Center for
Economic Theories and Policies
Sofia University St. Kliment Ohridski
Faculty of Economics and Business Administration

ISSN: 2367-7082

Bulgarian Economic Papers

Changes in Temporal Patterns of the Momentum Effect in Times of Turmoil: Evidence from the Bulgarian Stock Exchange

Boryana Bogdanova
Bozhidar Nedev

BEP 11-2017
Publication: December 2017

Changes in Temporal Patterns of the Momentum Effect in Times of Turmoil: Evidence from the Bulgarian Stock Exchange

Boryana Bogdanova[*], *Bozhidar Nedev*[**]

Abstract

This paper studies the momentum effect at the Bulgarian stock exchange in terms of its temporal structure for a period spanning from Jan-2004 to Jul-2017. Our aim is to reveal insights on the changes that took place with the beginning of the 2008 Financial crisis. The application of continuous wavelet analysis allows us to gain an in-depth knowledge on the cyclical patterns of the times series of raw profits on momentum trading strategy. This enables us to carry on further analysis aimed at identifying the drivers behind the phenomenon of significant momentum raw profits and the observed breaks during and after the crisis. Our findings contribute mainly to the process of delivering thorough understanding of the momentum effect from an empirical as well as from a behavioral perspective.

Keywords: momentum trading strategy, 2008 Financial crisis, wavelet spectrum, frontier stock markets

JEL: C32; G11; G14; G17; G40

[*] Sofia University "St. Kliment Ohridski", Faculty of Economics and Business Administration, Department of Statistics and Econometrics; corresponding author: bpelova@gmail.com
[**] Sofia University "St. Kliment Ohridski", Faculty of Economics and Business Administration, Department of Finance and Accounting, bozhidar.nedev@gmail.com

1 Introduction

Since the seminal paper of Jagadeesh & Titman (1993), momentum effect has been extensively studied by researchers in the field of empirical finance. As argued by Jagadeesh & Titman (2011) it might be considered as the strongest evidence against the Efficient Market Hypothesis. By its essence, momentum effect represents short-term return predictability based on past performance of assets over a period of less than 12 months. Currently, a huge body of literature is engaged with this phenomenon, that has been registered in the US equity market (Jagadeesh & Titman, 1993), in futures markets (Asness, et al., 2013), in currency markets (Menkhoff, et al., 2012), in US industries (Moskowitz & Grinblatt, 1999), in developed European stock markets (Rouwenhorst, 1998). Yet, most of the papers are focused on developed or emerging markets, while frontier markets are barely studied (Svolka, et al., 2011). Among others, one of the reasons behind is the considerable illiquidity of these markets that results into gappy datasets of past price records. Nevertheless, a recent research by Nedev & Bogdanova (2017) addresses the latter issue and investigates the presence of momentum effect for the Bulgarian Stock Exchange (BSE) for a period spanning from the beginning of 2004 to the mid of 2017. A major finding is that following a momentum trading strategy the zero-cost portfolio delivers significant profits before the beginning of the Financial Crisis of 2008. However, during the crisis as well as in the aftermath period relying on momentum trading strategy yields negative or insignificant raw profits.

On one hand, these findings are consistent with results documented recently for emerging markets[1]. On the other hand, the paper of Daniel & Moskowitz (2016) analyzes the time variation in momentum premium and states that momentum strategies crash in times of high market volatility and market rebounds following market downturns. In this course of study, the paper of Chabot, et al. (2014) investigates momentum crashes in a longer time setting. In particular, two eras are considered – the first one spanning in the period 1867 – 1907 and the second one covering the time of 1926 – 2012. A major finding is that in practice momentum trading undergoes rare periodic crashes in both eras, exposing investors to severe losses, where momentum effect disappears, only to reappear later. Furthermore, Markowitz, et al. (2012)

[1] For example, similar effects are documented for the Vietnamese Stock Exchange (Alphonse & Nguyen, 2013).

study time series momentum[2] and conclude that it drives cross-sectional momentum, what is more, the partly observed return reversion in the long run indicates consistency with behavioral explanations of momentum in terms of underreaction and delay overreaction.

To sum up, studying momentum is important for both academics and investors. Its presence evidences market inefficiency that is subject to further studies of behaviorists. For investors it constitutes an opportunity to design profitable trading strategies. At the same time, previous research results document periodic changes in momentum effect that appear in times of turmoil and during stock market rebounds. Therefore, the goal of our paper is to study these temporal changes and breaks as their occurrence is associated with severe losses for investors on one hand. On the other hand, the obtained knowledge provides an alternative research perspective when studying stock market crashes. We focus on the common stock equity market of the BSE since as already mentioned frontier markets have been barely researched whereas they provide important diversification opportunities for investors. Furthermore, in-depth analysis of this phenomenon for a low-liquidity stock market would reinforce the thorough understanding of the momentum effect.

We build on the results delivered by Nedev & Bogdanova (2017). Through application of wavelet analysis we reveal new insights on the term structure of the documented momentum effects in the pre-crisis period and describe the structural changes that take place during the Financial crisis of 2008 as well as in the aftermath period. This forms a major contribution of our paper. Furthermore, we contribute to the literature that aims to identify sources of momentum. In particular, we find that the observed temporal patterns are consistent with the behavioral explanations. In addition, the wavelet transform has numerous applications in the empirical finance[3] and this paper proposes one more application that might be replicated in other researches engaged with the momentum effect.

The rest of the paper is organized as follows. Section 2 outlines the methodology. Section 3 presents the data and the major research results, followed by a discussion. Section 4 ends the paper with some concluding remarks.

[2] Time series momentum focuses entirely on a security's own past returns rather than on its relative performance on cross-sectional basis.
[3] See for example Rua & Nunes (2009), Aguirar-Conrara & Soares (2014), Bogdanova & Ivanov (2015), Ivanov, et al. (2016) as well as the references therein.

2 Methodology

We apply wavelet analysis on a time series of average profits on portfolios that exploit momentum trading strategy for the Bulgarian stock exchange. For the construction of this time series we replicate the procedure outlined by Alphonse & Nguyen (2013), with regard to the major research results of Nedev & Bogdanova (2017). The time-frequency characteristics of the average portfolio profits are studied through application of the continuous wavelet transform. The following text summarizes the idea behind the utilized momentum trading strategy and provides a brief introduction of the continuous wavelet transform.

2.1 Construction of a momentum strategy

As already mentioned we would use the procedure developed by Alphonse & Nguyen (2013), which is briefly described below and might be found in a greater detail in Alphonse & Nguyen (2013, pp. 188-189).

In week *t* we divide stocks into quintiles according to their average lagged returns over the past *K* weeks (*K* = 1, 2, 4, 8, 13, 26, 39 and 52 weeks – formation period). Thus, we examine 64 different momentum strategies. The stocks in the highest and lowest quintile are called respectively "winners" and "losers". Using quintiles instead of quantiles as in Jegadeesh & Titman (1993) is a standard practice in research literature of emerging markets due to the limited number of securities and the need for a certain degree of portfolio diversification (Muga & Santamaria, 2007). We weight all component stocks in both portfolios equally. As in the classical approach, transaction costs are not allowed for. That is why, the constructed winner-minus-loser-portfolio (WML) is called a zero-cost portfolio, consisting of a long position in "winners" and a short one in "losers" from week *t* to week *t*+*J* (*J* = 1, 2, 4, 8, 13, 26, 39 and 52 weeks – the holding period). Hence, we use the term profit instead of return on WML.

Consequently, the raw profits for WML portfolios, formed *k* weeks ago (*k = 1,…, J*), are denoted by: $R_{k,t}^{WML}$. As common in literature, we examine overlapping portfolios, since at week *t* there are *J* WML portfolios, that have been formed in week *t*-1, *t*-2,…, *t-J.* Their profits in a given calendar week *t* are equally averaged:

$$OR_{J,t}^{WML} = \frac{1}{J}\sum_{k=1}^{J} R_{k,t}^{WML}. \tag{1}$$

In Nedev & Bogdanova (2017) the profits delivered by eq. (1) are averaged over the pre-crisis (Jan-2004 – Dec-2007), the crisis[4] (Jan-2008 – Dec-2012) and the post-crisis period (Jan-2013 – Jul-2017). Only for the pre-crisis period is identified significant momentum. For this period the momentum trading strategy, based on the lagged 26 week returns reports the highest average profit for all holding periods. Furthermore, the authors found that among them highest profits are registered for a holding period of 8 weeks. Therefore, for the purposes of this study we set $K = 26$ and $J = 8$ and apply eq. (1) so as to deliver a time series of averaged profits which is subject of further research via wavelet analysis.

2.2 Wavelet analysis

As argued by Aguirar-Conrara & Soares (2014), the application of wavelets provides the possibility to trace transitional changes across time. For the empirical part of the paper, we take use of this property in order to shed light on the change of average WML portfolio profits that took place with the beginning of 2008 Financial crisis. For this purpose we analyze the wavelet spectrum of the time series obtained through application of eq. (1). The text that follows explains briefly the idea behind wavelet spectrum while the reader might find an exhaustive discussion on the issue in Aguirar-Conrara & Soares (2014).

The function $\psi(t) \in L^2(\mathbb{R})$, called mother wavelet is chosen for the continuous wavelet analysis. It should satisfy a decay condition, which ensures the function is well localized both in time and frequency. For functions with sufficient decay the admissibility condition is equivalent to requiring that $\Psi(0) = \int_{-\infty}^{\infty} \psi(t)dt = 0$, where $L^2(\mathbb{R})$ denotes the set of square

[4] We undertook this particular sample division, motivated by Mileva (2014), who investigated the problems on the BSE during the financial crises. The author states, that the time period 2003-2006 represented a market boom with predominantly increasing stock prices, driven rather by capital inflows than by artificial reasons. BSE realizes its highest results ever in 2007. The annual registered volume of 9,946 billion Leva is three times as big as the one in 2006. There are also an 200%-increase in realized trades. Mileva (2014) argues, that the Global Financial Crisis (GFC) has also hit regional market, that are relatively more closed like the BSE. The equity stock indexes like SOFIX and BG-40 have decreased by around 300-350% from 2008 to 2010. Their decline as of 2011 on annual basis, compared to 2010, amounts to 10%. First signs of market rebound on an annual basis occurred in 2012, when the volume on the regulated market increased by 9.36%. The following 2013 marks increases for all the equity indexes on the BSE (SOFIX by over 43%, BG-40 – by 27% and BGTR30 – by almost 12%). That is why, we decide to isolate the period of the GFC between Jan-2008 and Dec-2012 from the pre-crisis boom period and the post-crisis one.

integrable functions and $\Psi(\omega)$ denotes the Fourier transform of $\psi(t)$. A family $\psi_{\tau,s}$ of wavelet daughters can be obtained by scaling and translating the mother wavelet ψ: $\psi_{\tau,s} = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)$, $s,\tau \in \mathbb{R}, s \neq 0$, where s is a scaling factor controlling the width of the wavelet and τ is a translation parameter controlling its location. Given a time series $x(t)\epsilon L^2(\mathbb{R})$ its continuous wavelet transform with respect to the wavelet ψ is defined as follows:

$$W_{x;\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right)dt, \tag{2}$$

where the asterisk denotes complex conjugate. For simplicity of notation the wavelet transform $W_{x;\psi}(\tau, s)$ will be denoted by W_x in the text that follows. If complex valued wavelet is used for the transform, then the wavelet spectrum as defined below might be viewed as the amplitude of the transform. A common choice is the Morlet wavelet which is utilized in the current paper as well. The wavelet power spectrum that is subject to our further analysis is defined by eq. (3):

$$WPS_x = |W_x|^2. \tag{3}$$

We use the freely available toolbox that is referenced in the article of (Aguirar-Conrara & Soares (2014) in order to apply eq. (3) to the time series delivered through eq. (1).

3 Results

For the empirical part of this study we take past price records on weekly basis for all stocks traded at the Bulgarian stock exchange[5] for the period Jan-2000 – Jul-2017. As of 31-Jul-2017 their total number amounts to 90. Since some of the stocks are characterized by long periods of missing values, we use the applied algorithm of Nedev & Bogdanova (2017) in order to deal with this issue. The approach of the authors relies on spline interpolation and a careful aftermath analysis assuring that data properties are preserved in accordance with the guidelines defined in Lazarov (2013). After completion of this algorithm, the number of retained stocks in our sample varies from 35 in earlier periods to 69 for the later periods of operation of the BSE. Also following the algorithm, we consider only the period spanning form Jan-2004 to Jul-2017.

[5] The raw data is downloaded from http://www.infostock.bg.

We apply eq. (1) to the returns series of the retained stocks and obtain a time series of averaged raw profits on the WML portfolio that is visually presented at Figure 1.

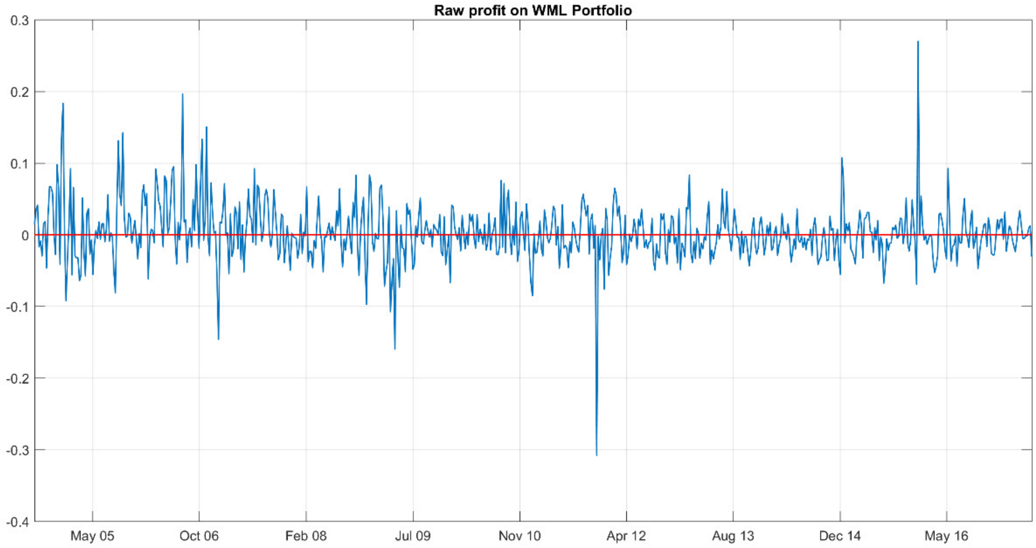

Figure 1: Averaged raw profits on the WML portfolio for the period 2004-2017.

Table 1 provides a statistical summary on the average performance of this portfolio for the pre-crisis, crisis and post-crisis period for the Bulgarian stock exchange. As might be noted the WML portfolio registers statistically significant raw profit only for the pre-crisis period. The crisis and the post-crisis period are characterized by negative results that, however, are insignificant.

Table 1: Average raw profit on the WML portfolio for the pre-crisis, crisis, and post-crisis period for the BSE.

	Average raw profit	**t-stat**	**p-value**
Jan-2004 - Dec-2007	1.34%	4.2987	0.0000
Jan-2008 - Dec-2012	-0.19%	-0.8374	0.4033
Jan-2013 - Jul-2017	-0.13%	-0.6647	0.5070

As stated in the introduction the goal of our paper is to provide a time-frequency analysis of the temporal patterns and the changes in momentum that took place with the beginning of the 2008 Financial crisis. Therefore, we apply consecutively eq. (2) and eq. (3) in order to estimate the wavelet power spectrum of the averaged raw profits on the WML portfolio. The calculations are performed through a freely available MATLAB toolbox associated with the theoretical framework presented in Aguirar-Conrara & Soares (2014)[6].

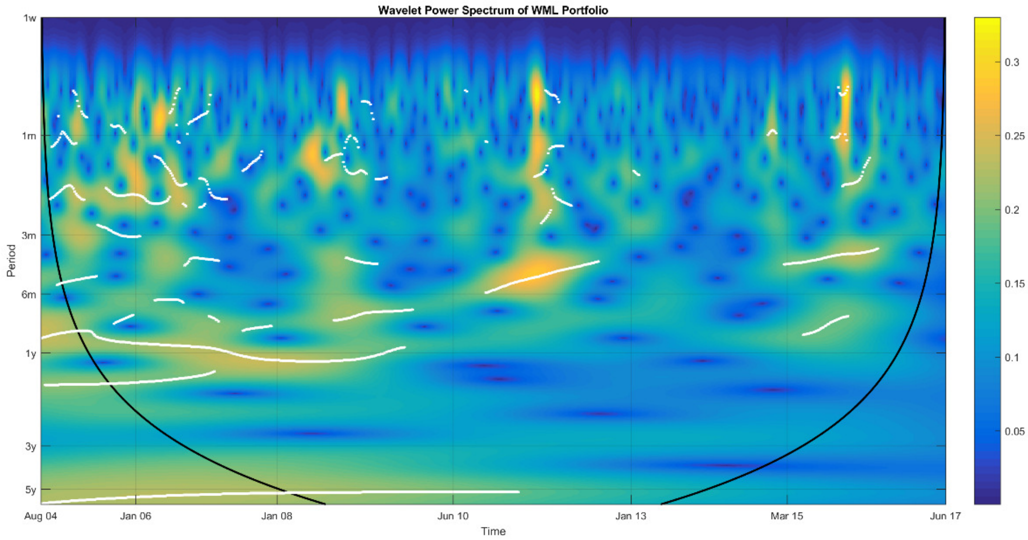

Figure 2: Wavelet power spectrum of the WML portfolio with a formation period of 26 weeks and holding period of 8 weeks.

Our results are summarized at Figure 2 and at Figure 3. Figure 2 is essentially a color map while Figure 3 is its three-dimensional counterpart, the latter is provided in order to ease understanding and interpretation of results. Each pixel of the color map corresponds to a particular value of WPS_x and the color code is provided next to the map. The x-axis represents the time line and the y-axis corresponds to the utilized frequencies, which are converted into time units in order to ease interpretation of results. The highest frequency is one week and the lowest frequency corresponds to six years. The cone of influence represents the region in which the transform suffers from edge effects and it is plotted with tick black line. In this region the results should be interpreted with special care. The white lines indicate local maxima of the wavelet power spectrum and might be interpreted as estimates of the cycle periods.

It might be easily seen that different patterns are observed for the three pre-defined periods in the sample. The period spanning form Jan-2004 to Dec-2007 is characterized by numerous local maxima in the higher frequencies of 1 week to 3 months. However, the frequency band of 3 months to 1 year is of particular interest for our study since as suggested by (Jagadeesh & Titman, 1993), stocks that perform best (worst) over a 3 to 12 month period tend to continue to perform well (poorly) over the subsequent 3 to 12 months. Indeed, along with the observed

[6] The toolbox is available at http://sites.google.com/site/aguiarconraria/joanasoares-wavelets.

cyclical patterns of short duration, the figure displays a steady cycle since the beginning of the period until its end. The period of the cycle is of approximately 9 month – 1 year and we note that at the end of the 2007 it switches to a periodic component of length that is more than a year. This change indicates that momentum dies out after the beginning of 2008 Financial crisis and it does not re-emerge in the aftermath period.

Another interesting finding that might be observed at Figure 2 is a longer term pattern of approximate duration of 1.5 years. As Figure 3 suggests this component contributes to the variation in the averaged raw profits on the WML portfolio only for the pre-crisis period and it might be associated with the long term equilibrium of the time series. The latter result might be easily linked to behavioral explanations of the momentum. Some of them assume that it is due to underreaction and others hypothese that it is the investors' overreaction that causes momentum. Yet, both underreaction and overreaction might be viewed as deviation of stock prices from their fundamental values that should be reached in the long term equilibrium state. Therefore, momentum effect represents a short-term disequilibrium state of 3 to 12 months duration. Our findings reported at Figure 2 and Figure 3 are in compliance with this behavioral setting. Furthermore, Figure 2 suggests that prior to the momentum crash, we observe a break in the long term equilibrium followed by a temporal change in the short term fluctuations. Moreover, Figure 3 reveals that variation in average profits on the WML portfolio are driven mainly by the highest frequency components that might be associated with the news influence. Therefore, regarding the BSE, we might conclude that significant momentum is observed for the pre-crisis period that might be explained with behavioral theories. On the other hand, severe irrational behavior driven by bad news dominates in the following periods.

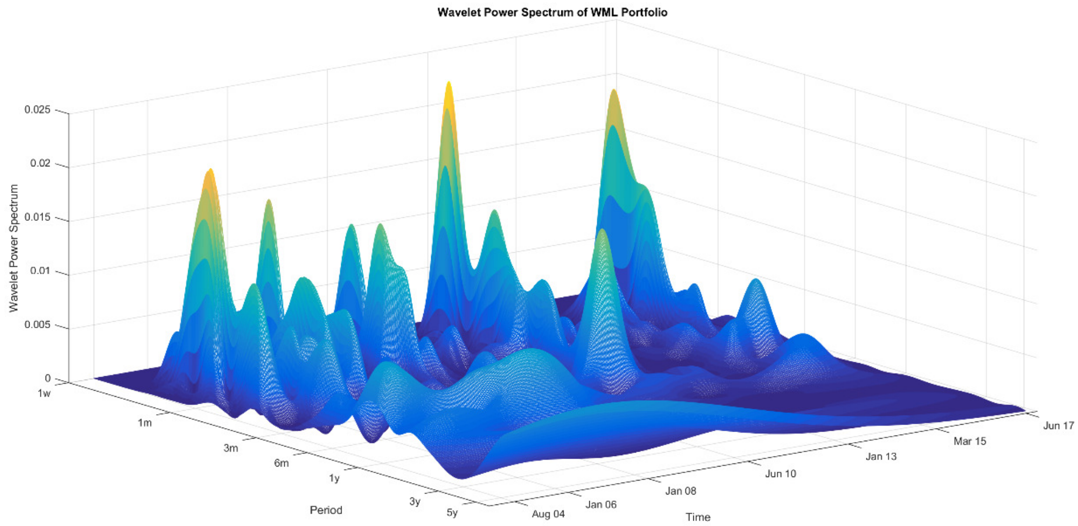

Figure 3: Wavelet power spectrum of the WML portfolio with a formation period of 26 weeks and holding period of 8 weeks

4 Conclusion

Our study shows, that wavelet analysis explicitly reveals the structural transitions of momentum effect and its cyclical drivers over time and proves to be a profound tool for temporal investigation on the patterns of the observed phenomenon. Periods of momentum boom are characterized by lots of local maxima in higher frequencies and by a short-term periodic component of 9 to 12 months. The former factors tend to decrease with the outbreak of the financial crisis, whereas the latter transforms into a long-term cycle. Moreover, the disappearance of the 1.5-year pattern following the boom period indicates the occurrence of high market volatility and distortion in the long-term stocks` fundamentals. Thus, we contribute to existing literature by not only deriving the applicability of continuous wavelet transform to both periods of momentum profitability and crashes, but also to barely studied frontier markets. Our results, concerning the pre-crisis period, imply a consistency with behavioral explanations of momentum effect, wherein a further research should reveal the specific patterns.

5 References

Aguirar-Conrara, L. & Soares, M., 2014. The continuous wavlet transform: moving beyond uni-and bivariate analysis. *Journal of Economic Surveys,* 28(2), pp. 344-75.

Alphonse, P. & Nguyen, T., 2013. Momentum effect: Evidence from the Vietnamese stock market. *Asian Journal of Finance & Accounting,* 5(2), pp. 183-202.

Asness, C. S., Moskowitz, T. J. & Pedersen, L. h., 2013. Value and Momentum Everywhere. *The Journal of Finance,* 68(3), pp. 929-985.

Bogdanova, B. & Ivanov, I., 2015. A wavelet-based approach to the analysis and modelling of financial time series exhibiting strong long-range dependence: the case of Southeast Europe. *Journal of Applied Statistics,* 43(4), pp. 655-73.

Chabot, B., Ghysels, E. & Jagannathan, R., 2014. *Momentum trading, return chasing, and predictable crashes,* No. w20660: National Bureau of Economic Research.

Daniel, K. & Moskowitz, T., 2016. Momentum crashes. *Journal of Financial Econometrics,* 122(2), pp. 221-47.

Ivanov, I., Kabaivanov, S. & Bogdanova, B., 2016. Stock market recovery from 2008 financial crisis: The differences across Europe. *Research in International Business and Finance,* 37, pp. 360-74.

Jagadeesh, N. & Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance,* 48(1), pp. 65-91.

Jegadeesh, N. & Titman, S., 2011. Momentum. *Annual Review of Financial Economics,* 3(1), pp. 493-509.

Lazarov, D., 2013. Simmulations with missing values. *Vanguard Scientific Instruments in Management,* 2(7), pp. 10-46.

Markowitz, T., Ooi, Y. & Pedersen, L., 2012. Time series momentum. *Journal of Financial Economics,* 104, pp. 228-50.

Menkhoff, L., Sarno, L., Schmeling, M. & Schrimpf, A., 2012. Carry Trades and Global Foreign Exchange Volatility. *The Journal of Finance,* 67(2), pp. 681-718.

Mileva, Y., 2014. State and issues of the trade at the Bulgarian stock exchage in times of turmoil. (in Bulgarian). *New Knowledge Journal of Science (University of Agrobusiness and Rural Development Academic Publishing House Bulgaria),* 3(3), pp. 49-54.

Moskowitz, T. J. & Grinblatt, M., 1999. Do Industries Explain Momentum?. *The Journal of Finance,* 54(4), pp. 1249-1290.

Muga, L. & Santamaria, R., 2007. The momentum effect in Latin American emerging markets. *Emarging Markets Finance and Trade,* 43(4), pp 24-45.

Nedev, B. & Bogdanova, B., 2017. A study on the momentum effect of the Bulgarian Stock Exchange: Some practical issues of applied importance. *Vanguard Scientific Instruments in Management (accepted for publication).*

Rouwenhorst, G. K., 1998. International Momentum Strategies. *The Journal of Finance,* 53(1), pp. 267-284.

Rua, A. & Nunes, L., 2009. International comovement of stock market returns: a wavelet analysis. *Journal of Empirical Finance,* 16, pp. 632-39.

Svolka, A., Pilinkus, D. & Bartkus, E., 2011. *Momentum Effect: Developed vs. Emerging Stock Markets.* Berlin, Heidelberg, Springer, pp. 111-122.