attribution) and increase holding position in case of positive direction for the portfolio (due to overconfidence and herding behavior).

Therefore profitable strategy for a stock market is likely to be based on the movements along the market main trend. The most well-known strategy for stock markets that supports this claim is momentum portfolio trading strategy.

The intuition behind the momentum strategies was stated by Graham and Dodd (1962) who claim that investors overemphasize short-term prospects of "winners" by overpricing them and underpricing last period "losers". Another explanation was developed by Chan, Jegadeesh and Lakonishok (1996). They claim that stock prices react gradually to earning news but in the same direction as news predicted. Therefore, the main rule of momentum strategies is to keep the tendency that was dominating recent trading periods.

During last decades momentum strategies became one of the most influential methods for constructing investment portfolios all over the world. There are many studies (Griffin et al, 2005; Chan et al, 1999; Jegadeesh et al, 1999; Hong et al, 1999 and others) demonstrating that indeed these strategies produce higher returns than the market portfolio.

Recent studies of stock market efficiency for Ukraine done by Zadoroshna (2009) and Klesov (2008) used only exogenous but did not rely on historical path of the price itself. This study fills the gap. Momentum strategies are studied using past performance of stocks without exogenous parameters as it suggested by Biglova et al. (2004), Daniel et al.(1998) and others.

There are many methods that were used by different economists to evaluate effectiveness of momentum strategies based on past performance. The main differences between those were determinants of tendency and time dimensions for the observations. This study examines most popular combinations of determinants recommended for emerging markets.

Perhaps, the most influential factor that gives different results for different studies is the method to determine momentum shock in stock prices. Essentially, this shock is the quantitative measure to evaluate stock performance during the latest relevant trading period.

The first method is introduced by Jegadeesh and Titman (1993) and defines momentum strategy as buying stocks that performed well during the last period and selling bad performers. Chan et al. (1996), Chan et al. (1999), Griffin et al. (2005), Chui et al. (2000) and Moskowitz et al. (2012) follow the same methodology claiming that it is the most widely used one by investors and therefore is likely to explain the behavior of the market price.

The second method – known as the Sharpe Ratio – was introduced by Sharpe (1994) and is well known among portfolio investors as the simplest adjustment of return for investment risk. The last method – called the Rachev Ratio – was proposed by Rachev et al. (2007). This ratio tries to mimic the behavior of a smart investor. As Rachev et al. (2007) claim, the method focuses on the distribution of tail losses and captures different types of investor – a risk-averse investor that is more focused on the maximum possible loss than on profit, a risk-neutral investor that equally weights the maximum possible loss and profit, and a risk-loving investor that is focused on maximum profits and pays less attention to possible losses.

Time dimensions determine formation and holding period for each momentum strategy. At the moment of decision making investor evaluates momentum over formation period and makes decision about portfolio structure. After the decision investor hold portfolio over the holding period. In this study we equalize formation and holding period following a common practice for momentum strategies trading (Chan et al., 1996, Griffin et al., 2005 and others). Different studies could be divided into 3 main categories of formation and holding period. Short term period models (less than one, one and three month) were used by Chan, Hameed and Tong (1999), Jegadeesh and Titman (1993, 1999), Michaelly et al.(1995) and others. Middle time period models (half or 1 year) were implemented by Biglova et al. (2004), Hong, Limm and Stein (1999) and others. Long term period model (from 3 to 5 years) were used by De Bondt and Thaler (1985, 1987), Fama and French (1988). However, long term period model is applied for long time series. For example, De Bondt and Thaler (1985) used data for time period of 56 years. Middle term momentum strategies also require a long trading history for the stocks. For example, Hong, Limm and Stein (1999) used time interval of 16 years for their strategy. As we have much less data the long term and middle term prospects cannot be used. Moreover, Chan, Hameed and Tong (1999) and Daniel et al. (1998) emphasized that the best results of momentum strategies for emerging markets were reached within short and middle term period. In this study results for 1 week, 1 and 3 months period are analyzed.

Compounding of these factors give us momentum strategies that are analyzed. Each of these strategies is tested on a history pass and positive aggregate return passes are determined. Modeling of the momentum profits pass is done using Box-Jenkins selection methodology from Enders (2010). Following the approach by Tsay (2010) we generalize the model using ARMA-GARCH. Then, using these models we use Monte-Carlo simulations approach to make forecasts for the next trading period. Each of the forecasts is valued under independent performance measure valued by STARR Ratio as Biglova et al. (2004) suggests. The best performing strategy is used as a benchmark for determining weak form efficiency for the stock market following Jensen (1978).

Chui, Titman and Wei (2010) claim that results of momentum strategies implementation could highly differ from one country to another due to institutional and cultural differences. Therefore we cannot rely on the outcome of studies for other countries and should do a separate study of the Ukrainian stock market.

It should also be emphasized that the size of companies whose stocks will be used in momentum portfolios is highly important. Since Hong, Limm and Stein (1999) claim in their research that the stocks of big companies have higher trading volumes and therefore are less sensitive to marginal trader's actions than small ones are. Hence, big companies' stocks' returns are better explained by momentum strategies. Here we are going to follow Hong, Limm and Stein (1999) and take companies with top 25% capitalization in the Ukrainian stock market.

Chapter 3

METHODOLOGY

The null hypothesis for this study is weak form efficiency for the Ukrainian stock market. The first step is to analyze the performance of different momentum strategies in-sample over the given data period. The second step is devoted to modeling the return generating process for each profitable strategy. On the third step we will forecast returns on each trading strategy and rank results in order to independent performance ratio that reflects an optimal risk-return performance as suggested by Biglova et al. (2004). Finally conclusion about market efficiency is based on the performance of the best trading strategy return.

In this paper we use log returns to evaluate performance of each stock:

$$r_t^i = \ln\left(\frac{S_t^i}{S_{t-1}^i}\right) \quad (1)$$

where S_t^i is a price of stock i at moment t.

This is a most widespread method to evaluate stock returns as it is most convenient to calculate compounded returns on stock. Portfolio return on stock i at moment t is determined as risk-adjusted return on a stock i position that is held:

$$P_t^i = I_t^i r_t^i - r_t^f \quad (2)$$

where I_t^i is an index of direction for stock i at moment t.

Index of direction is determined by momentum strategy and equals 1 for a long position on stock at moment t, -1 for short position and 0 for no position on a stock i.

Each strategy of trading assumes equal value of each stock in portfolio. Hence, $\frac{1}{N}$ part of portfolio funds each stock. Therefore, at each moment of time t the total portfolio return is determined as a sum of all stocks' return for the period weighted by their fraction in portfolio:

$$Port_t = \frac{1}{N}\sum_{i=1}^{N} \exp\{P_t^i\} \quad (3)$$

where N is the number of stocks in the portfolio

In equation (3) we stepped from log returns to percent returns for convenience of interpreting results. Portfolio returns is the array that will be modeled and forecasted. The total return for each strategy is determined as multiplication of all daily returns and reflects compounding effect of investment:

$$R = \prod_{t=1}^{T} Port_t \quad (4)$$

where T is the number of periods relevant for each strategy.

Momentum strategies determine indicator matrix I and describe full pass of decisions. Each strategy has two features: a method to determine momentum and portfolio holding/formation period. Both characteristics reflect different types of investors' behavior mentioned earlier. For example, overconfidence about the private information better fits the method to determine momentum that neglects adjustment for risk as overconfident investor is more focused on profit and therefore underestimate forecast error variance. At the same time, overconfidence will force investor not to change his decisions frequently. Therefore, this investor will prefer relatively longer formation/holding period. However, instability of Ukrainian political and economic environment makes less sense in long term investments.

We use three methods to determine momentum with different adjustments for risk – from risk-neutral to risk-averse investors. The most famous method to deal with momentum is to buy last period market stock price winners and sell last period market stock price losers (Jegadeesh and Titman, 1993):

$$\rho(r) = r - r_f \tag{5}$$

where r is return of the stock for the last holding period, r_f is risk-free rate and $\rho(r)$ is indicator for further actions. If it is negative, investor holds short position on the stock for the next holding period, if positive – long position, and if zero – no position in this stock is taken. The main disadvantage of this method is that it tells nothing about the pass of the stock within a holding period and has no adjustment for risk – the strategy takes into account only the first and the last value of stock price during the period. However, it is quite simple to calculate and has straightforward intuition behind.

Another frequently used strategy is based on the Sharpe ratio which is described by Sharpe (1994). The Sharpe ratio is a ratio between expected excess return and its standard deviation:

$$\rho(r) = \frac{E[r - r_f]}{STD_{r-r_f}} \tag{6}$$

where $E[x]$ is an expectation of x within formation period and STD_x is a standard deviation of returns for the same time interval. In contrast to the previous strategy, Sharpe ratio relies on pass of returns within the trading interval and risk is determined by standard deviation of the distribution. This method is the simplest one among those relying not only on return but also on risk. It is frequently used for determining riskiness of funds.

The last and most risk-sensitive method is called the Rachev Ratio (or R-Ratio) and is proposed by Rachev et al. (2007). It depicts a ratio of expected tail losses for the opposite to excess return and of expected tail losses for the excess return at a different confidence levels:

$$\rho(r) = \frac{ETL_{\gamma_1\%}[r_f - r]}{ETL_{\gamma_2\%}[r - r_f]} \quad (7)$$

where expected tail losses are defined as $\mathrm{ETL}_{\alpha\%}[\mathrm{r}] = \mathrm{E}\big[\,\mathrm{L} \,\big|\, \mathrm{L} > \mathrm{VaR}_{\alpha\%}\big]$, $\gamma_1, \gamma_2 \in [0; 1]$ and the value-at-risk is defined as $\mathrm{VaR}_{\alpha\%}$: $\mathrm{P}\big[\,\mathrm{L} > \mathrm{VaR}_{\alpha\%}\big] = \alpha, \alpha \in [0; 1]$.

This ratio points to fat tails of the returns' distribution commonly observed for stock returns. The numerator describes the average of extreme profits from the right part of the distribution (the most profitable part of the returns) and denominator describes average extreme losses from the left part (the largest negative returns). However this method requires relatively complex calculations and does not have a straightforward intuition behind it.

Parameters γ_1 and γ_2 describes behavioral patterns of different investors. The first one captures the strength of focus on profits and the second one – on losses. If $\gamma_1 = 0{,}05$ and $\gamma_2 = 0{,}5$ the model depicts an investor that cares about profits much more than about downside risks. This type of investor follows self-attribution bias described earlier and is classified as risk-lover. In the case $\gamma_1 = 0{,}5$ and $\gamma_2 = 0{,}05$ the main focus is on the maximum losses that can be reached and much less than profits. This model is followed by risk-averse investors. When $\gamma_1 = 0{,}5$ and $\gamma_2 = 0{,}5$ the model depicts risk-neutral well diversified investor that cares more on average profits and is hedged against extreme losses. $\gamma_1 = 0{,}05$ and $\gamma_2 = 0{,}05$ model also depicts behavior of risk-neutral investor, but with focus on extreme values for loss and profit.

For monthly and 3 months periods, as Rachev et al. (2007) suggests, we use 4 nodes (γ_1, γ_2) to calculate R-ratio: $(0.5,0.5)$, $(0.5,0.05)$, $(0.05,0.5)$ and $(0.05,0.05)$. For weekly data we have only 5 observations for each week therefore the most strict restriction for tail losses is 0.2 instead of 0.05 and we use $(0.5,0.2)$ values for γ_1 and γ_2 to calculate R-Ratio for weekly returns. Each of these bundles describes different behavior of investors. Distinguish between investors is obtained by using different values to parameters – first captures strength of focus on profits and second – on losses.

For the first two strategies, whose decision criteria are described by equations (5) and (6), the indicator I for the next period is determined by the sign of last period return:

$$I = \begin{cases} 1, if\ \rho(r) > 0, \\ 0, if\ \rho(r) = 0, \\ -1, if\ \rho(r) < 0. \end{cases}$$

However, for the last strategy (7) we use different benchmark as we compare extreme absolute losses and profits:

$$I = \begin{cases} 1, if\ \rho(r) > 1, \\ 0, if\ \rho(r) = 1, \\ -1, if\ \rho(r) < 1. \end{cases}$$

Therefore, the indicator shifts towards "buy" if tail profits exceed tail losses and shifts towards "sell" in the opposite case. The value $\rho(r) = 1$ reflects uncertainty and forces to close position in the instrument.

The second feature of a strategy is portfolio formation and holding periods. Here we choose the time period over which the "winners" and "losers" will be determined, and the time period over which portfolio will be held. For convenience, we use a common practice equalizing formation and holding periods, as proposed by most part of related studies. These periods give us time intervals between rebalancing points for portfolio trading. For example, a 1-month time period means that at the end of each month investor reevaluates performance of each stock based on last period trading information and rebalances the portfolio with respect to it.

In this study a 1-week, 1-month and 3-month time periods are used as Chan, Hameed and Tong (1999) and Daniel et al.(1998) proposed as most profitable for emerging markets. The intuition behind such short intervals is that emerging markets have relatively short periods of high quality trading data and it is better to use shorter periods that take into account structural market changes.

Compounding of these factors gives us 18 momentum strategies – 3 strategies for each simple momentum and Sharpe ratio based strategies and 3 strategies for each of 4 nodes of R-ratios with different parameters.

As we have a time series of stock returns on emerging market, there could be both linear and heteroscedastic dependence in the series. For linear dependence modeling we use Box-Jenkins selection methodology described by Enders (2010). For volatility model building we use four-step algorithm proposed by Tsay (2010). The general ARMA(p,q) model is defined as:

$$r_t = c + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{i=1}^{p} \theta_i \varepsilon_{t-i} + \varepsilon_t, \quad (8)$$

If the ε_t^2 is not a white noise (is tested by Portmanteau test for white noise), we assume process to be heteroscedastic, obtain fit of volatility process and resulting ARMA(p,q)-GARCH(m,l) model:

$$\begin{cases} r_t = c + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{i=1}^{p} \theta_i \varepsilon_{t-i} + \varepsilon_t, \\ \sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 . \end{cases} \quad (9)$$

Where r_t is a profit of the momentum portfolio at time t, σ_t^2 is a conditional variance at time t, and $\varepsilon_t \sim N(0, \sigma_t^2)$ is assumed to be distributed normally with 0 mean and σ_t^2 variance. Other parameters are constant.

At this step we obtain parameters for each path of portfolio returns. Plug it into the (9) to obtain the law of motion for portfolio returns. Based on this information we can use Monte-Carlo simulations in order to predict future returns on these strategies.

Following Biglova et al. (2004) we introduce independent performance measure also known as STARR ratio:

$$IPM(r) = \frac{E[r - r_f]}{CVaR_{(1-\alpha)\%}(r - r_f)} \qquad (10)$$

It gives the ratio between the expected excess return and its conditional value at risk. The ratio is one of the popular modern approximations of risk/return tradeoff for portfolio returns. Therefore, we can calculate cumulative compounded return and independent performance measure for each simulated portfolio. We use the independent performance measure to find the best performing strategy over the simulation period. If the return for this strategy is positive we reject the null hypothesis of weak form market efficiency for the Ukrainian stock market.

C h a p t e r 4

DATA DESCRIPTION

To investigate momentum strategies for stocks traded in the Ukrainian market we use the top 25% of companies with the highest capitalization, as suggested by Hong, Limm and Stein (1999). As a result, 47 stocks have been selected.

Daily data are used to analyze short term implementation, as Chan, Hameed and Tong (1999) emphasized.

World crisis and currency devaluation in late 2008 had a great influence on the Ukrainian stock market and provoked structural changes in it – many of Ukrainian banks collapsed, the National Bank of Ukraine imposed strict rules to stabilize the economy, most part of external financing sources to develop the economy became unavailable, local currency depreciated dramatically. At the same time, the Ukrainian Exchange stock exchange was introduced. It is based on the same platform as more developed Russian MICEX and performs easy online access to trading process. This stimulates private investors' activity on the UX. The data from 26 March 2009 till 20 February 2013 or in other words 974 daily observations are used for this study. The trading data is performed in free access on the UX website.

Table 1 contains descriptive statistics of daily log prices for the UX top listed stocks. It was downloaded from the UX website and is performed in log price form.

Table 1. Descriptive statistics of the UX stocks log prices

Stock	Obs	Mean	Std.Dev.	Min	Max
ALKZ	974	-.503923	.26699	-1.07486	0
ALMK	974	-.9203752	.2291701	-1.373318	0
AVDK	974	.8865758	.2854186	0	1.248292
AVTO	974	1.799014	.5252886	0	2.399143
AZST	974	.2462839	.2357521	-.2596373	.6614972
BAVL	974	-.6572574	.2690526	-1.195406	-.3013196
CEEN	974	.9808166	.1692744	0	1.292249
CGOK	974	.6597049	.2971065	0	.9866225
DAKOR	974	1.03406	.6334955	0	2.120409
DMKD	974	-.5206808	.3451928	-1.220885	.0666986
DNEN	974	2.825421	.3451482	0	3.169772
DNON	974	1.994636	.7992745	0	2.778151
DNSS	974	2.905599	.8929022	0	3.389166
DOEN	974	1.597275	.2877866	0	2.04369
ENMZ	974	1.991753	.294053	0	2.481275
FORM	974	.4744057	.4061756	-.3872161	.986906
GFARM	974	1.640288	.6668611	0	1.980685
GLNG	974	-.6392465	.343687	-1.124939	0
HRTR	974	.0365425	.1008878	-.2194427	.2692638
KIEN	974	.8753315	.3681411	0	1.382617
KRAZ	974	-.7862072	.4180659	-1.662874	0
KREN	974	.3265622	.2164036	-.2123034	.8095597
KRHLB	974	.5603927	.383944	0	.9614211
KVBZ	974	1.285364	.2935019	0	1.594393
LSHP	974	.2150249	.33165	0	.9542425
LTPL	974	.4313439	.1563444	0	.7855671
LUAZ	974	-.7250311	.2590777	-1.505845	0
MMKI	974	-.1640764	.4530844	-.8857227	.6387887
MSICH	974	3.288683	.2408816	0	3.585159
MTBD	974	1.992289	.7492627	0	2.88855
MZVM	974	.3993633	.9849255	-1.026872	1.607562
NITR	974	.6005215	.3860347	0	1.263241
NVTR	974	.0274017	.382491	-.9208188	.667453
PGOK	974	1.362542	.2930651	0	1.900185

Table 1. – Continued

Stock	Obs	Mean	Std.Dev.	Min	Max
SGOK	974	.8261188	.3574764	0	1.204256
SHCHZ	974	.3743461	.3348289	-.2492346	.9401677
SHKD	974	.3342019	.2896726	-.0268721	.9323046
SMASH	974	1.028187	.5983068	0	1.922743
STIR	974	1.55785	.3788734	0	2.032699
SVGZ	974	.5705211	.2789034	0	1.060887
UNAF	974	2.427811	.2678699	1.924934	2.95213
USCB	974	-.5175187	.2349934	-1.116339	0
UTLM	974	-.3843916	.1697768	-.8789876	0
YASK	974	.3049604	.2841801	-.1958606	.7551886
ZAEN	974	2.431926	.268271	0	2.758407
ZHEN	974	.1310991	.2054294	-.2798407	.5925468
ZPST	974	.4460212	.2655519	0	.820858

As one can notice, there are many zero values in min-max statistics. Actually, stock could not reach 0 log value during the pass. At the beginning of the trading not all stocks used were performed on the market – they became listed on average in three month after the UX was lauched. Price on these stocks was assigned 0 if omitted by construction. Therefore, while stock is not traded and hence return is 0, it is not included into the trading process.

The NBU interest rate was used as a risk free rate for further calculations. It is calculated as a discount rate at which NBU credits private banks. It had a 4% spike during 2008-2009 and now is stabilized on 7.5% value.

Chapter 5

EMPIRICAL RESULTS

For the empirical programming of trading process Matlab was used. The stocks that are not traded initially imply zero value for initial period and therefore do not influence portfolio construction (if price of the asset is zero, the criteria used in this study will imply a zero position in this asset).

For convenience let (I) be an identifier for simple return momentum strategy method specified by equation (5), (II) – for Sharpe ratio momentum strategy method specified by equation (6).

After application of criteria for each trading strategy and programming trading process we have obtained distributions of returns for momentum portfolios corresponding to each strategy with holding period of 1 week, 1 month and 3 months. Portfolio passes for each strategy are presented on Figure 1.

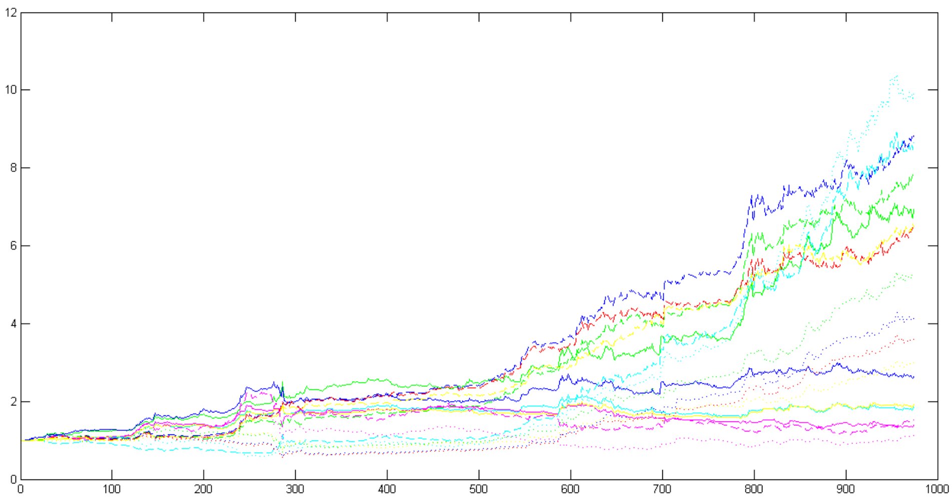

Figure 1. The in-sample passes of portfolio returns for the strategies

As one can see, the resulting cumulative returns significantly differ among strategies. However, there is strong evidence of the trend component for each strategy. Also cumulative returns for most trading strategies are high and are listed in Table 2. Notice that for first two momentum criteria (simple momentum and Sharpe ratio) 1 month strategy is the most profitable.

Table 2. Cumulative profit for momentum strategies within the history pass.

Criterion \ Time	1 week	1 month	3 months
Simple momentum	5,9384	6,7489	4,2706
Sharpe ratio	1,6272	7,7991	3,1492
R-ratio (0,5;0,5)	0,8502	-	-
R-ratio (0,5;0,2)	0,8502	-	-
R-ratio (0,2;0,5)	0,3941	-	-
R-ratio (0,2;0,2)	0,9223	-	-
R-ratio (0,5;0,5)	-	5,4128	2,6046
R-ratio (0,5;0,05)	-	7,6396	8,9449
R-ratio (0,05;0,5)	-	0,5301	0,1252
R-ratio (0,05;0,05)	-	5,4796	1,9912

There is a big difference in calculating momentum profits with Rachev criterion for different formation/holding period. For 1 week time horizon criterion is calculated only if formation week contained 5 observations. For shorter series it makes no sense to calculate 20% tail loss that is used in Rachev criterion. Therefore, the weeks after truncated ones were skipped for trading and have return 0. This may be a motivation for dramatically lower portfolio returns than in case of other time horizons. For next statements we use a relation between Rachev ratio specification and investor's behavior described by Rachev et al. (2007). For monthly and 3 months formation period portfolios returns there is strong evidence that overconfident investors underperform relative to others – when criterion is focused on extreme profits and averages losses (in other words investor focuses on profits and neglects losses) the profit is dramatically lower than for other investors. In contrast, the risk-averse investor (is focused on extreme losses and neglects extreme profits) shows the highest return for monthly and 3 months formation/holding period. Maximum average monthly return for Rachev ratio based 1 week formation/holding period momentum strategy is 1,3%. However, this type of strategies requires rebalancing 4 times per month. For the stock market of the Ukrainian emerging economy transaction costs of such rebalancing are likely to be higher than the average return. Therefore these strategies are not profitable and are dropped out of further modeling. The same intuition is behind the drop of monthly and 3 months portfolios for risk-loving investors – 0,9% per month and 0,7% per 3 months returns respectively are comparable with transaction costs to maintain a strategy.

For each of 10 left momentum strategies the Dickey-Fuller test rejects the null hypothesis of the existence of unit roots. The results with the tests are presented in the Table 3. Therefore the pass of portfolio returns for each strategy is stationary and we can proceed with ARMA process modeling.

Table 3. The augmented Dickey-Fuller test for unit root – Z(t) values.

Criterion \ Time	1 week	1 month	3 months
Simple momentum	-27,937	-29,467	-27,530
Sharpe ratio	-30,218	-30,052	-28,161
R-ratio (0,5;0,5)	-	-29,807	-28,298
R-ratio (0,5;0,05)	-	-28,027	-27,252
R-ratio (0,05;0,05)	-	-29,608	-28,237

1% critical value = -3,430

We follow Tsay (2010) methodology to determine the order of ARMA process. The order of moving average component is given by autocorrelation function (Figures 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24). The order of autoregressive component is given by partial autocorrelation function (Figures 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25). We use the Ljung-Box test to exam the residuals of the model for white noise. If the distribution of residuals is performed by white noise, we accept the order of ARMA. Results are presented in Table 4. For monthly period path of portfolio returns for (0,05;0,05) node there is no autoregressive or moving average components. Ljung-Box Q-statistics tells us that each strategy in Table 4 has white noise residuals.

Table 4. Parameters of ARMA(p,q) model with (Q-statistics: Prob>χ^2).

Criterion \ Time	1 week	1 month	3 months
Simple momentum	ARMA(1;1) (0,5645)	ARMA(3;3) (0,8142)	ARMA(1;1) (0,2834)
Sharpe ratio	ARMA(0;0) (0,8331)	ARMA(3;3) (0,8754)	ARMA(1;1) (0,3070)
R-ratio (0,5;0,5)	-	ARMA(3;3) (0,9521)	ARMA(1;1) (0,3029)
R-ratio (0,5;0,05)	-	ARMA(1;1 2) (0,2414)	ARMA(1,1) (0,1011)
R-ratio (0,05;0,05)	-	ARMA(0,0) (0,6597)	ARMA(1 4 7;1 4 7) (0,3452)

We obtain squared residuals for each ARMA model as a squared difference between the ARMA model forecast and the real data. Autocorrelation (Figures 26, 28, 30, 32, 34, 36, 38, 40, 42, 44, 46, 48) and partial autocorrelation (Figures 27, 29, 31, 33, 35, 37, 39, 41, 43, 45, 47, 49) functions help us to determine the order of GARCH process. If the model selection is unclear, we compare different assumptions for the GARCH models using both Akaike information criteria (AIC) and Bayesian information criterion (BIC) post estimation criteria and take the best fit. For example, for the first strategy (criterion (I), weekly rebalancing) we compare results for GARCH(1,1), GARCH(1 2,1), GARCH(1 2 10,1), GARCH(1 10,1) and the minimum both AIC and BIC has GARCH(1,1) model. Results are presented in a Table 5.

The most part of series are represented by GARCH(1,1) process and are a common evidence for momentum strategies on financial markets as it was claimed by Rachev et al. (2007) and Biglova et al. (2004). However, 3 monthly returns for simple momentum and Sharpe ratio follow ARCH(1) process.

Table 5. Parameters of GARCH(p,q) model with given ARMA.

Criterion \ Time	1 week	1 month	3 months
Simple momentum	(1;1)	(1;1)	(1;0)
Sharpe ratio	(1;1)	(1;1)	(1;0)
R-ratio (0,5;0,5)	-	(1 2 7;1)	(1;1-4)
R-ratio (0,5;0,05)	-	(1;1)	(1,1)
R-ratio (0,05;0,05)	-	(1,1)	(1;1)

We run derived ARMA-GARCH model for each series. Results are presented in the Table 7 and Table 8 respectively.

We use Monte-Carlo simulations to forecast future portfolio returns. The prospect of forecast is 1 month (20 observations) and is chosen in order to keep consistent with time intervals for strategies. 10000 passes for each strategy are generated as it is commonly implied for time series simulations. The forecasted returns are presented on Figure 50.

The value of independent performance measure for $\alpha = 90\%$ is calculated for each result of simulations. Results are presented in Table 6.

As one can see, maximum independent performance measure is related to the simple return method and 1-month rebalancing. Therefore, we use this pass to evaluate weak form of stock market efficiency.

Table 6. Independent performance measure and return for simulations.

Strategy parameters: method and holding period	Independent performance measure	Cumulative return forecast, %
(I) simple momentum 1 week period	1,0272	0,22
(I) simple momentum 1 month period	1,0616	0,07
(I) simple momentum 3 months period	1,0470	1,09
(II) Sharpe ratio 1 week period	1,0129	0,1
(II) Sharpe ratio 1 month period	1,0313	0,09
(II) Sharpe ratio 3 months period	1,0861	1,29
Rachev(0.5,0.5) ratio 1 month period	1,0227	0,05
Rachev(0.5,0.5) ratio 3 months period	1,1347	0,53
Rachev(0.5,0.05) ratio 1 month period	1,3888	0,35
Rachev(0.5,0.05) ratio 3 months period	0,8960	-0,01
Rachev(0.05,0.05) ratio 1 month period	1,0209	0,08
Rachev(0.05,0.05) ratio 3 months period	1,0708	0,01

Chapter 6

CONCLUSION

In this study efficient market hypothesis has been examined using momentum strategies. Based on the simple momentum, Sharpe ratio and Rachev ratio we determine arrays of momentum portfolio returns for 1 week, 1 and 3 month formation and holding period. The strongly positive payoff strategies are modeled by ARMA-GARCH process.

Using Monte-Carlo simulations we obtain forecast for each of these strategies. We used STARR ratio as independent performance measure to determine the best profitable, risk adjusted momentum strategy.

The strategy is based on Rachev ratio (0.5,0.05) criteria with 1 month formation/holding period. As it was explained earlier, it depicts risk-averse short term investor. The forecasted monthly return for this strategy is 0,35% and is not leading profitable strategy. This is because of relatively high volatility related to most profitable strategies. Therefore, these strategies could not be taken as a benchmark in this study.

The monthly return 0,35% is low comparably to transaction costs related to monthly rebalancing. Therefore, we cannot reject the null hypothesis of Ukrainian market efficiency. This can be related to highly significant positive changes in trading process and information availability during the recent years.

For future studies one can try use more sophisticated trading strategies and develop studies related to more developed CIS countries' markets.

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APPENDIX

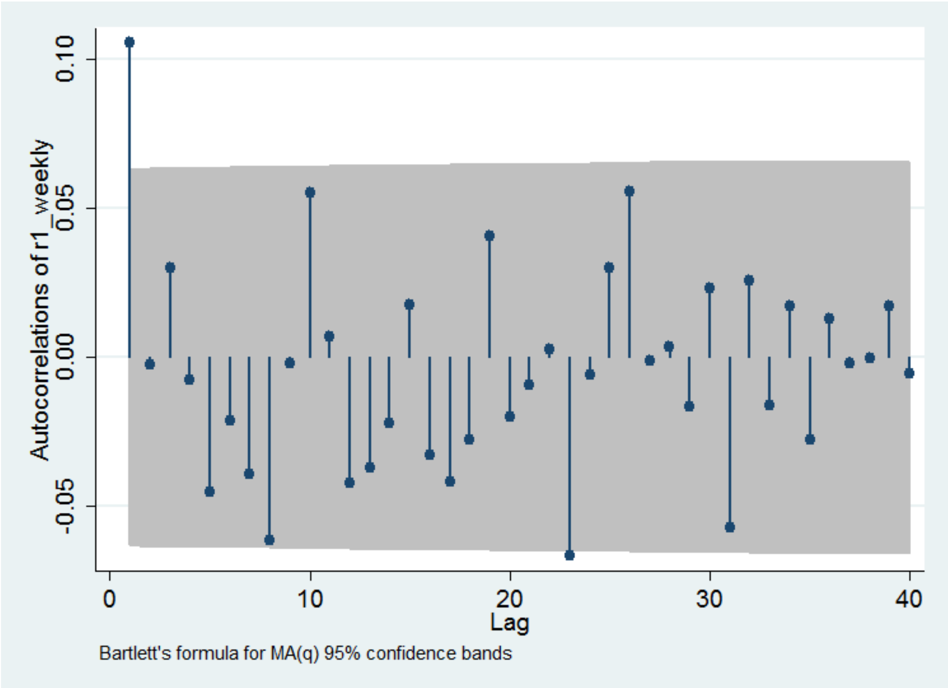

Figure 2. Autocorrelation function of (I) criterion with weekly rebalancing.

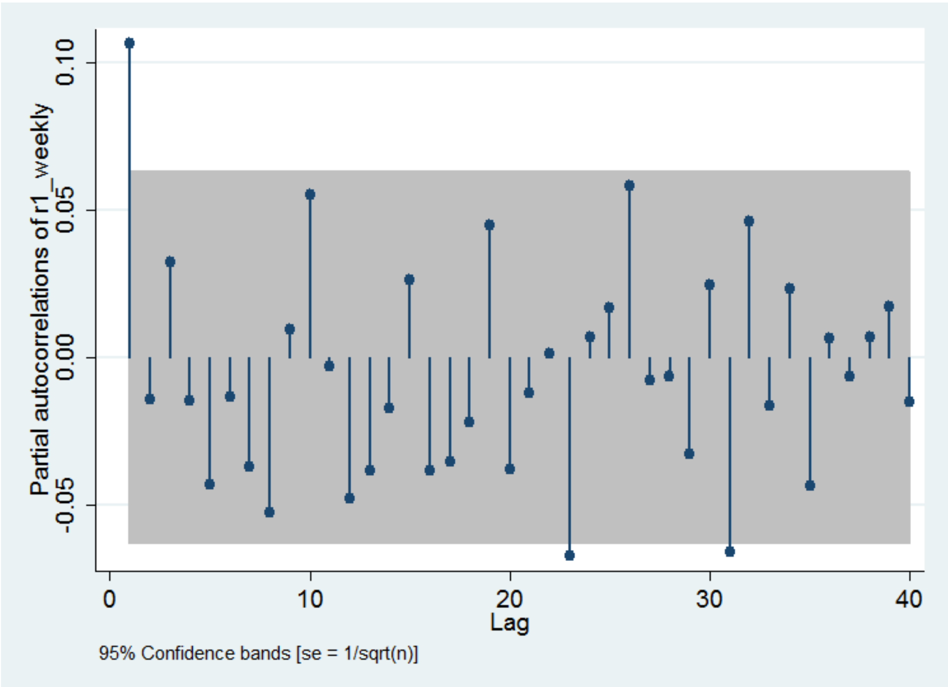

Figure 3. Partial autocorrelation function of (I) criterion with weekly rebalancing.

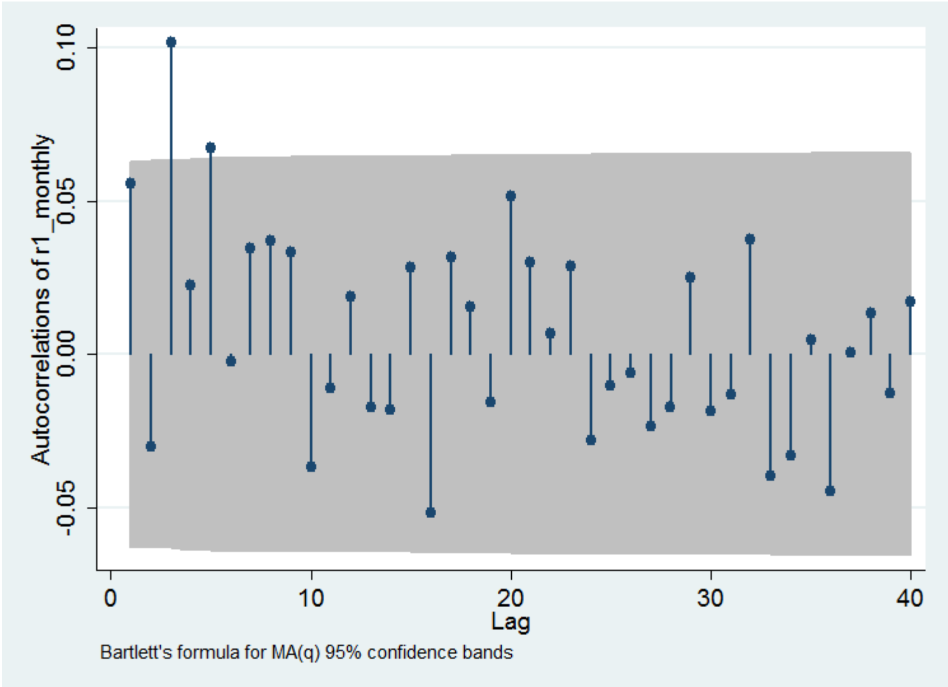

Figure 4. Autocorrelation fuction of (I) criterion with monthly rebalancing.

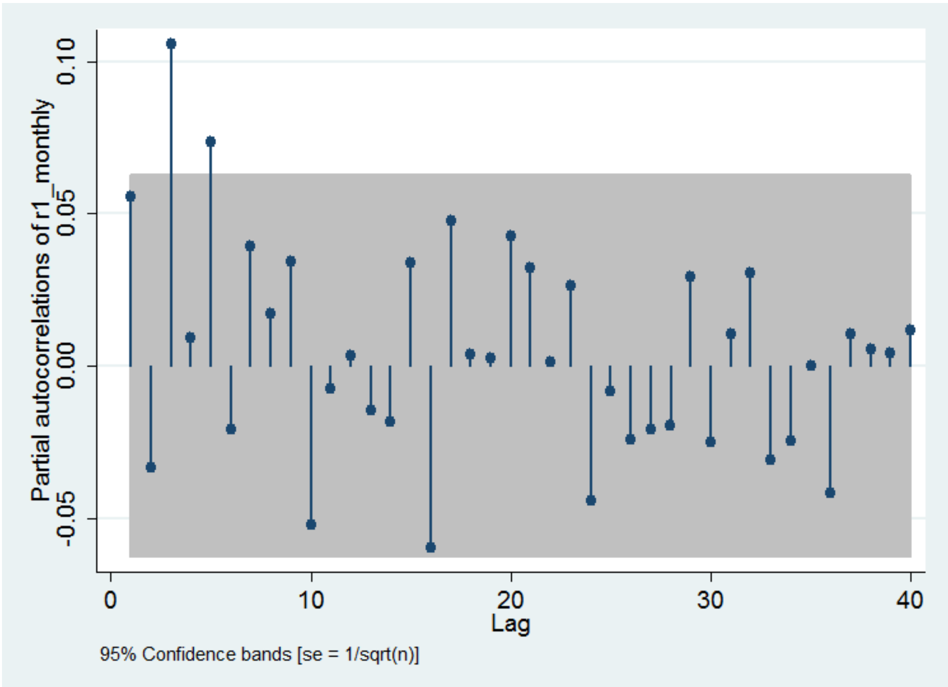

Figure 5. Partial autocorrelation function of (I) criterion with monthly rebalancing.

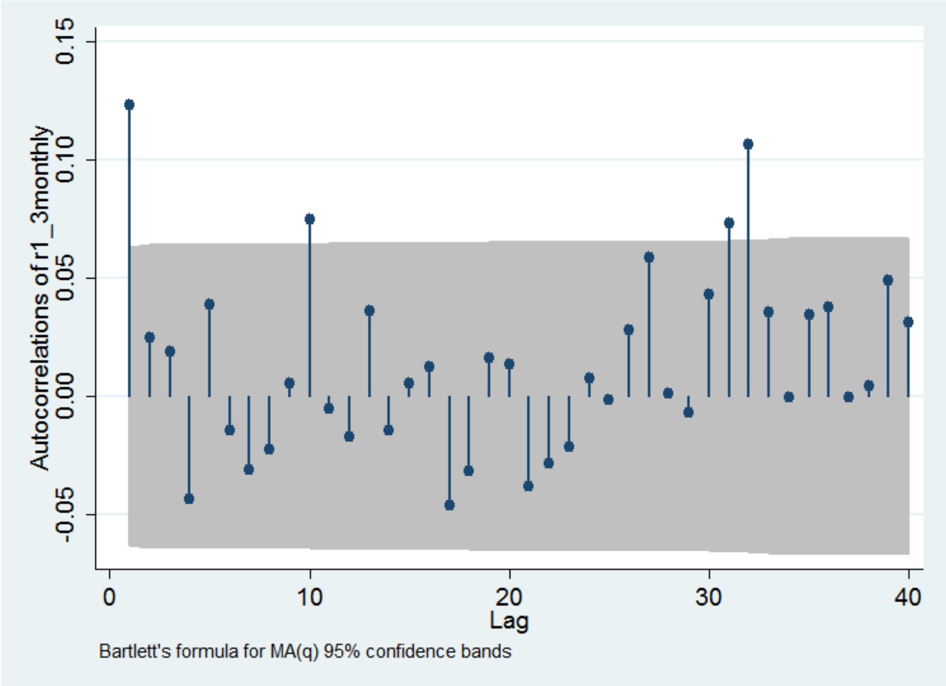

Figure 6. Autocorrelation function of (I) criterion with 3 months rebalancing.

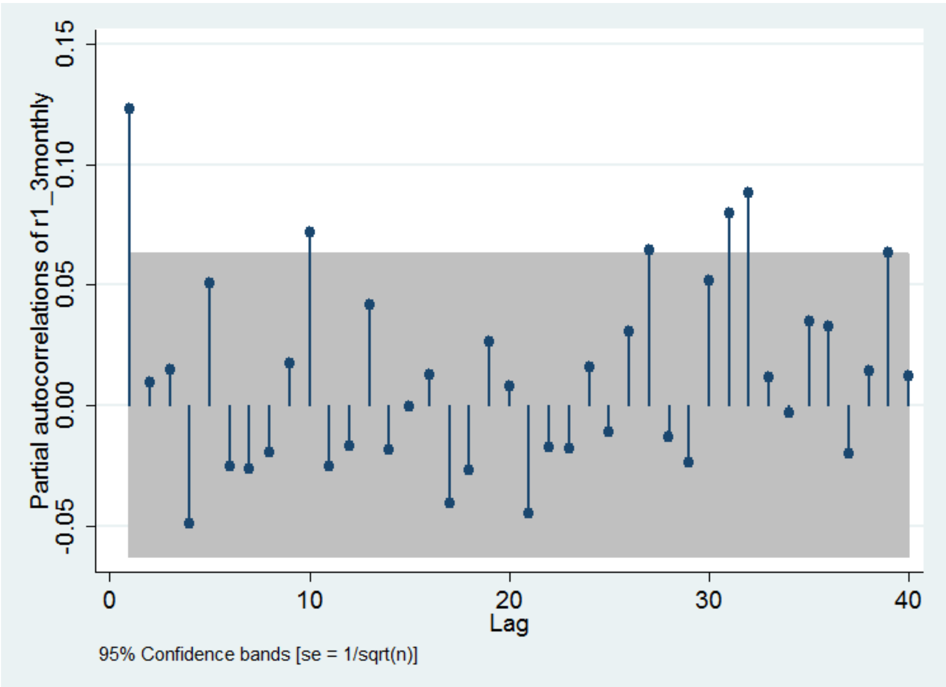

Figure 7. Partial autocorrelation function of (I) criterion with 3 months rebalancing.

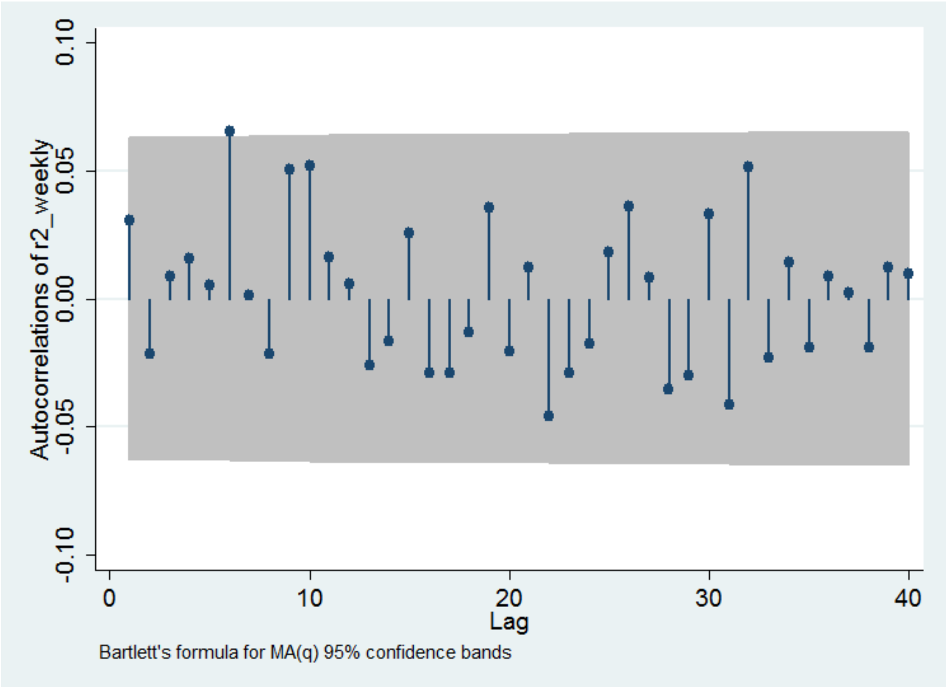

Figure 8 Autocorrelation function of (II) criterion with weekly rebalancing.

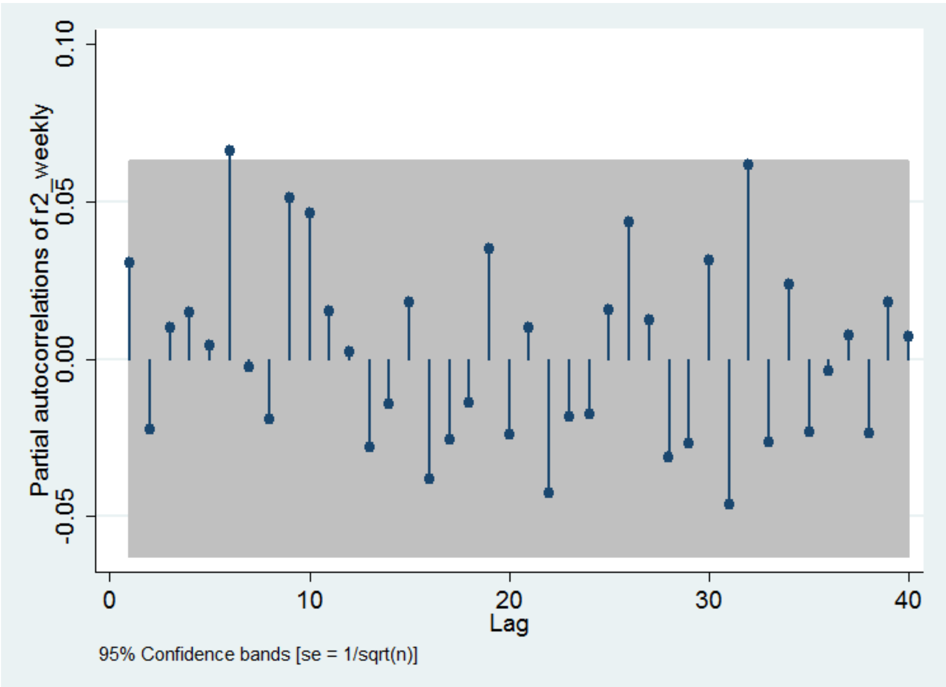

Figure 9. Partial autocorrelation function of (II) criterion with weekly rebalancing.

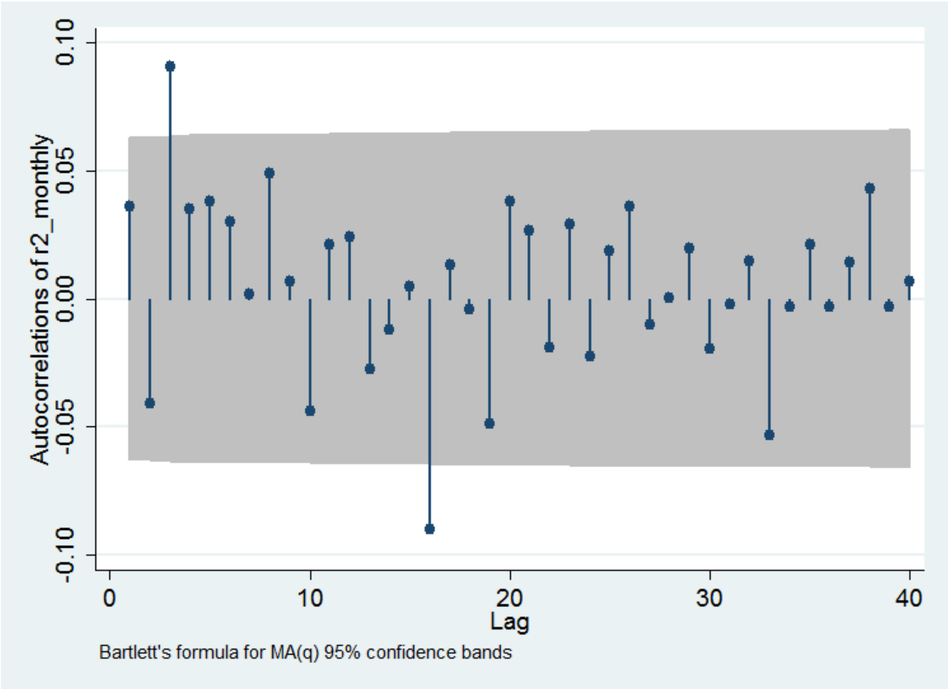

Figure 10. Autocorrelation function of (II) criterion with monthly rebalancing.

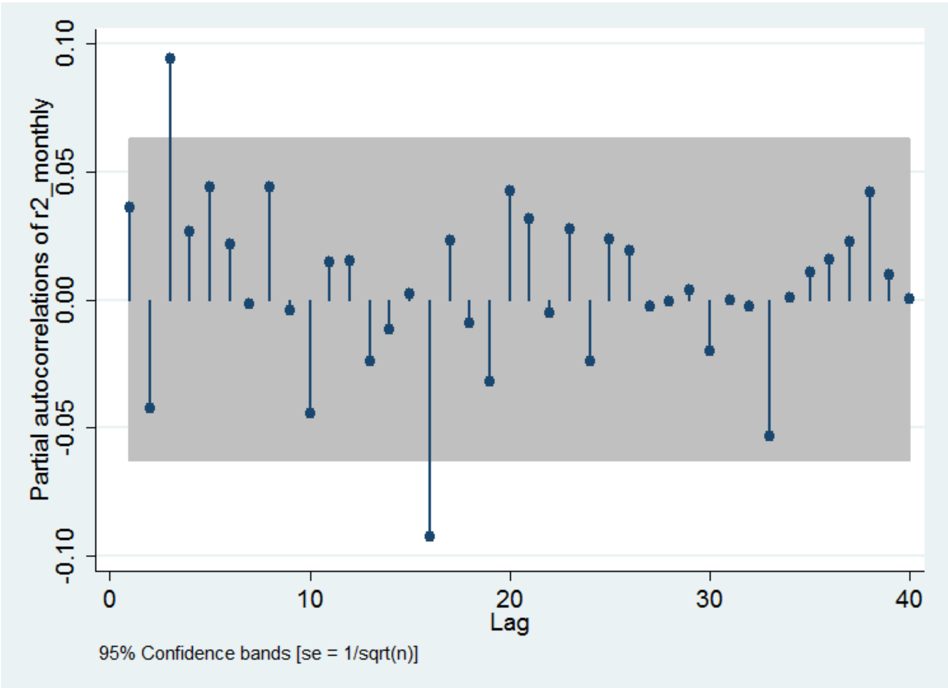

Figure 11.Partial autocorrelation function of (II) criterion with monthly rebalancing.

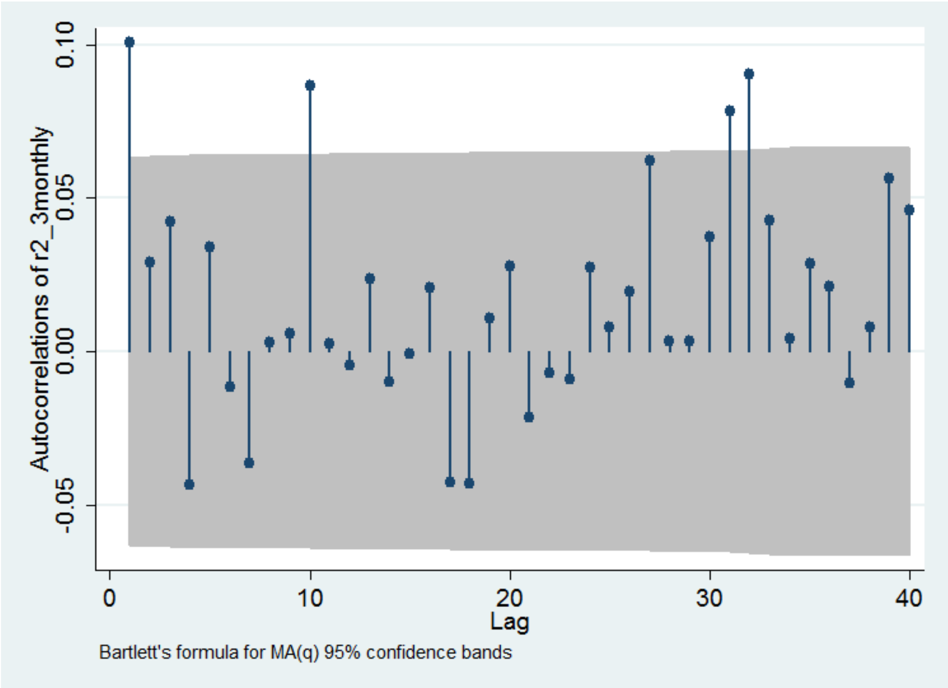

Figure 12. Autocorrelation function of (II) criterion with 3 months rebalancing.

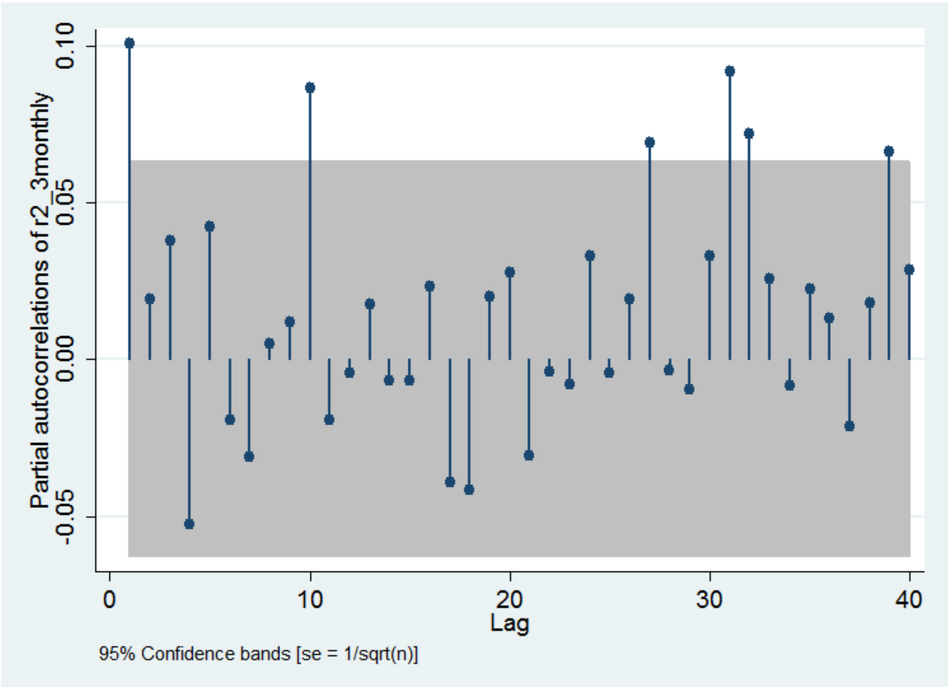

Figure 13. Partial autocorrelation function of (II) criterion with monthly rebalancing.

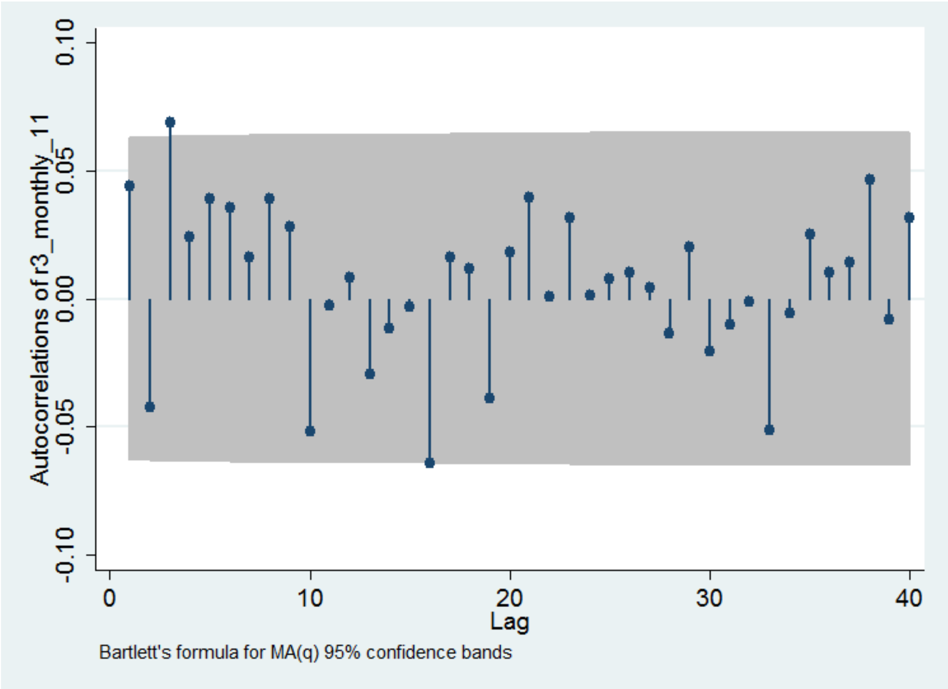

Figure 14. Autocorrelation function of R(0.5,0.5) criterion with monthly rebalancing.

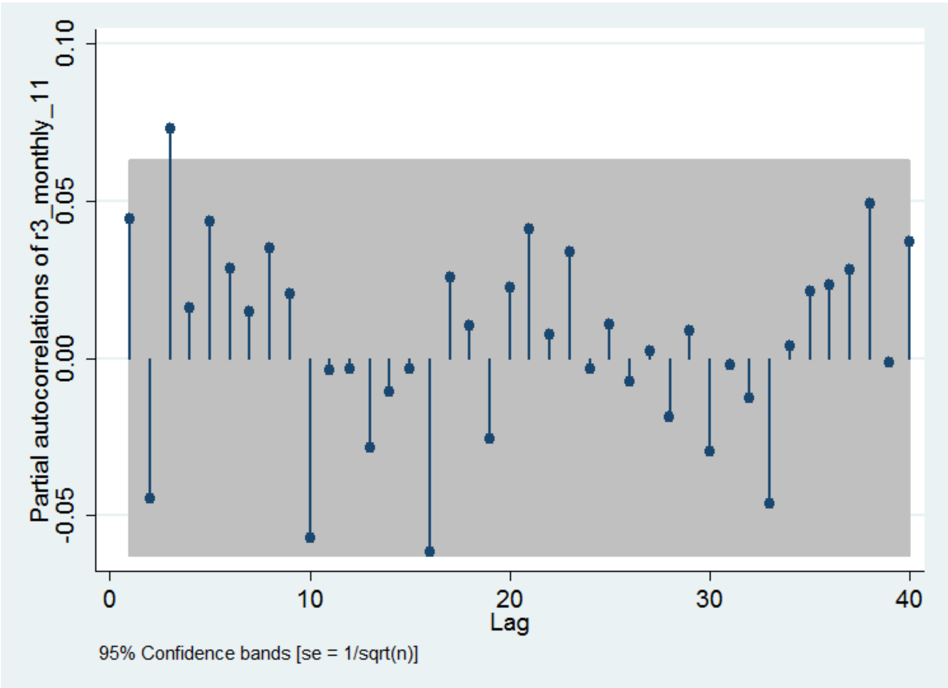

Figure 15. Partial autocorrelation function of R(0.5,0.5) criterion with monthly rebalancing.

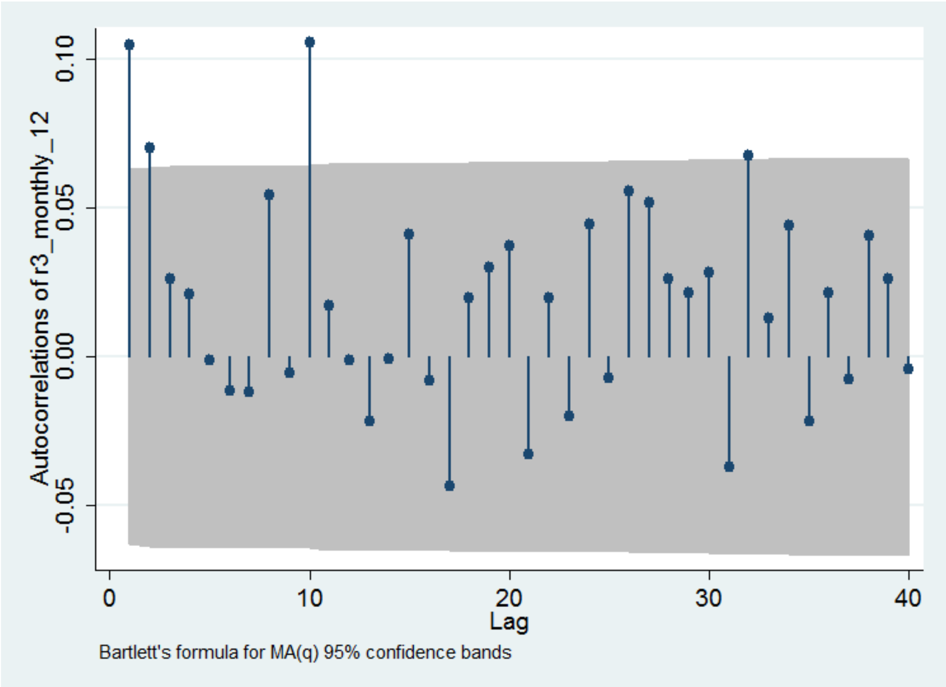

Figure 16. Autocorrelation function of R(0.5,0.05) criterion with monthly rebalancing.

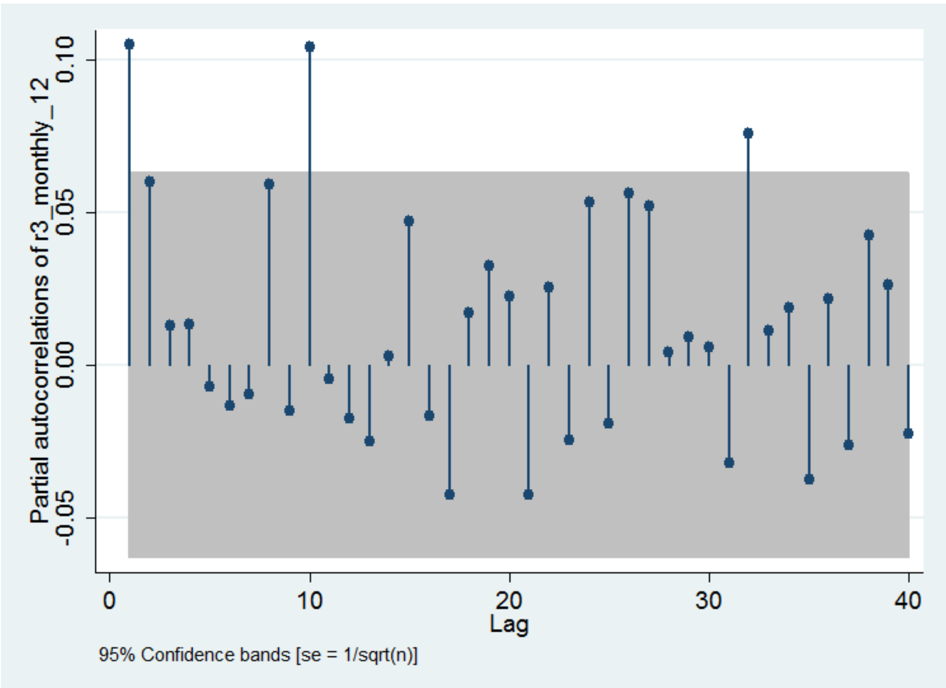

Figure 17. Partial autocorrelation function of R(0.5,0.05) criterion with monthly rebalancing.

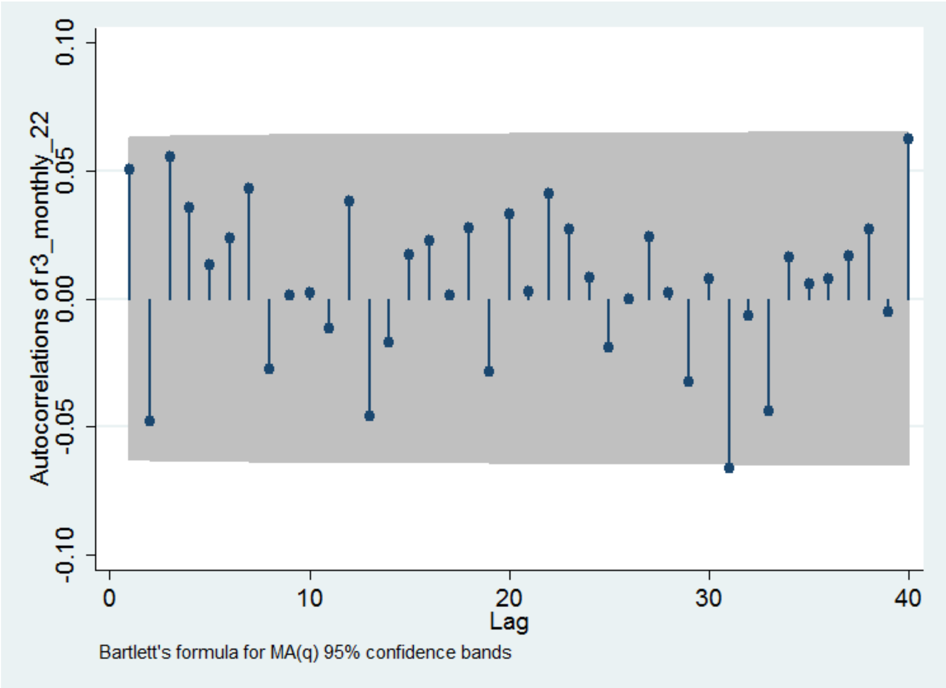

Figure 18. Autocorrelation function of R(0.05,0.05) criterion with monthly rebalancing.

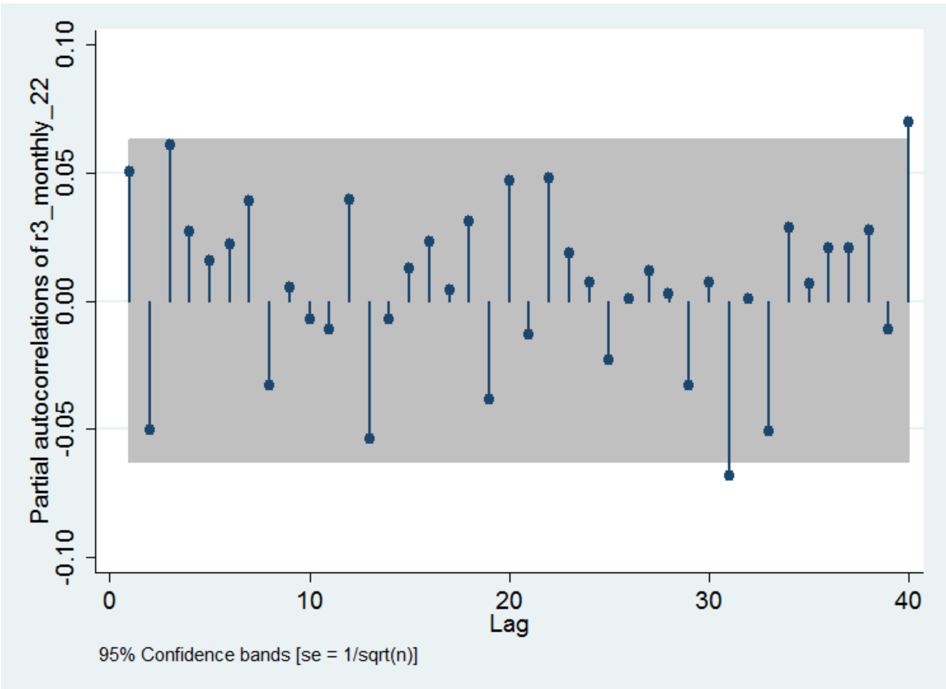

Figure 19. Partial autocorrelation function of R(0.05,0.05) criterion with monthly rebalancing.

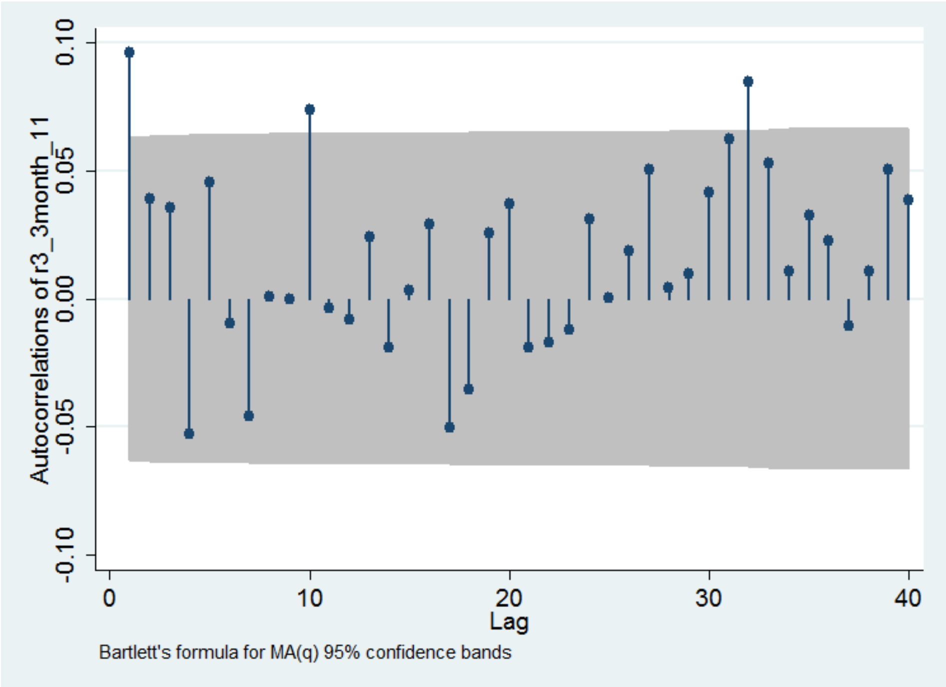

Figure 20. Autocorrelation function of R(0.5,0.5) criterion with 3 months rebalancing.

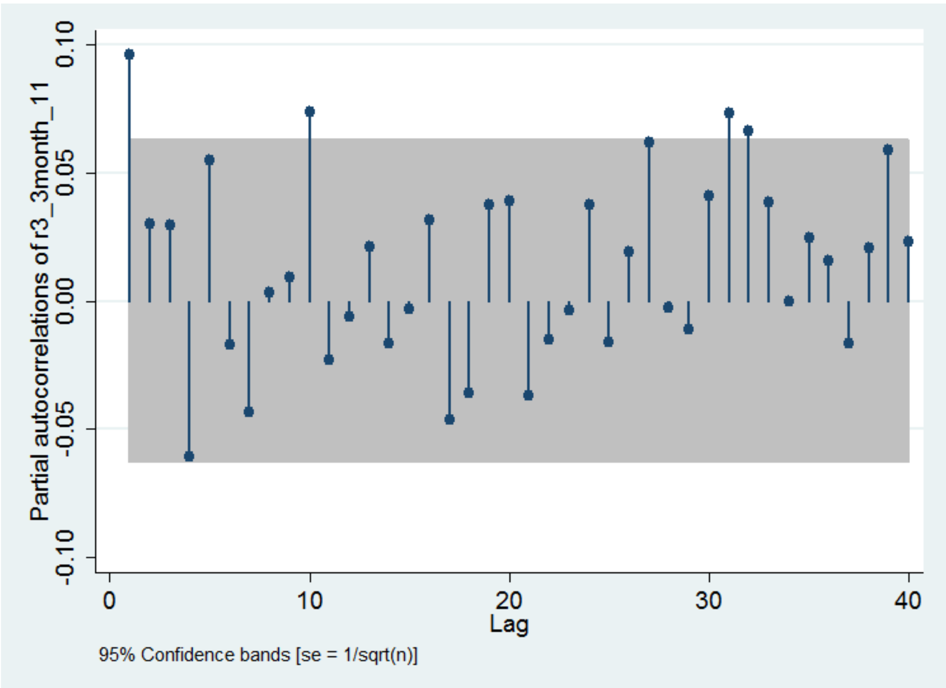

Figure 21. Partial autocorrelation function of R(0.5,0.5) criterion with 3 months rebalancing.

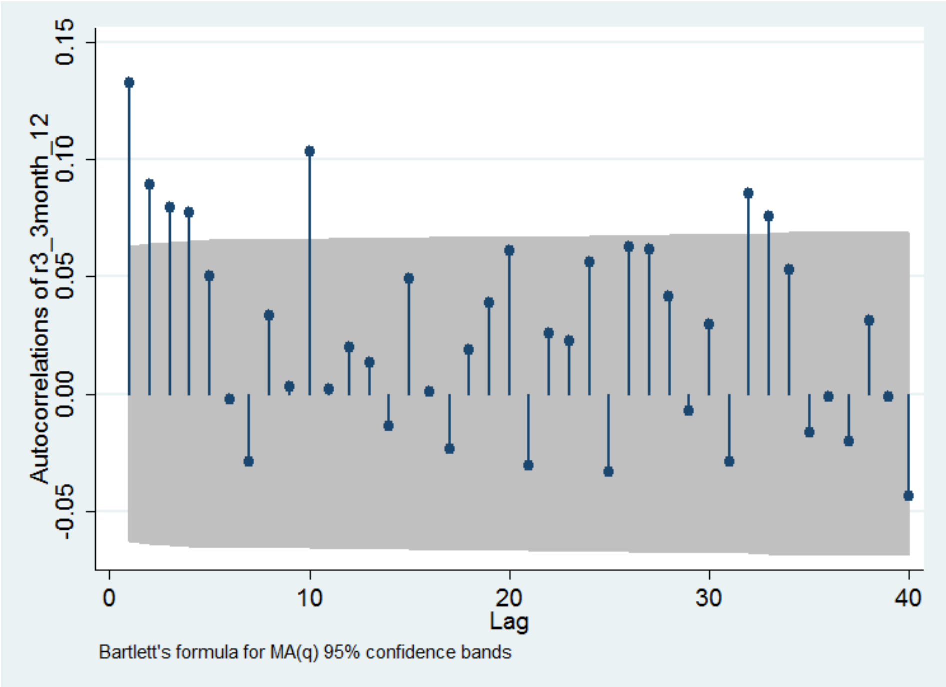

Figure 22. Autocorrelation function of R(0.5,0.05) criterion with 3 months rebalancing.

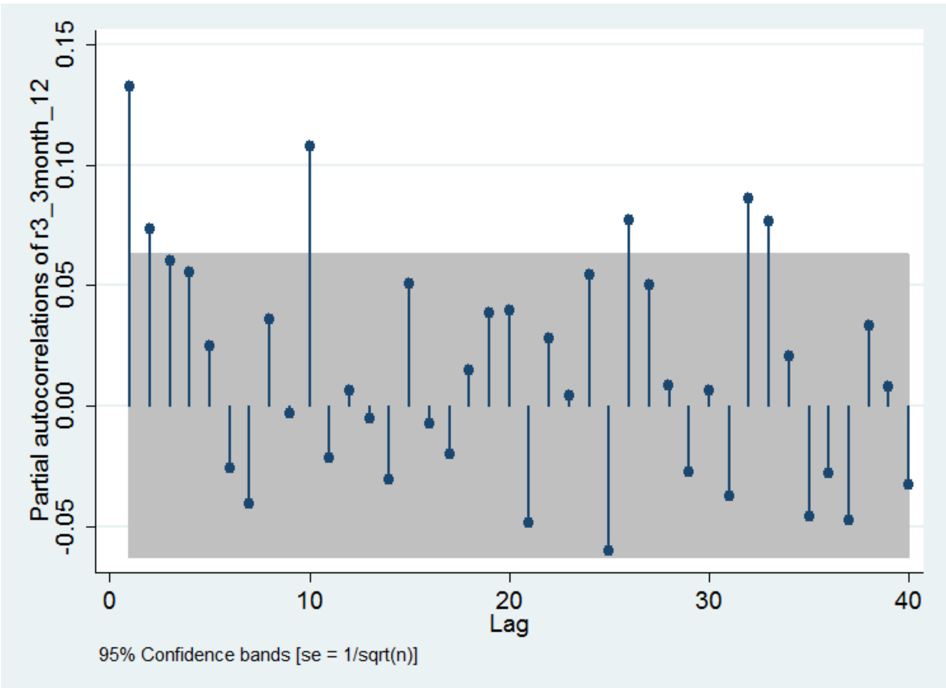

Figure 23. Partial autocorrelation function of R(0.5,0.05) criterion with 3 months rebalancing.

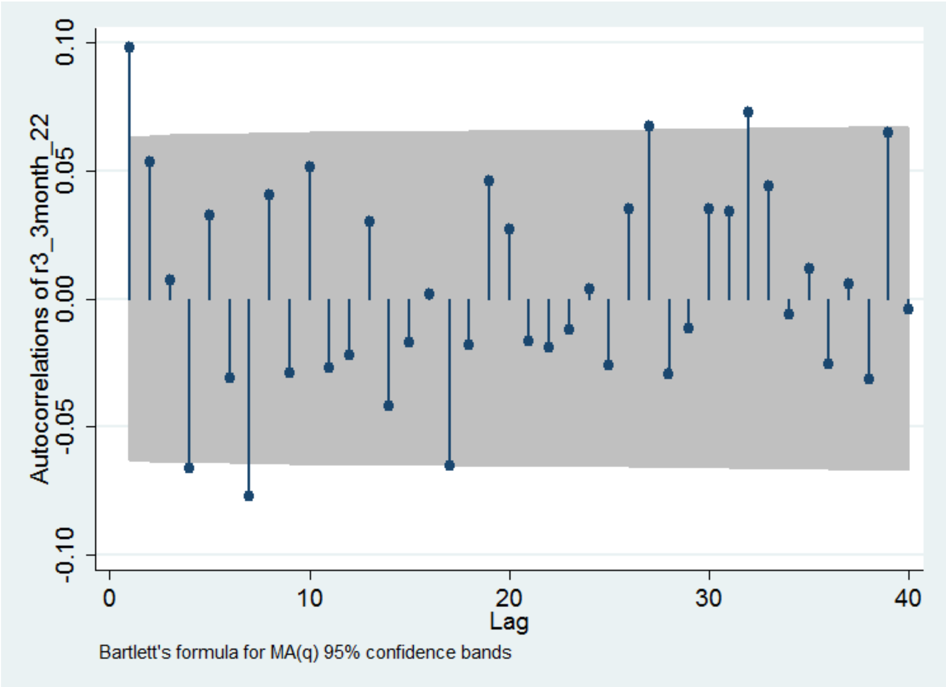

Figure 24. Autocorrelation function of R(0.05,0.05) criterion with 3 months rebalancing.

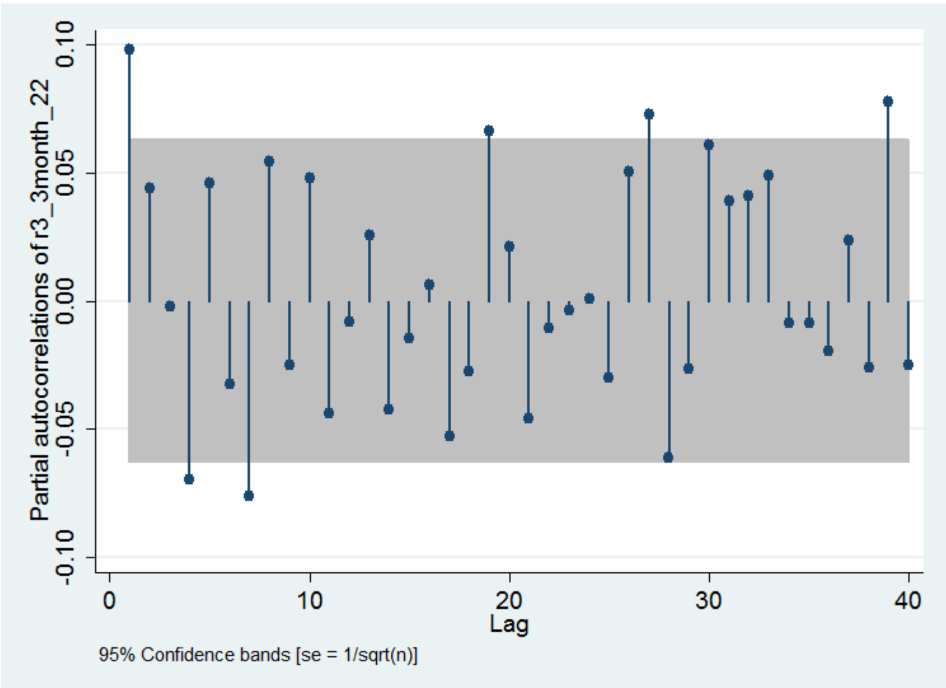

Figure 25. Partial autocorrelation function of R(0.05,0.05) criterion with 3 months rebalancing.

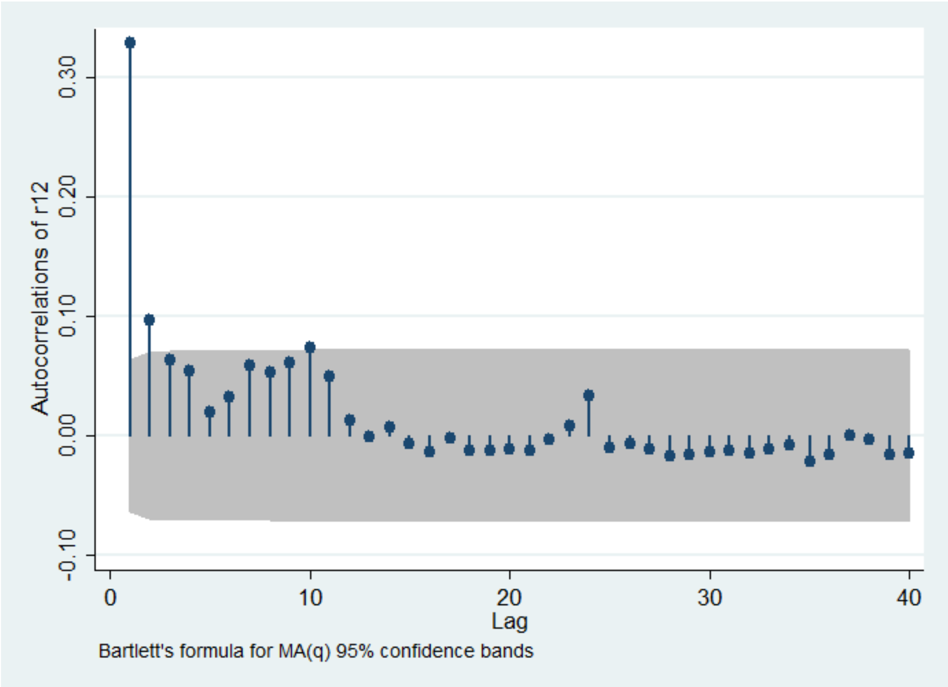

Figure 26. Autocorrelation function of squared residuals of the strategy: (I) criterion with weekly rebalancing.

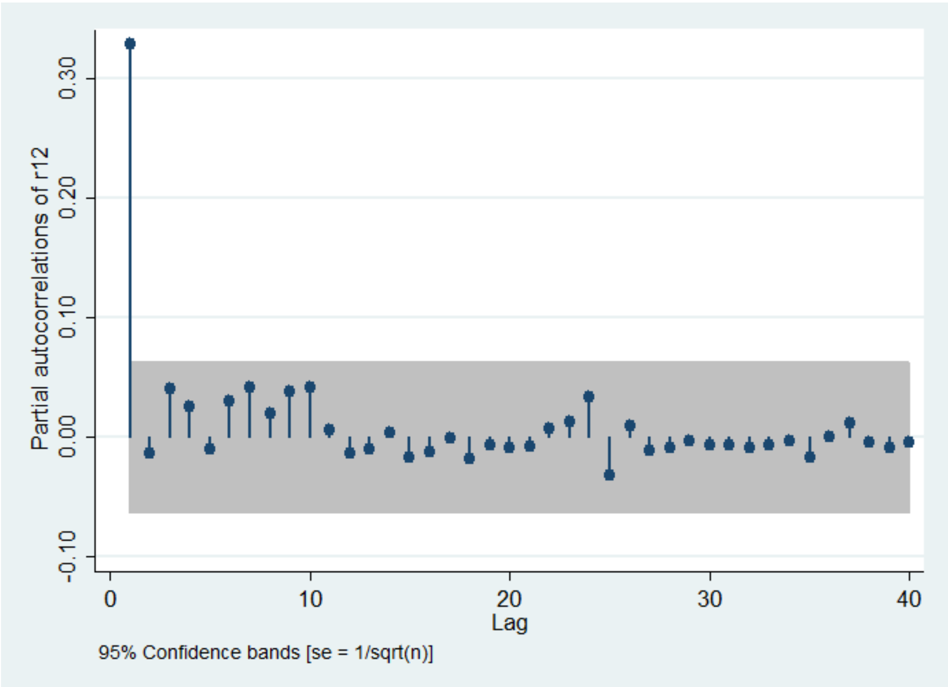

Figure 27. Partial autocorrelation function of squared residuals of the strategy: (I) criterion with weekly rebalancing.

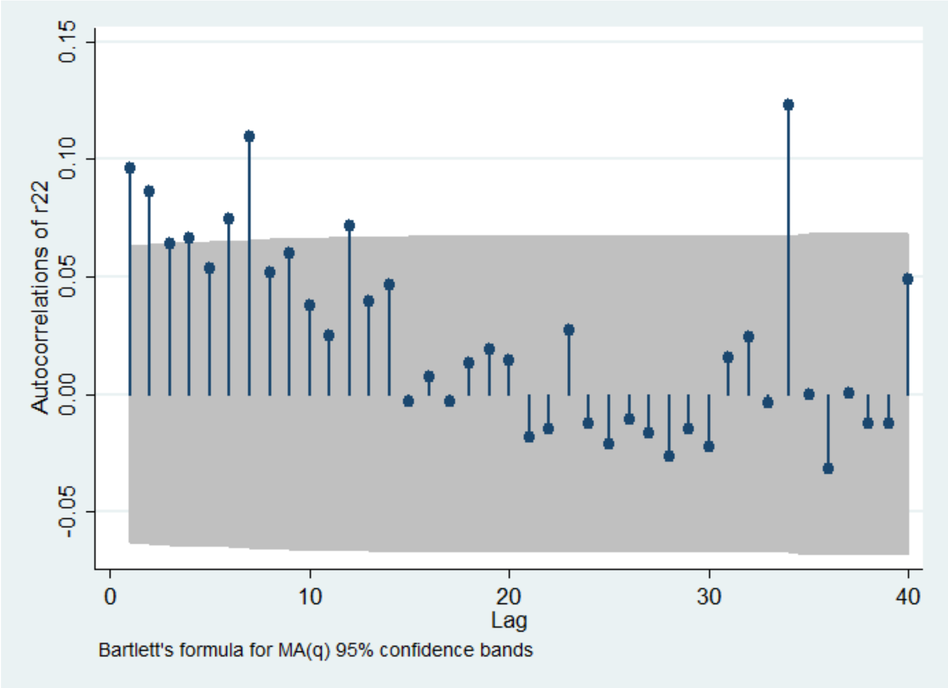

Figure 28. Autocorrelation function of squared residuals of the strategy: (I) criterion with monthly rebalancing.

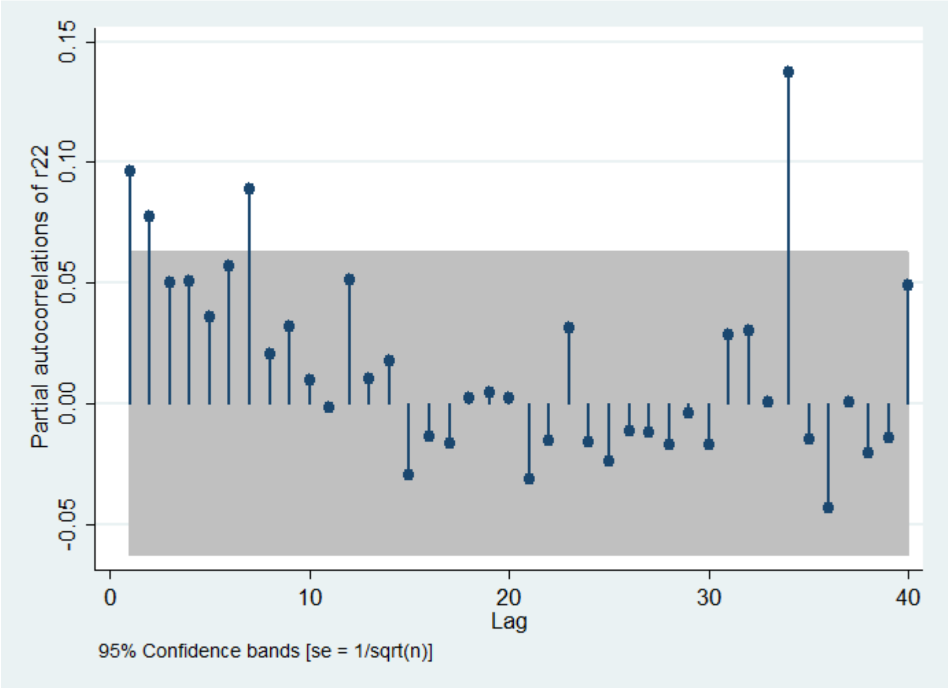

Figure 29. Partial autocorrelation function of squared residuals of the strategy: (I) criterion with monthly rebalancing.

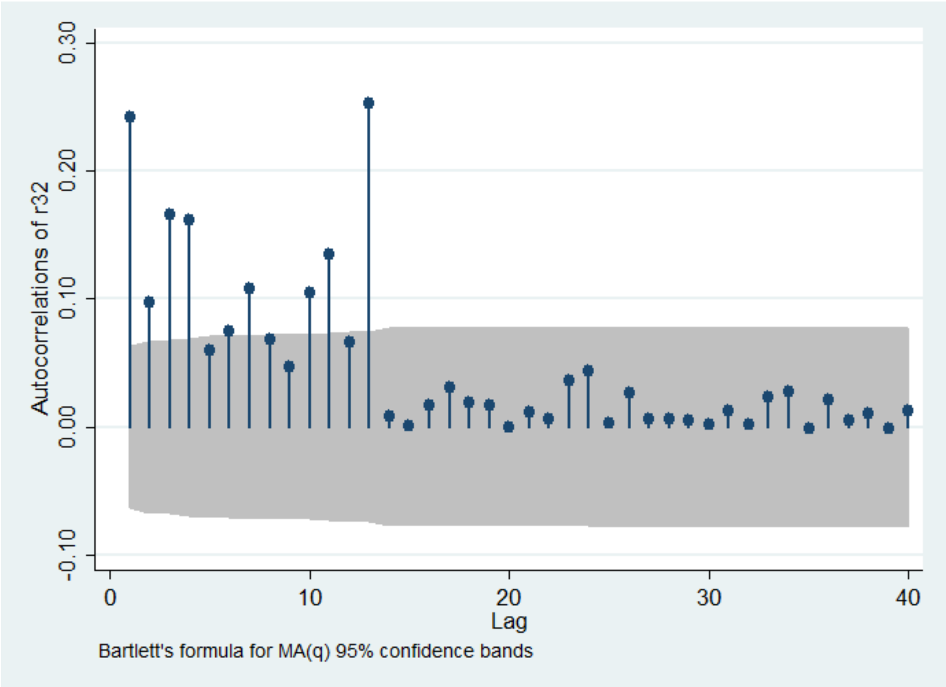

Figure 30. Autocorrelation function of squared residuals of the strategy: (I) criterion with 3 months rebalancing.

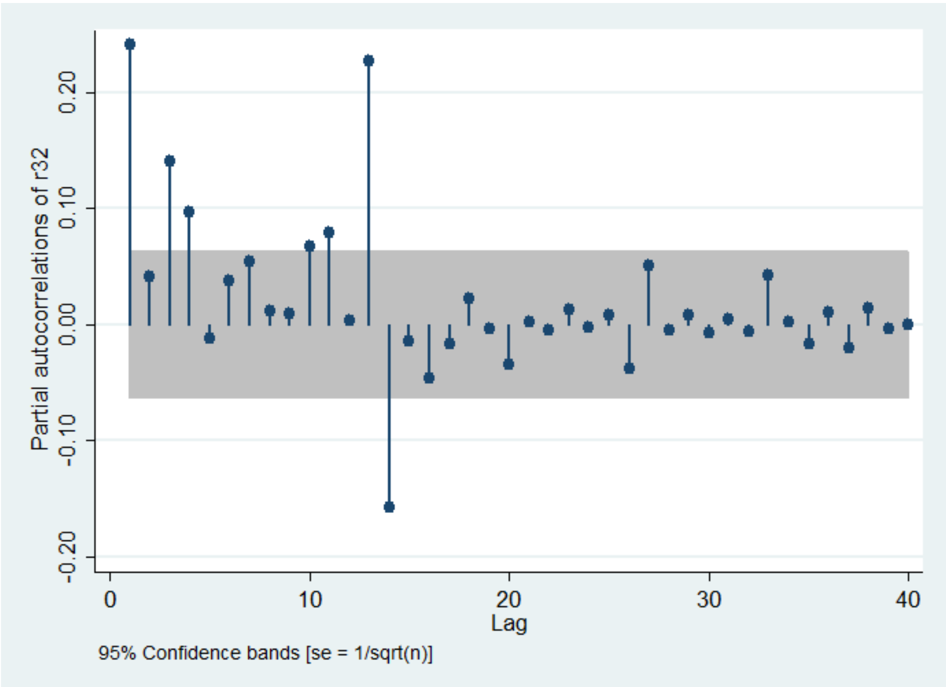

Figure 31. Partial autocorrelation function of squared residuals of the strategy: (I) criterion with 3 months rebalancing.

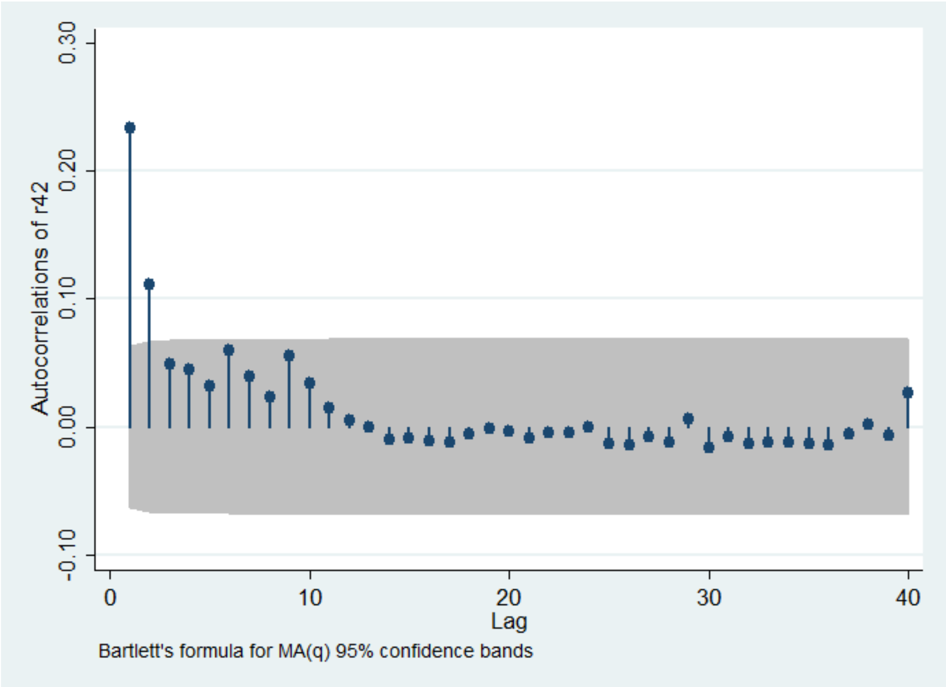

Figure 32. Autocorrelation function of squared residuals of the strategy: (II) criterion with weekly rebalancing.

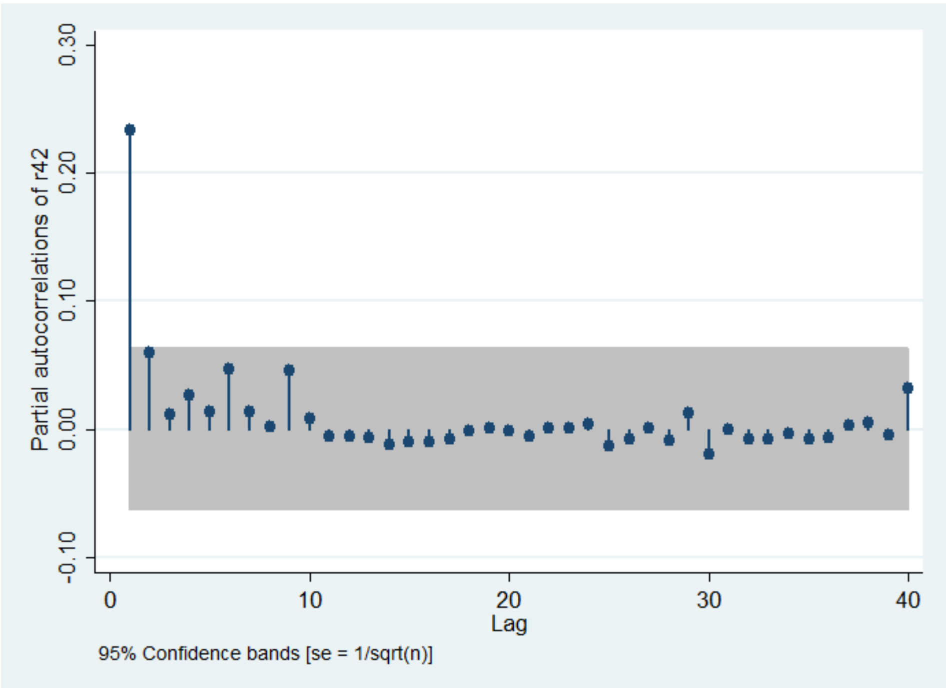

Figure 33. Partial autocorrelation function of squared residuals of the strategy: (II) criterion with weekly rebalancing.

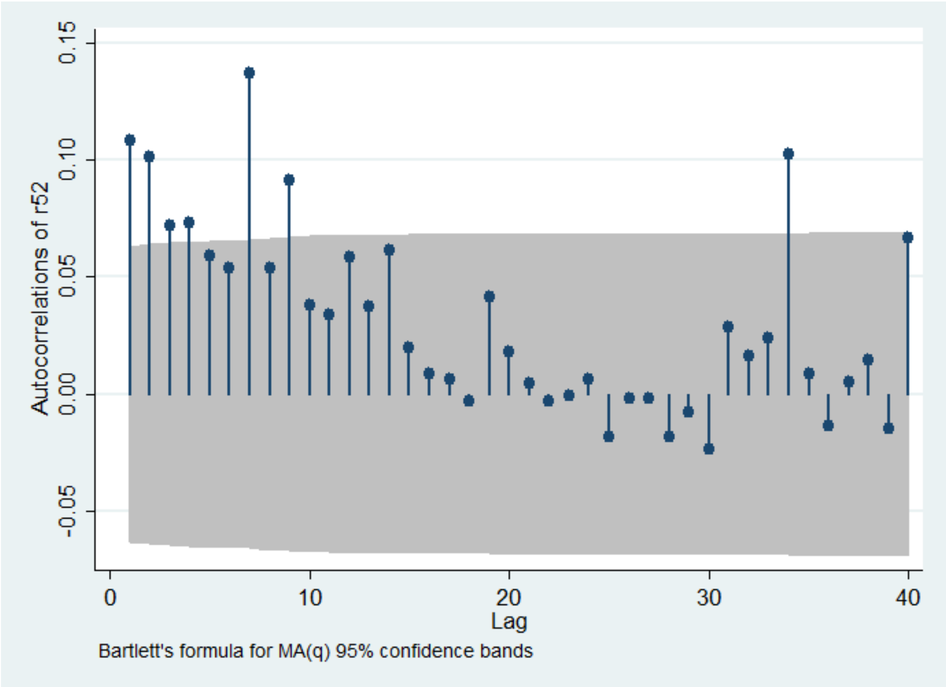

Figure 34. Autocorrelation function of squared residuals of the strategy: (II) criterion with monthly rebalancing.

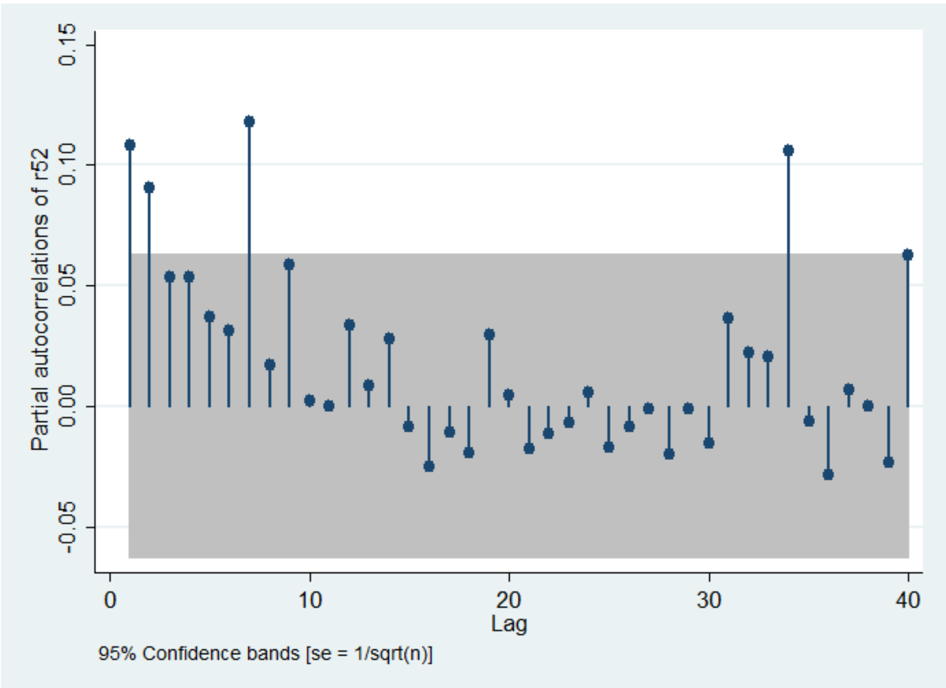

Figure 35.Partial autocorrelation function of squared residuals of the strategy: (II) criterion with monthly rebalancing.

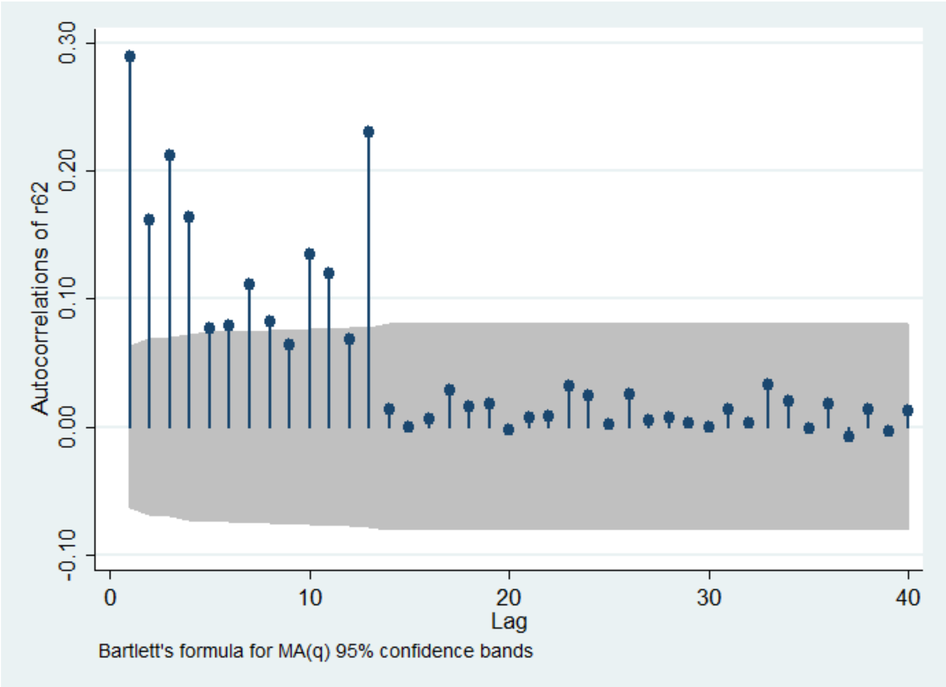

Figure 36. Autocorrelation function of squared residuals of the strategy: (II) criterion with 3 months rebalancing.

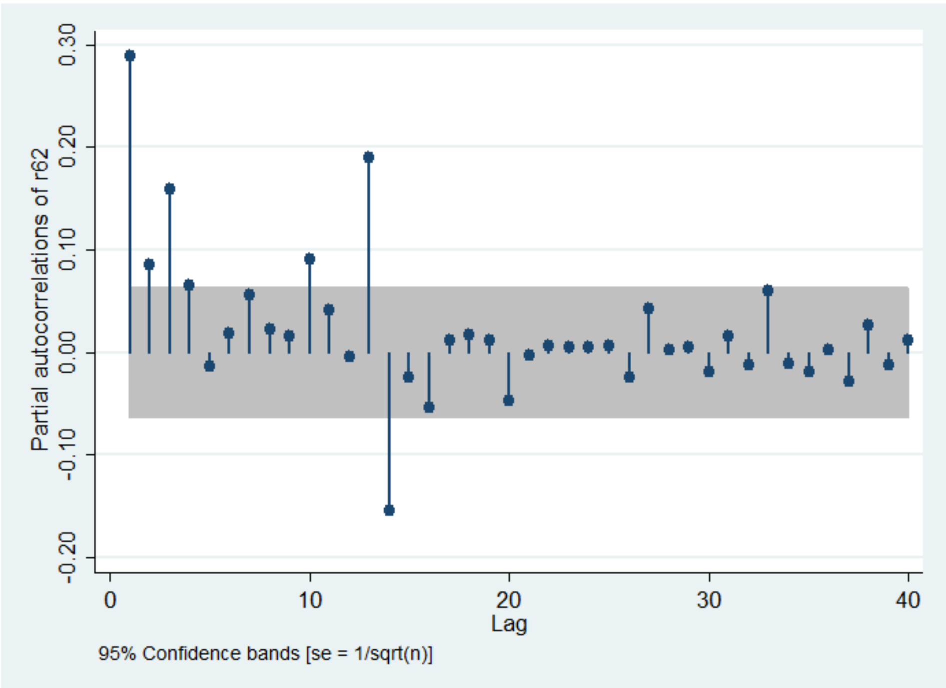

Figure 37. Partial autocorrelation function of squared residuals of the strategy: (II) criterion with monthly rebalancing.

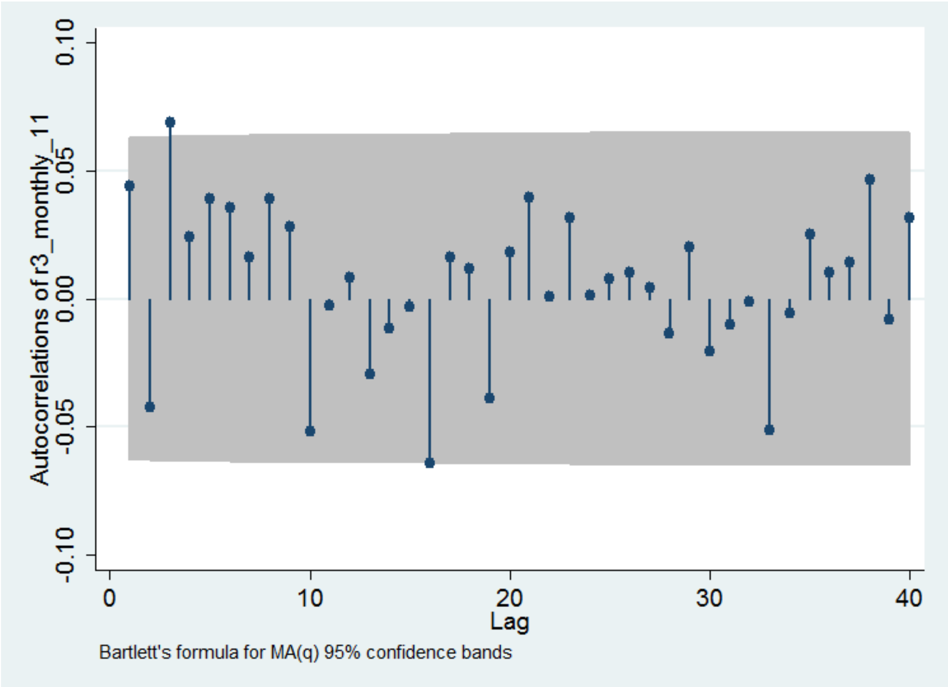

Figure 38. Autocorrelation function of squared residuals of the strategy: R(0.5,0.5) criterion with monthly rebalancing.

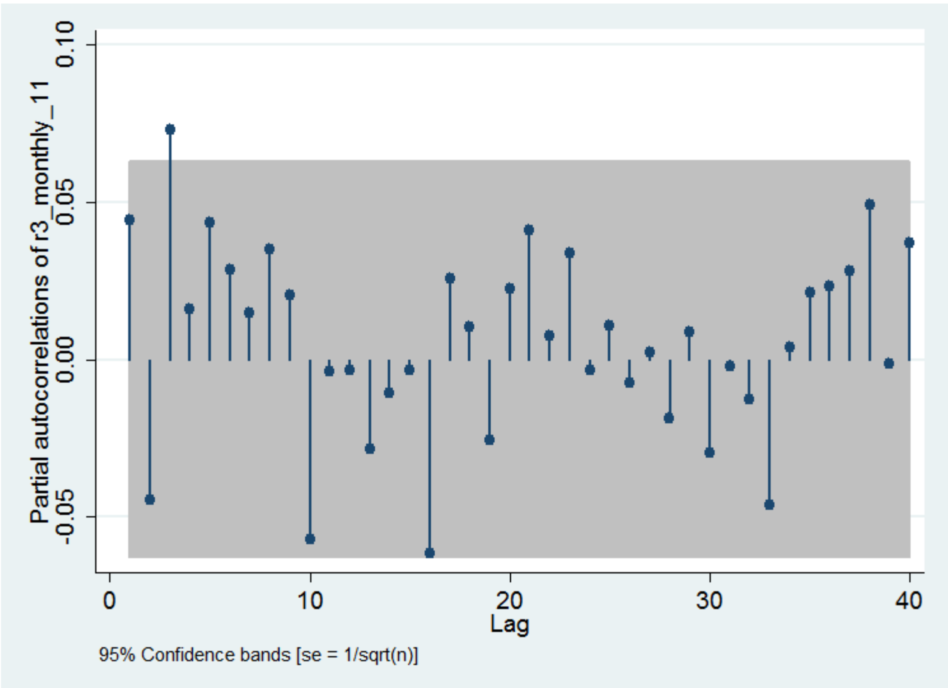

Figure 39. Partial autocorrelation function of squared residuals of the strategy: R(0.5,0.5) criterion with monthly rebalancing.

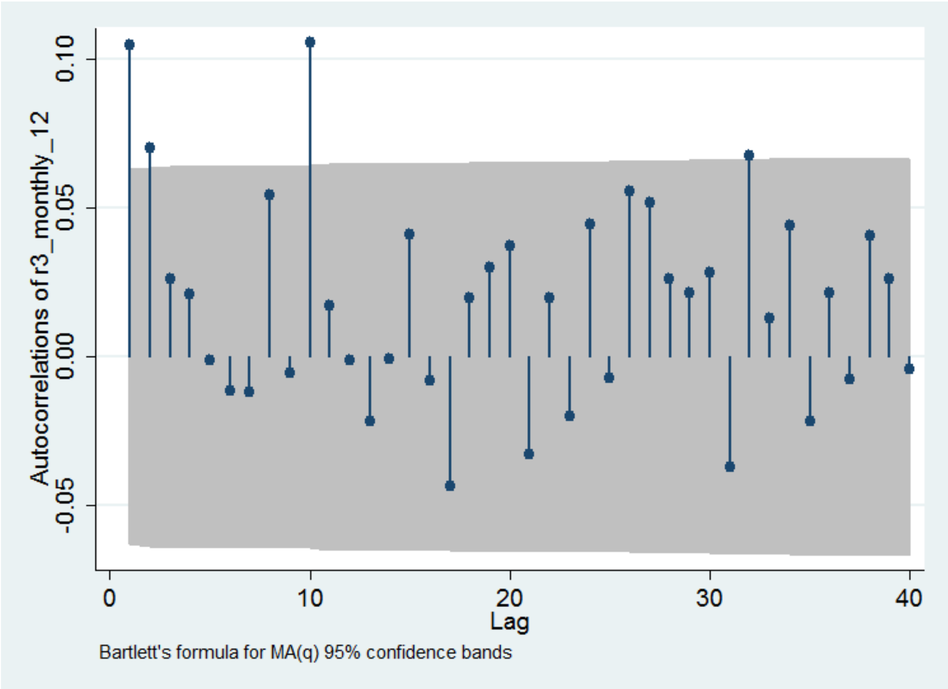

Figure 40. Autocorrelation function of squared residuals of the strategy: R(0.5,0.05) criterion with monthly rebalancing.

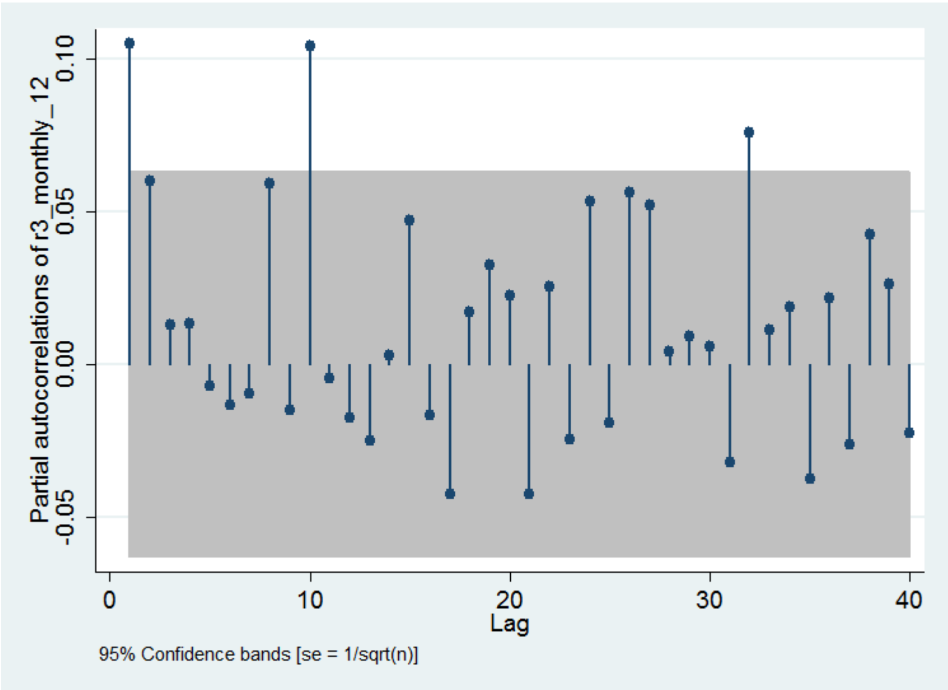

Figure 41. Partial autocorrelation function of squared residuals of the strategy: R(0.5,0.05) criterion with monthly rebalancing.

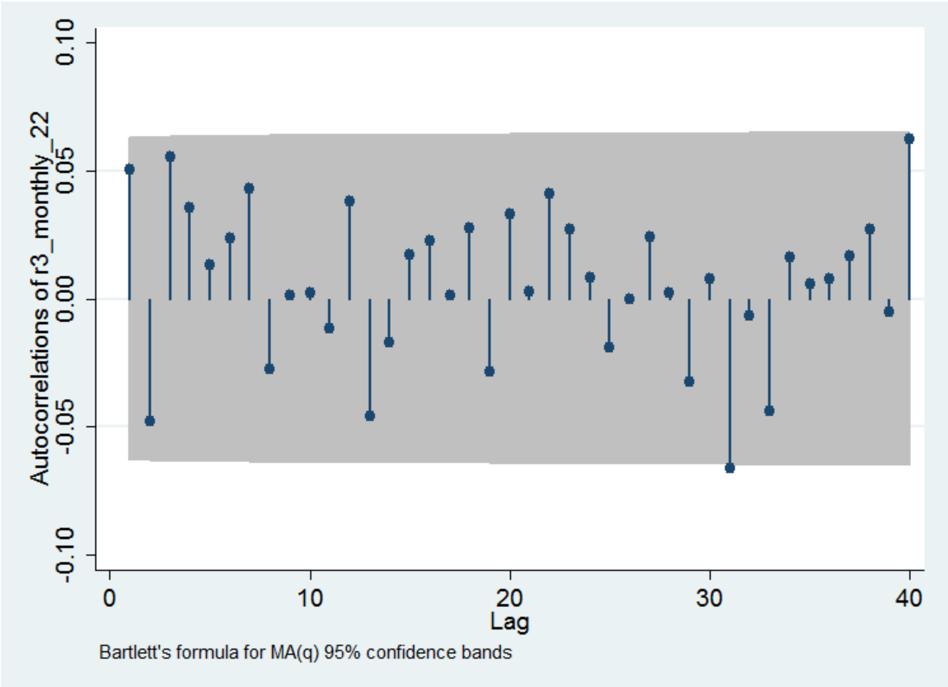

Figure 42. Autocorrelation function of squared residuals of the strategy: R(0.05,0.05) criterion with monthly rebalancing.

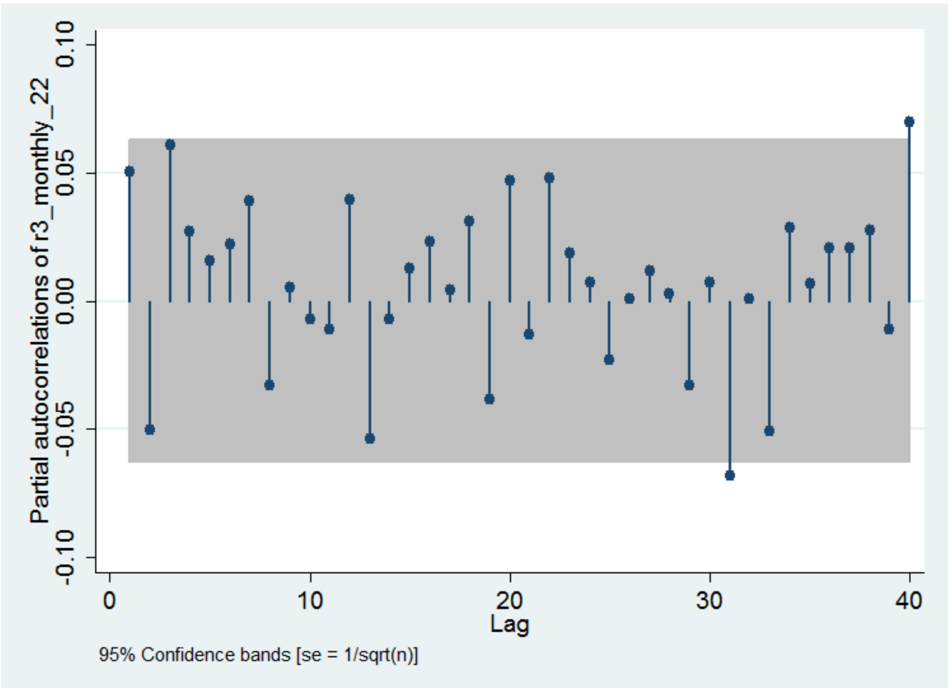

Figure 43. Partial autocorrelation function of R(0.05,0.05) criterion with monthly rebalancing.

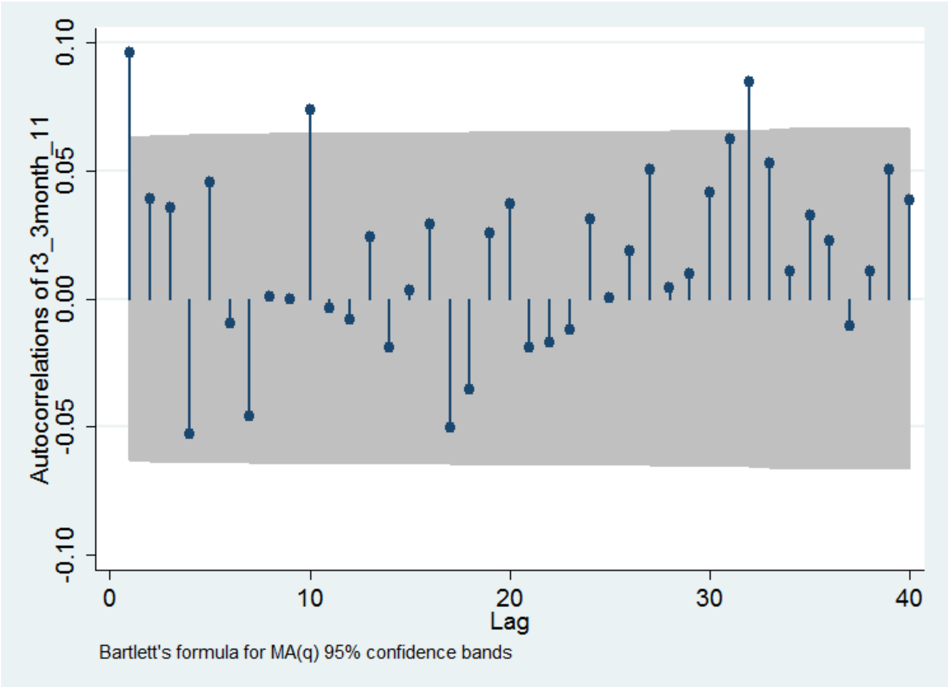

Figure 44. Autocorrelation function of squared residuals of the strategy: R(0.5,0.5) criterion with 3 months rebalancing.

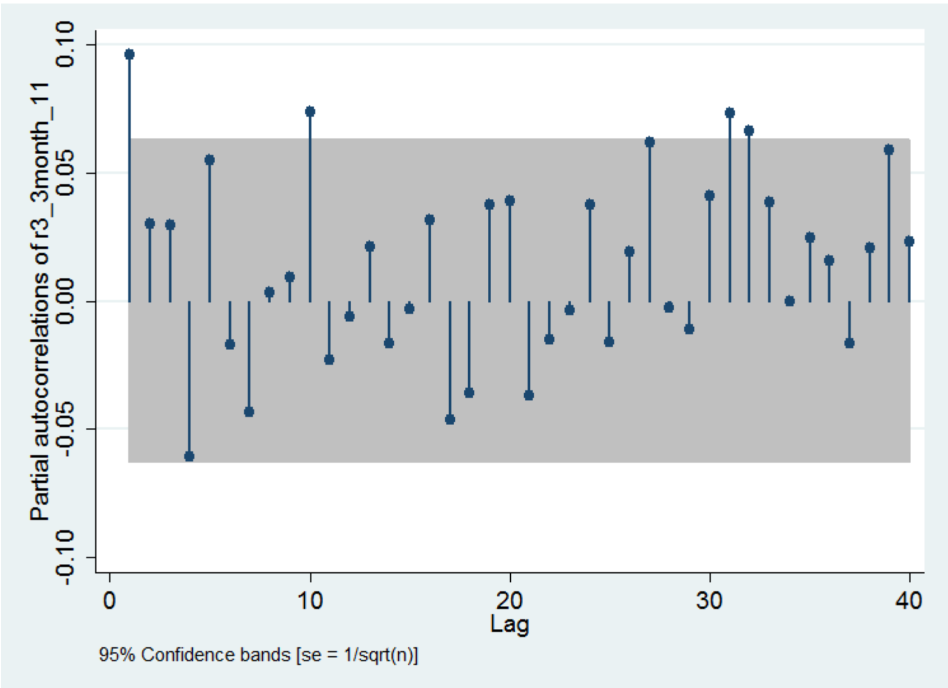

Figure 45. Partial autocorrelation function of R(0.5,0.5) criterion with 3 months rebalancing.

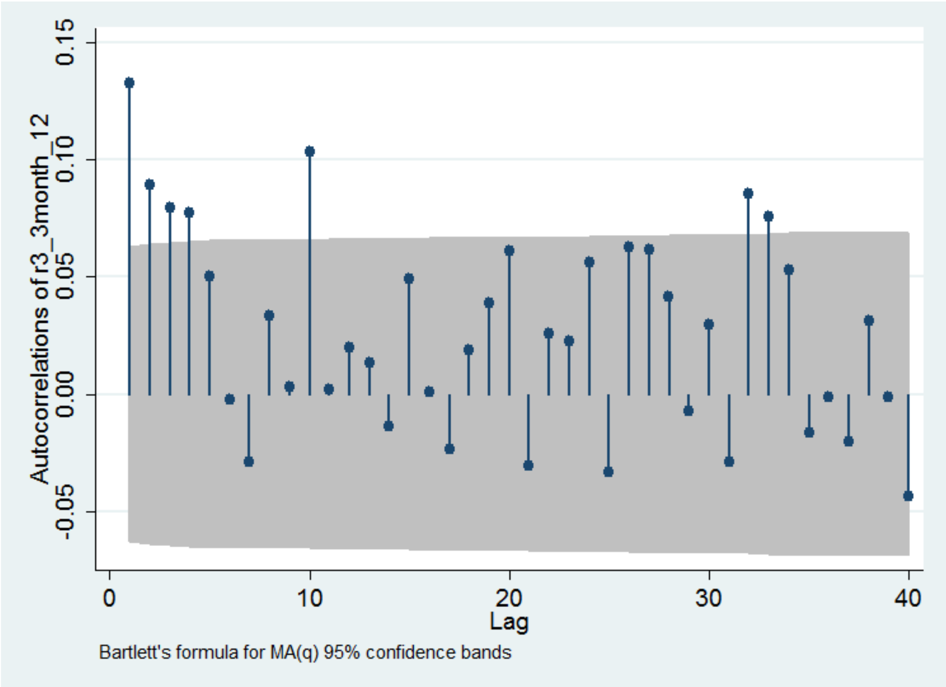

Figure 46. Autocorrelation function of squared residuals of the strategy: R(0.5,0.05) criterion with 3 months rebalancing.

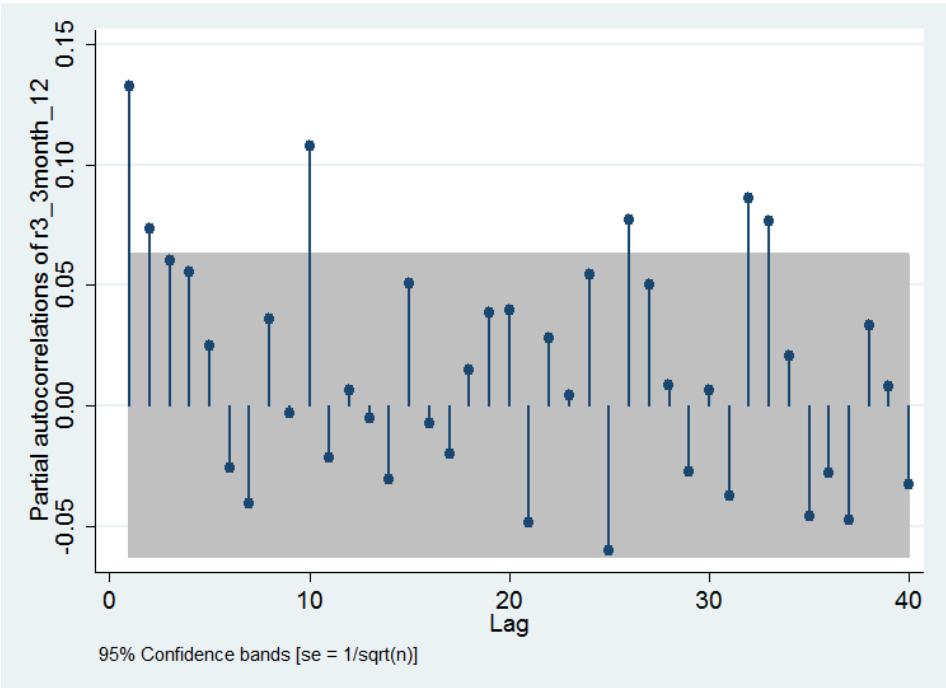

Figure 47. Partial autocorrelation function of squared residuals of the strategy: R(0.5,0.05) criterion with 3 months rebalancing.

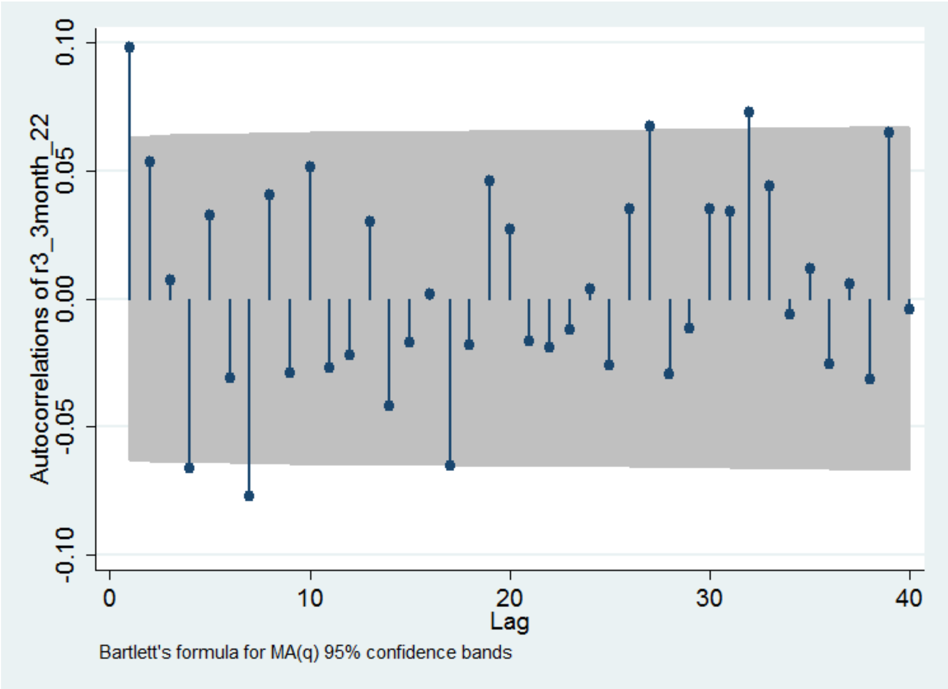

Figure 48. Autocorrelation function of squared residuals of the strategy: R(0.05,0.05) criterion with 3 months rebalancing.

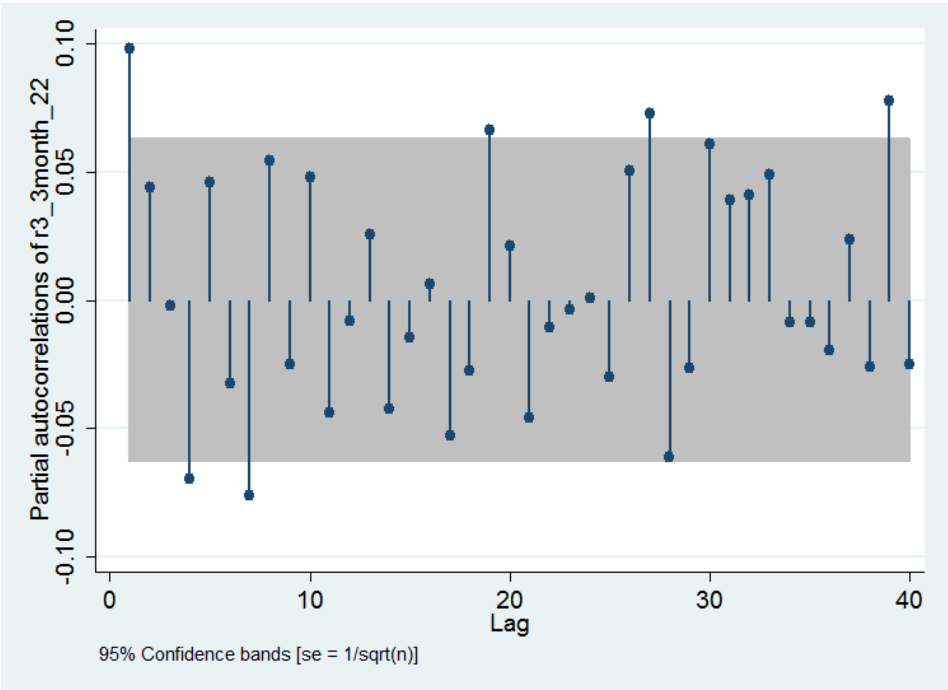

Figure 49. Partial autocorrelation function of squared residuals of the strategy: R(0.05,0.05) criterion with 3 months rebalancing.

Table 7. Estimated ARMA parameters of ARMA-GARCH models.

ARMA parameters ($P < \|z\|$)			
Strategy parameters: method and holding period	c	φ_i	θ_i
Simple return, 1 week	0.0009857 (0.015)	0.5662889 (0.001)	-0.4698466 (0.017)
Simple return, 1 month	0.0011288 (0.000)	-0.5683538 (0.000)	0.7020392 (0.000)
Simple return, 3 month	0.0020358 (0.000)	0.8172227 (0.000)	-0.7847721 (0.000)
Sharpe ratio, 1 week	0.0009685 (0.003)	-	-
Sharpe ratio, 1 month	0.001252 (0.000)	-0.2624043 (0.226)	0.3766927 (0.067)
Sharpe ratio, 3 month	0.0014006 (0.044)	0.9057521 (0.000)	-0.8053549 (0.000)
R-ratio (0,5;0,5), 1 month	0.0007408 (0.003)	0.1047374 (0.679)	-0.0045816 (0.986)
R-ratio (0,5;0,5), 3 months	0.0003266 (0.474)	0.974547 (0.000)	-0.9455934 (0.000)
R-ratio (0,5;0,05), 1 month	0.0013593 (0.146)	0.962129 (0.000)	L1: -0.8305888 (0.000) L2: -0.0879223 (0.012)
R-ratio (0,5;0,05), 3 months	-0.0000249 (0.970)	0.793621 (0.000)	-0.6534139 (0.000)
R-ratio (0,05;0,05), 1 month	0.0009715 (0.000)	-	-

Table 7. – Continued

R-ratio (0,05;0,05), 3 months	0.0003071 (0.411)	L1: 0.0010534 (0.993) L4: 0.4670147 (0.000) L7: 0.246724 (0.011)	L1: 0.1414596 (0.153) L4: -0.3980041 (0.000) L7: -0.320795 (0.000)

Table 8. Estimated GARCH parameters of ARMA-GARCH models.

GARCH parameters:			
Strategy parameters: method and holding period	ω	β_1	α_1
Simple return, 1 week	0.0000149 (0.000)	0.3751446 (0.000)	0.6300372 (0.000)
Simple return, 1 month	0.0000055 (0.000)	0.2509458 (0.000)	0.7611122 (0.000)
Simple return, 3 month	0.000137 (0.000)	0.5228102 (0.000)	-
Sharpe ratio, 1 week	0.00000576 (0.000)	0.2426579 (0.000)	0.782972 (0.000)
Sharpe ratio, 1 month	0.00000379 (0.000)	0.2619114 (0.000)	0.7643457 (0.000)
Sharpe ratio, 3 month	0.0001299 (0.000)	0.5504089 (0.000)	-
R-ratio (0,5;0,5), 1 month	0.00000706 (0.000)	L1: 0.2329827 L2: 0.2305787 L7: 0.133983 (0.000) each	0.489261 (0.000)

Table 8. – Continued

R-ratio (0,5;0,5), 3 months	0.000000724 (0.000)	0.3811056 (0.000)	L1: 0.547468 L3: 0.5788173 L4: - 0.3477645 (0.000) each L2: -0.015145 (0.362)
R-ratio (0,5;0,05), 1 month	0.0000138 (0.000)	0.2533467 (0.000)	0.7310765 (0.000)
R-ratio (0,5;0,05), 3 months	0.000000584 (0.000)	0.369038 (0.000)	0.7495471 (0.000)
R-ratio (0,05;0,05), 1 month	0.00000532 (0.000)	0.3440952 (0.000)	0.7101415 (0.000)
R-ratio (0,05;0,05), 3 months	0.000000382 (0.000)	0.3822096 (0.000)	0.7647226 (0.000)