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Crisis and financial data properties: A persistence view

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Abstract. This paper investigates persistence in Ukrainian financial data during the recent local crisis of 2013-2015. Using R/S analysis with the Hurst exponent method and its dynamic modification we show that data properties (case of persistence) are unstable and vary over time. Persistence increases dramatically during the crisis periods. These results can be used both to predict crises at early stages and to model financial data with the appropriate methods: to determine models for the cases of persistent data and stochastic ones for the cases of non-persistent data. It is concluded that financial markets become less efficient during crises.

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1. INTRODUCTION

In the 21st century turbulence at financial markets and within world economy overall has increased significantly. Different macroeconomic shocks and crises appear more often and their consequences are more and more painful. Asian crisis and Russia default at the end of the 1990s, the dot-com bubble at the beginning of the 2000s, the global financial crisis of 2007-2009 clearly evidence in this favor. As the result, the problem of crisis prediction is very actual today.

Traditional macroeconomic indicators (GDP, inflation, unemployment etc.) are characterized by a very crucial flaw – significant time lags. They manage to state the fact of crisis after a certain period of time, but show rather weak predicting abilities.

Nevertheless, some elements of economic system are able to generate information almost in the real-time regime. This is about financial markets and data they generate – prices, volumes, tendencies, volatility etc. Special indicators like VIX index help measure market sentiments and show good predicting abilities in crises forecasting. According to (Whaley, 2000) it (VIX index) reaches higher levels during the periods of market turmoil. Bekaert and Hoerova (2013) show that VIX is a significant predictor of financial instability; specifically, it has high predictive power for the one- and three-months ahead indicator of financial stress created by the European Central Bank (ECB).

There is an alternative approach to crisis detection which is based on financial data properties' analysis. As a rule, long-memory property called persistence is analyzed. In a very general sense, persistence is the characteristic of state that outlives the process that created it. Alvarez-Ramirez et al. (2008) used daily data for the period of 1950-2007 and reported that the long-term memory properties of the S&P500 change over time, especially during crisis periods. Similar conclusions were reached by (Dominique and Rivera, 2011) who showed that the S&P500 Index is persistent but the degree of persistence varies over time.

Most of such studies are based on the data from developed countries during the global crisis. The present paper aims to expand the existing literature by analyzing an emerging economy (Ukraine) during a purely local crisis. Using R/S analysis with the Hurst exponent method and its dynamic modification, persistence of Ukrainian financial data is analyzed. The tested hypothesis is: persistence varies over time; during the crisis it increases significantly.

The results of analysis provide additional evidences about long-memory properties of financial data and can be used both to predict crises and to model financial data with the appropriate methods: determining methods for the cases of persistent data and stochastic ones for the cases of non-persistent data.

The layout of the paper is the following. Section 2 contains a brief literature review on long-memory properties of financial data. Section 3 is dedicated to the anatomy of the Ukrainian crisis 2013-2015. Section 4 describes the data and outlines the Hurst exponent method used for the analysis. Section 5 presents the empirical results. Section 6 provides concluding remarks.

2. LITERATURE REVIEW

Financial data properties are widely discussed among academicians. According to the Efficient market hypothesis (EMH) financial data are random and thus unpredictable (see Fama, 1965). This theory was highly criticized since 80-s in the academic literature. Shiller (2000) and a number of other behaviorists find evidences in favor of irrational behaviour of investors (different cognitive traps like herd instinct, fear and greed, mass panic etc) which results the non-randomness of the financial data and the presence of different behavioral and price patterns (Schwert, 2003).

One of the data properties inconsistent with the EMH is persistence (the presence of memory properties in financial data).

The first who provide evidence of persistence in financial markets was Mandelbrot (1972). Based on his findings Peters (1991) proposed an alternative to the EMH theory called the Fractal Market Hypothesis (FMH). According to this hypothesis prices in financial markets have memory. Long- and short-term memory properties of financial data series are explored in different markets and financial assets (Greene & Fielitz, 1977; Granger & Ding, 1995; Caporale et al., 2018 and many others). Nevertheless there are many opposite evidences as well (Lo, 1991; Jacobsen, 1995; Chow et al., 1996).

Another interesting aspect is instability of persistence. Corazza and Malliaris (2002) show that the degree of persistence varies over the time.

Ukrainian financial market and persistence in its data are not widely discussed among academicians. Existing studies (Mynhardt et al., 2014, Caporale et al, 2016) evidence in favor of long-memory properties presence. Still these studies mostly concentrate on data from Ukrainian stock market. As for the other data there are no results. This study claims to fill existing gaps in the results and to explore how the financial data properties (persistence) are changed in different conditions (pre-crisis, crisis and post-crisis). Ukraine provides data for the pure experiment, because its latest crisis was not related to the global processes and thus is rather unique – information can be analyzed without any financial contagion effects.

3. ANATOMY OF THE UKRAINIAN CRISIS 2013-2015

During the last decade Ukrainian economy has faced two serious crises. The first one was mostly connected with the global financial crisis 2007-2009 and was caused by the contagion effects. The second one in 2013-2015 had purely local nature: difficult military and political situation in the country, banking and economic crises, combined with the failure of structural and anti-corruption reforms. In both cases a substantial fall of Ukrainian stock market was observed (see Figure 1).

Figure 1. UX index in 2008-2018 (Ukrainian Stock Exchange daily data, points)

Ukrainian crisis 2013-2015 was caused by a huge set of macroeconomic problems and disproportions in economic system triggered by the unprecedented mix of economic, banking, military and political crises as well as political instability and military conflict.

Partially they were based on the structural disproportions in Ukrainian commodity economy and political crisis in the end of 2013. In 2014 crisis was reinforced by a series of dramatic political events:

– revolutionary events and mass protests (January 2014);
– political leadership changes in the country as a result of armed conflict (February 18-21, 2014);
– annexation of the Crimea by the Russian Federation (February 26, 2014);
– invasion of the Donbas by the Russian Federation (April 12, 2014).

Economic crisis development can be illustrated by the dynamics of traditional indicators – real GDP and inflation index (Fig. 2).

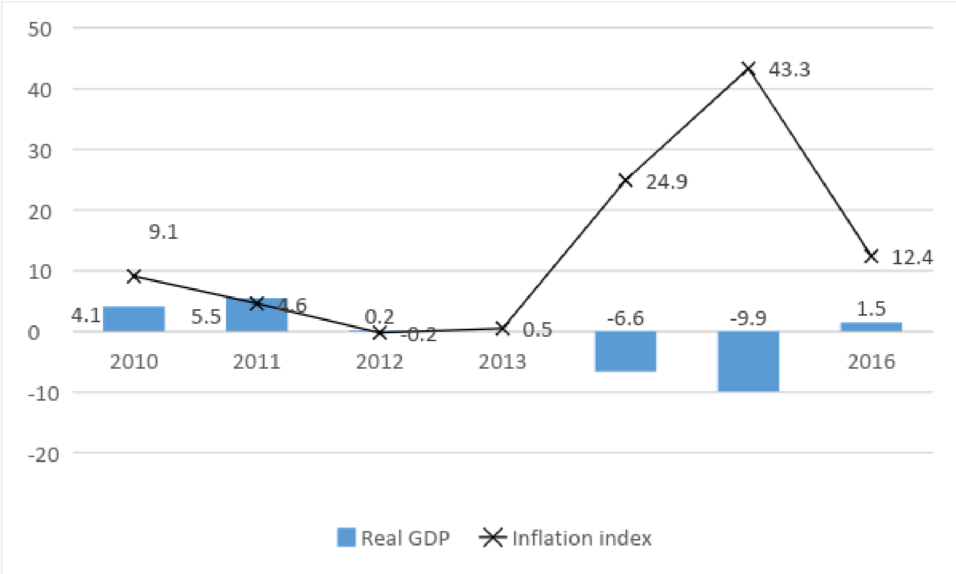

Figure 2. Dynamics of real GDP (in 2010 prices) and inflation index in 2010-2016, % to the previous period, State statistical service data

Despite some revival in 2016 (GDP growth was 1.5%), the presented data clearly indicate the recessionary processes in the economy and return of the Ukrainian economy to the levels of the 2000's, as well as the expansion of the inflationary spiral. The cause of the economic recession was primarily the loss of production capacities and resource potential of the two main industrial regions as the result of military conflict. Inflation was the result of unproductive increase of the budget deficit in 2014.

Further disinflation policy and inflation targeting along with the abolition of the fixed exchange rates by the NBU in 2014 had even worse consequences. They led to the decrease in business activity and ability to attract financing.

Banking crisis, along with economic, blocked access for companies to the credit resources. Liquidation of 88 banks by the NBU, transition to a floating exchange rate in February 2014 led to unprecedented devaluation of the national currency and large deposits outflow. In 2013-2015 they have reduced by 50 billion USD (according to the NBU data).

Critical growth of the current account deficit since 2013, following the revolutionary events of 2014, was multiplied by a significant bank capital and portfolio investments outflow ($ 9.1 billion, State statistical service).

Government policy with attracting loans from international financial institutions to cover both the budget deficit and current account deficit in the absence of structural changes provoked the emergence of a debt crisis. Restructuring of Ukraine's debt in September 2015 can be considered as a technical default. Debt to GDP ratio increased from 78% in 01.01.2014 to 131% in 01.01.2016.

Crisis period 2013-2015 is confirmed by the downward trend in the UX index (Figure 1), dynamics of macroeconomic indicators (Figure 2) and different rating assessments:

– in September 2013 Ukrainian stock market was excluded not only from the group of frontier markets but also from the candidate markets for its membership by the international rating agency FTSE;

– the absence of IPOs of Ukrainian companies on domestic and foreign stock markets (in 2013-2015);

– reduction of the Ukrainian Global Competitiveness Index cases of the stock market regulation (107th out of 148 countries); the macroeconomic environment (134th place) and the development of the financial market (121st place) in 2015;

– fall in the World Bank Doing Business rating of minority investors protection (109th out of 189 countries).

A slight market recovery was observed from the second half of 2016 till the end of 2017 (illustrated by the slow growth of the UX index, Fig. 1). Slight recovery may indicate the end of the sharp phase of the crisis and the transition to the post-crisis period 2016-2017.

4. DATA AND METHODOLOGY

This paper uses daily data of the following indicators: Ukrainian stock market indexes UX and PFTS, currency pair USDUAH, NBU discount rate, interest rates for loans and deposits. This choice is explained mostly by the data availability: only these indicators have daily observations which are crucial for this research (data set requirements). The sample goes from 05.01.2011 to 31.12.2017. Three sub-samples are also considered: pre-crisis (05.01.2011-31.12.2012), crisis (01.01.2013-31.12.2015) and post-crisis (01.01.2016-31.12.2017). The data sources are the National Bank of Ukraine (www.bank.gov.ua), Ukrainian Exchange (www.ux.ua), Stock Exchange PFTS (www.pfts.com.ua).

To measure persistence in this study R/S analysis and its dynamic modification are used. The algorithm of R/S analysis is as follows:

1. A time series of length M is transformed it into one of length N = M - 1 using logs and converting prices into returns:

$$N_i = \log\left(\frac{Y_{t+1}}{Y_t}\right), \quad t = 1,2,3,\ldots (M-1) \tag{1}$$

2. This period is divided into contiguous A sub-periods with length n, so that An = N, then each sub-period is identified as Ia, given the fact that a = 1, 2, 3. . . , A. Each element Ia is represented as Nk with k = 1, 2, 3. . . , N. For each Ia with length n the average is defined as:

$$e_a = \frac{1}{n}\sum_{k=1}^{n} N_{k,a}, \quad k = 1,2,3,\ldots N, \quad a = 1,2,3\ldots, A \tag{2}$$

3. Accumulated deviations Xk,a from the average for each sub-period Ia are defined as:

$$X_{k,a} = \sum_{i=1}^{k}(N_{i,a} - e_a) \tag{3}$$

The range is defined as the maximum index Xk,a minus the minimum Xk,a, within each sub-period (Ia):

$$R_{Ia} = \max(X_{k,a}) - \min(X_{k,a}), \quad 1 \le k \le n. \tag{4}$$

4. The standard deviation is calculated for each sub-period Ia:

$$S_{Ia} = \left(\left(\frac{1}{n}\right)\sum_{k=1}^{n}(N_{k,a} - e_a)^2\right)^{0,5} \tag{5}$$

5. Each range RIa is normalised by dividing by the corresponding SIa. Therefore, the re-normalised scale during each sub-period Ia is RIa/SIa. In the step 2 above, adjacent sub-periods of length n are obtained. Thus, the average R/S for length n is defined as:

$$(R/S)_n = (1/A)\sum_{i=1}^{A}(R_{Ia}/S_{Ia}) \tag{6}$$

6. The length n is increased to the next higher level, (M - 1)/n, and must be an integer number. In this case, n-indexes that include the initial and ending points of the time series are used, and Steps 1 - 6 are repeated until n = (M - 1)/2.

7. The least square method is used to estimate the equation log (R / S) = log (c) + H*log (n). The angle of the regression line is an estimate of the Hurst exponent H. (Hurst, 1951). This can be defined over the interval [0, 1], and is calculated within the boundaries specified below:

– $0 \leq H < 0.5$ – the data are anti-persistent, returns are negatively correlated,

– H = 0.5 – the data are random, the series are normally distributed; the returns are uncorrelated, there is no memory in the series and they are white noise;

– $0.5 < H \leq 1$ – the data are persistent, returns are highly correlated, there is a trend in the market.

This algorithm provides static estimates of market persistence. To analyze dynamic properties of persistence modification of R/S analysis developed by Caporale et al. (2014) is used. According to this approach the Hurst exponent is calculated for the different data windows. The procedure is as follows: having obtained the first value of the Hurst exponent (for example, for the date 05.01.2012 using data for the period from 05.01.2011 to 31.12.2011), each of the following ones is calculated by shifting forward the "data window", where the size of the shift depends on the number of observations and a sufficient number of estimates is required to analyze the time-varying behaviour of the Hurst exponent. For example, if the shift equals 10, the second value is calculated for 15.01.2012 and characterizes the market over the period 15.01.2011 till 10.01.2012, and so on.

4. EMPIRICAL RESULTS AND DISCUSSION

Results of the R/S analysis on the data series for the whole sample and different sub-samples are presented in Table 1.

Table 1

Results of the R/S analysis for the whole sample and different sub-samples, 2011-2017

Period	UX	PFTS	USDUAH	Discount rate	Loan rates	Deposit rates
Whole sample	0.61	0.64	0.60	0.54	0.32	0.43
Pre-crisis (2011-2012)	0.62	0.66	0.81	0.56	0.34	0.4
Crisis (2013-2015)	0.57	0.6	0.6	0.56	0.35	0.31
Post-crisis (2016-2017)	0.6	0.64	0.69	0.56	0.3	0.36

Source: Authors' results.

As can be seen, different indicators are characterized by different levels of persistence. Stock market and exchange rate data are persistent (there is a positive correlation between their past and future values). Discount rate data are very close to the random. Instead data from banking sector (both loan and deposit rates) exhibit anti-persistence (there is a negative correlation between its past and future values).

Persistence of the data is unstable; it varies over the time. In different economic conditions, data exhibit different long-memory properties.

The dynamic R/S analysis shows the evolution of persistence over the time in Ukrainian financial data. The results are presented in Figures 3-8 respectively. The number of steps and the data window size are selected to provide sufficient data for the Hurst exponent calculations as well as to give enough data points to build charts (data window = 300, step = 50).

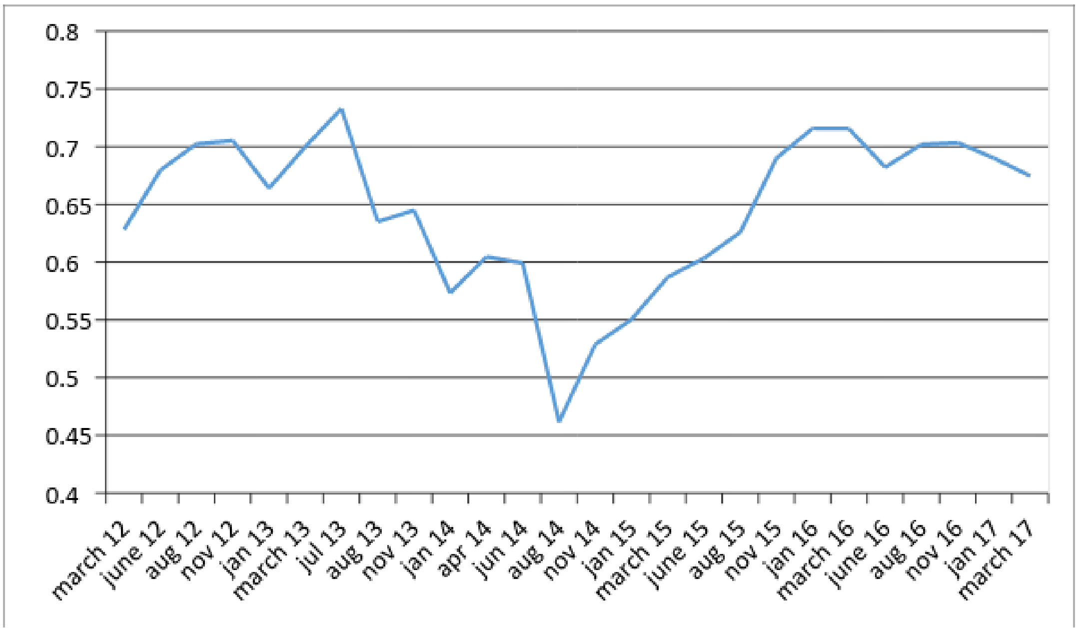

Figure 3. Results of the dynamic R/S analysis for the PFTS daily data, 2012-2017 (step=50, data window=300)

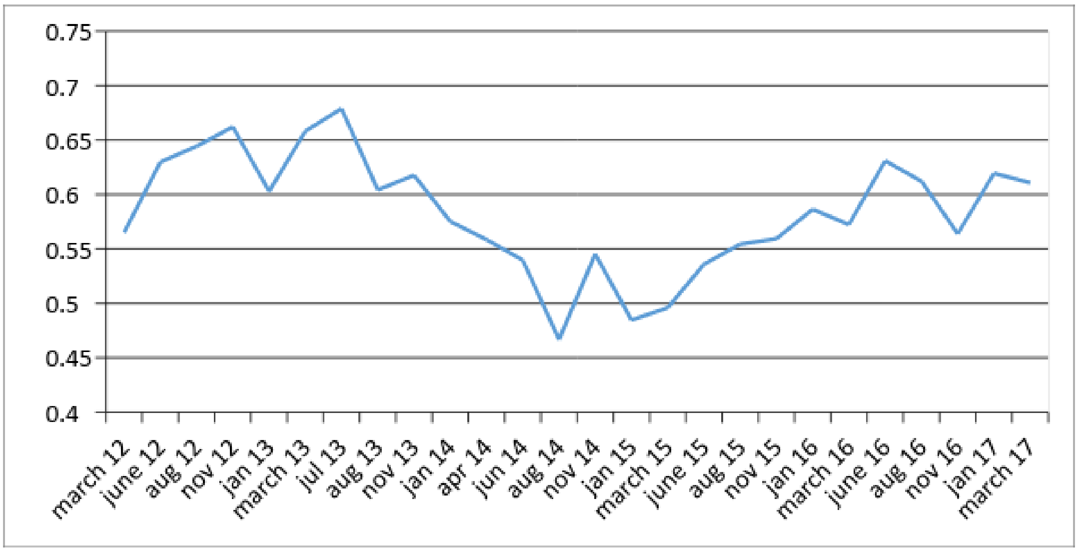

Figure 4. Results of the dynamic R/S analysis for the UX daily data, 2012-2017 (step=50, data window=300)

As can be seen both stock market indexes tend to demonstrate persistence in data which increases during the crisis periods. Persistence is unstable and varies over the analyzed periods from 0.48 to 0.70.

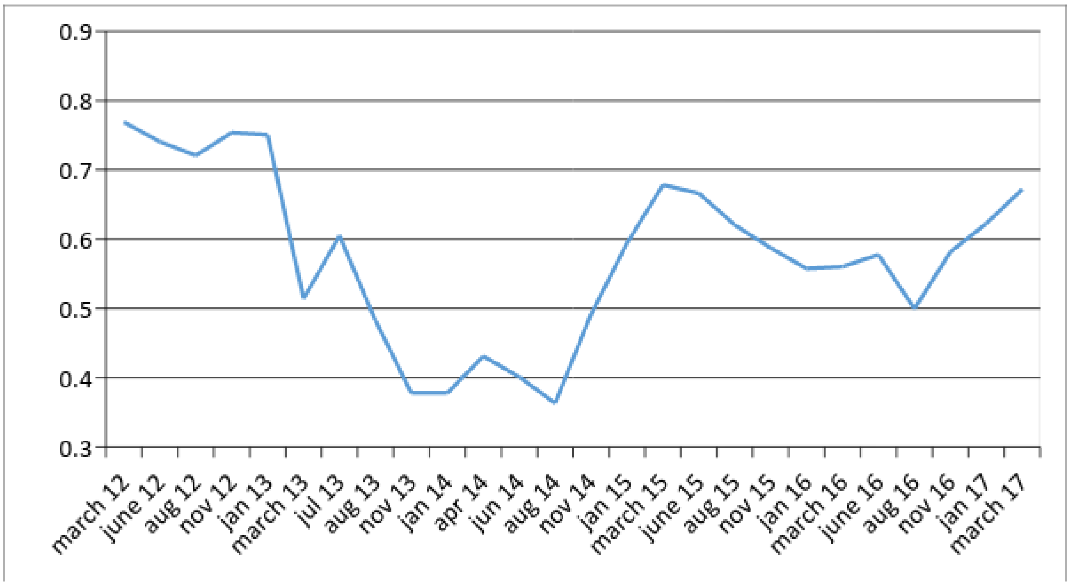

Figure 5. Results of the dynamic R/S analysis for the USDUAH daily data, 2012-2017 (step=50, data window=300)

USDUAH data show the signs of persistence. It is also very unstable and significantly increases during the crisis period: from 0.35 in 2013 to 0.65 in 2015.

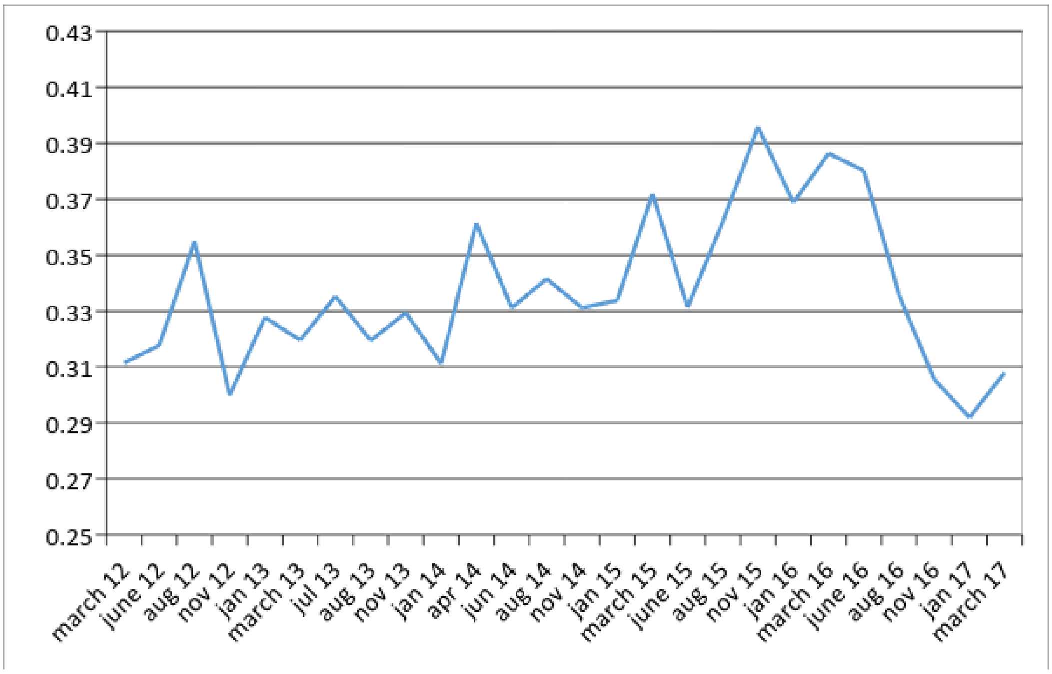

Figure 6. Results of the dynamic R/S analysis for the Loan Rates daily data, 2012-2017 (step=50, data window=300)

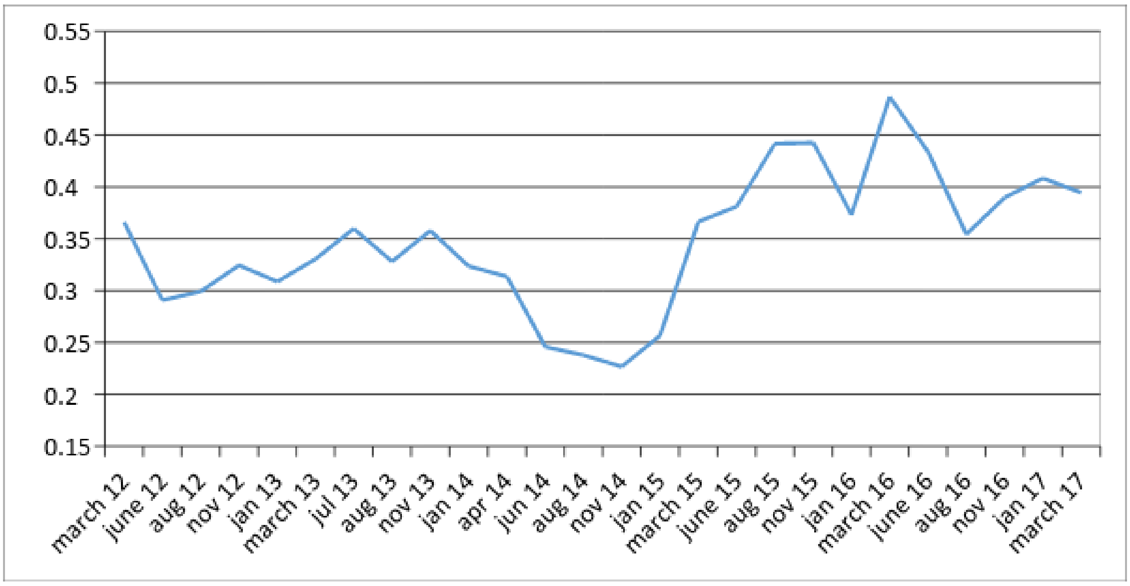

Figure 7. Results of the dynamic R/S analysis for the Deposit Rates daily data, 2012-2017 (step=50, data window=300)

Loan and deposit rates data shows anti-persistent properties. During the crisis period their persistence increases, but stays below 0.5.

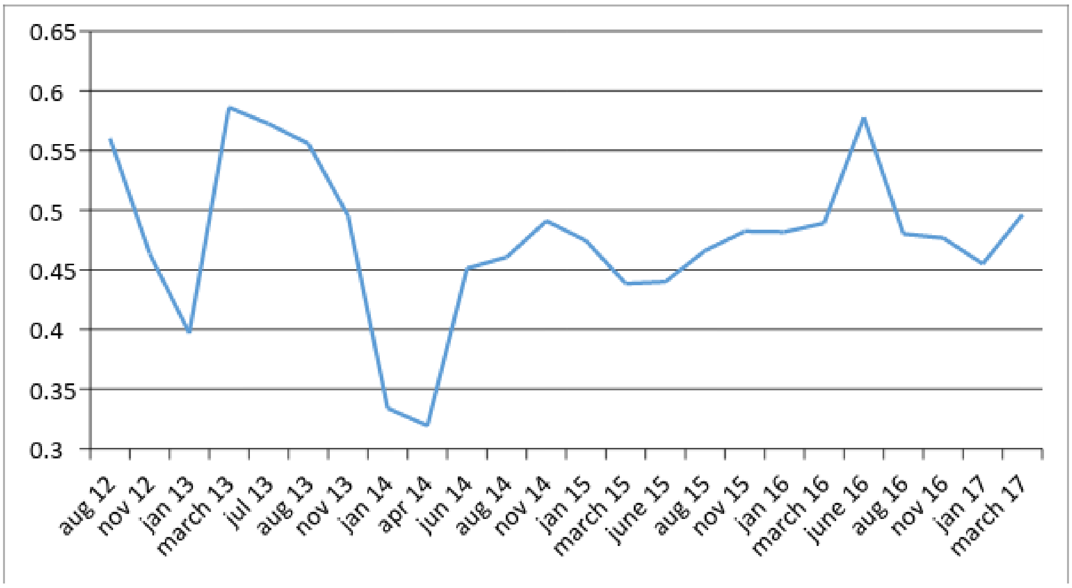

Figure 8. Results of the dynamic R/S analysis for the Discount Rate daily data, 2012-2017 (step=50, data window=300)

In general Discount Rate daily data show no signs of persistence The Hurst exponent is close to 0.50. Still it deviates from this point and tend to increase during the crisis.

For almost of the analyzed data sets (except the loan rates data) period since march-April 2013 till the august 2014 is characterized by significant drop in the Hurst exponent values, instead since august 2014 till June-August 2016 the level of persistence has increased significantly. These observations show that data properties are not stable and vary over the time. The degree of persistence varies over the time, being higher during the crisis period. These conclusions confirm results of previous researches for the developed countries. For example, Mynhardt et al. (2014) and Caporale et al. (2016) obtain similar results: during the crisis persistence of the data tends to increase. As the result different sorts of autoregressive models can be used during the crisis periods to predict data.

5. CONCLUSION

We investigate persistence properties of Ukrainian financial data by applying one of the most popular long-memory approaches namely the R/S analysis to daily series for the Ukrainian stock market indexes (PFTS and UX), currency pair USDUAH, discount rate and deposit and loan rates for the period from 2011 to 2016. To analyze the behavior of persistence in different conditions we divide sample period into sub-periods: 2011-2012 (pre-crisis), 2013-2015 (crisis), 2016-2017 (post-crisis).

Results indicate that Ukrainian financial data in general do not follow a random walk (the only exception is Discount rate data). Ukrainian stock market data and national currency exchange rate data exhibit persistence, but loan and deposit rate data are anti-persistent. During the crisis periods persistence increases in most of the cases (the only exception is loan rate data).

The fact that the long-memory properties of financial data are unstable and vary over the time is an important finding that can lead to a better understanding of the behavior of financial markets. One of the possible implications of these results is appropriate choice of the models used to predict behavior of financial data series. For example, during crises autoregressive models and other past-values dependent models will be the best proxies.

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REFERENCES

Alvarez-Ramirez, J., Alvarez, J., Rodriguez E., & Fernandez, A. (2008). Time-varying Hurst exponent for US stock markets. *Physica A: Statistical Mechanics and its Applications, 387*(24), 6159-6169.

Bekaert, G., & Hoerova, M. (2013). The VIX, the Variance Premium and Stock Market Volatility. *Journal of Econometrics, 183*(2), 181-192.

Caporale, G. M., Gil-Alana, L. A., & Plastun, A. (2018). Persistence in the cryptocurrency market. *Research in International Business and Finance (forthcoming)*. Retrieved from https://doi.org/10.1016/j.ribaf.2018.01.002

Caporale, G.M., Gil-Alana, L.A., Plastun, A,. & Makarenko, I. (2016). Long memory in the Ukrainian stock market and financial crises. *Journal of Economics and Finance, 40*(2), 235-257.

Chow, K. V., Ming-Shium, P., & Ryoichi, S. (1996). On the long-term or short-term dependence in stock prices: Evidence from international stock markets. *Review of Quantitative Finance and Accounting, 6*(2), 181–194.

Corazza, M., & Malliaris, A. G. (2002). Multifractality in Foreign Currency Markets. *Multinational Finance Journal, 6*, 387-401.

Dominique, C-R., & Rivera, S. L. (2011). Mixed fractional Brownian motion, short and long-term dependence and economic conditions: The case of the S&P-500 Index. *International Business and Management, 3*, 1-6.

Fama, E. F. (1965). The Behavior of Stock-Market Prices. *The Journal of Business, 38*(1), 34-105.

Granger, C.W.J. & Ding, Zh. (1995). Some properties of absolute returns. An alternative measure of risk. *Annales d'Economie et de Statistique, 40*, 67-91.

Greene, M.T. & Fielitz, B.D. (1977). Long-term dependence in common stock returns. *Journal of Financial Economics, 4,* 339-349.

Mandelbrot, B. (1972). Statistical Methodology For Nonperiodic Cycles: From The Covariance To Rs Analysis. *Annals of Economic and Social Measurement, 1*, 259-290.

Mynhardt, R. H., Plastun, A., & Makarenko, I. (2014). Behavior of financial markets efficiency during the financial market crisis: 2007 – 2009. *Corporate Ownership and Control, 11*(2), 473-488.

Peters, E. E. (1991) *Chaos and Order in the Capital Markets*. John Wiley and Sons, New York.

Schwert G. W. (2003). Anomalies and market efficiency. In G.M. Constantinides, M. Harris & R. M. Stulz (Ed.), *Handbook of the Economics of Finance* (ch. 15, pp. 939-974). Elsevier.

Shiller, R. J. (2000). *Irrational Exuberance*. Princeton University Press.

Whaley, R. (2000). The Investor Fear Gauge. *Journal of Portfolio Management*, *26*, 12-17.