An Econo-Physics View on the Historical Dynamics of the Albanian Currency vs. Euro Exchange Rates

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Abstract: The descriptive analysis for the very long-term behavior of the Euro/ALL exchange rates has identified a near to average .revert behavior which contradict some econometric arguments and economical level of the country. Apparent anxious regimes have continuously ended up without crashing and generally the national currency of the not competitive economy has shown a nearly stabilized dynamics toward EU currency. Some of those properties have been explained herein by employing the analysis of the system from complexity and econo-physics point of view. So, by approaching the trend we obtained that the time precursor is characterized by local self-organization regimes that never organized in long scale to produce dangerous move. Thermodynamic–like processes have acted constantly as stabilizer of the national currency value. More details and features have been considered by analyzing the distributions and multifractal structure of the series in the framework of the non-equilibrium statistical mechanics approach. Gathering the information about the stationarity of the states, presences of regimes and their properties, we realized to identify the optimal condition for measurement, modeling and steadfast descriptive statistics. Finally, by using neural network we have realized a forecasting example for one month time interval. The work aims to reveal the importance of interdisciplinary consideration for better results in the study of complex socioeconomic systems.

Keywords: Econophysics; exchange rate; q-statistics; multifractal; neural networks.

JEL Classification: C60; C45; C46; E7.

1. Introduction

The exchange rate signifies the price of one currency in terms of another one. It depends on the purchasing parity, prices level, interest rates, inflations, governments' debt or stock etc., in both economies, see references (Betts, 2000,

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Mohsin, 2002). Other additional variables can affect it depending on the specifics of the concrete liquidity markets on the country; see (Cheung, 2019). Various econometric models have been developed for such important variable for national economies. Additional and helpful dynamical analyses have been presented by physicists in the framework of the econo-physics studies, see (Mantegna, 2000), (Pavlos, 2019). In the context of the complexity, many socioeconomic processes have been considered as application of the non-equilibrium statistical mechanics, (Tsallis, 2017), (Tsallis, 2009), (Yan, 2012), (Tsallis, 2004), (Pavlos, 2019), (Sornette, 2001) etc. In the following we will employ some econo-physics arguments in the study of the historical exchange rate of national Albanian currency toward Euro, in an atypical economical environment with high informality, undertaking intensive reforms and having no active financial market. We note that the country has suffered a very bad financial event at 1997 when particularly the exchange rates of national currency (Lek) has depreciated toward a financial and economic collapse and since then, the exchange rates have been considered a very important indicator of the economy and financial system of the country.

1.1. The Use of Q-Distributions for Non-Equilibrium State

Tsallis in (Tsallis, 2009) has recapitulated the extension of statistical physics for non-equilibrium processes based on q-entropy. For two systems A and B, the q-entropy reads $\frac{S_q(A+B)}{k} = \frac{S_q(A)}{k} + \frac{S_q(B)}{k} + (1-q)S_q(A) * S_q(B)$ where $S_q = \frac{1}{q-1}\int p(x,t)^q dx$ and p(x, t) are the probabilities of microscopic states whereas q is the non-extensive parameter. When we consider the energy-like variable, q-entropy is optimized in the q-exponential distribution$\rho(x) \sim (1+(1-q)x)_+^{\frac{1}{1-q}}$, (Tsallis, 2009) and if we consider the velocity-like variables the optimization of the q-entropy leads to q-Gaussian, (Tsallis, 2009), (Umarov, 2010)

$$\rho(x) \sim \left(1-(1-q)\frac{(x-\mu)^2}{2b^2}\right)_+^{\frac{1}{1-q}} \qquad (1)$$

The q-parameter in (1) is called $q_{stationary}$ and $q-1$ measures the distance from the Gaussian distribution, and hence the level of non-stationary. Note that forms (1) are defined for positive arguments and are stationary for $1 > q > \frac{5}{3}$ see (Umarov, 2010), (Tsallis, 2009) etc. The q-Gaussian belongs to the t-distribution family and is the attractor of the non-stationary distributions (Umarov, 2010), (Pavlos, 2015). Referring to the original use, the q-parameter above is named non-additivity parameter for the entropy or q-entropy parameter too (Tsallis, 2004).

1.2. Tsallis Q-Indices and the Conjecture to the Multifractality

In the Tsallis' formalism a triplet of q-indices $\{q_{entropy}, q_{sensitive}\ q_{relaxasion}\}$ is particularly significant because each of them ascribes important quantities of the physical system. So, $q_{entropy}$ indicates the level of the stationarity of the distribution, $q_{sensitive}$ measures the q-entropy production and $q_{relaxation}$ gives the rate of the relaxation of actual state. The $q_{sensitvity}$ parameter establishes the q-exponential $e_q^{\Lambda t}$ which results as the solution of the relaxation equation $\frac{d\varepsilon}{dt} = \Lambda\varepsilon^q$ where $\varepsilon = \lim_{\Delta x(0)\to 0} \frac{((x_2(t)-x_1(t))}{\Delta x(0)}$ and $x_i(t)$ are the adjacent phase space trajectories for one dimensional dynamical system, see (Tsallis, 2004). According to (Tsallis, 2009), it represents the q-entropy production. Moreover, it is related with multifractal parameters by the formulae

$$q_{sensitive} = 1 - \frac{\alpha_{\max}\alpha_{min}}{\alpha_{max} - \alpha_{\min}} \qquad (2)$$

where, α_{max} and $\alpha_{\min}$ correspond to the zero values of the singularity spectrum (f(α)=0) and α is the singularity parameter for the structure. The degree of multifractality and the singularity asymmetry a given by $\Delta\alpha = \alpha_{max} - \alpha_{\min}$ and

$$\mathrm{A} = \frac{\alpha_0 - \alpha_{min}}{\alpha_{min} - \alpha_0} \qquad (3)$$

where α_0 is the solution of maximum of singularity spectrum (f(α)=1).

1.3. Discrete scale of invariance and Log-periodic precursor

Sornette, see (Sornette, 2009) has shown that the herding behaviour among agents in the market drives the dynamics of a traded financial asset to a special regime called Discrete Scale of Invariance (DSI). It leads to the self-organization behaviour. The hazard rate has been described by a log-periodic function (LPP)

$$y = y_0 + A(t - t_c)^m(1 + B\cos(\omega\log(t - t_c) + \varphi)) \qquad (4)$$

where t_c is the critical time, y is the logarithm of the price, ω is the cyclic frequency and A, B are constants. According to (Sornette, 2009), the critical point should be interpreted as a special time moment when the regime is most likely to change. The behaviors matching (4) have been obtained and analyzed in many financial behavior, see (Pele, 2019), (Lera, 2016), (Yan, 2012) etc.

2. A Preliminary Qualitative Econo-Physics View for some Factors that have Affected the Exchange Rate During 2000-2019

By an empirical view of daily historical exchange rate Euro/ALL, it appears that the mean reverting property is satisfied for the long term behavior despite significant differences between the economies of Albania (A) and Euro zone (E). It contradicts econometric prediction if considering the poor and not competitive Albanian economy, high CPI index and properties of the purchasing parities in the two economies. Next, it seems that the self-organization regimes are present, but do not affected seriously the national currency stability. In the followings, we employed econo-physics arguments to explain those specific features and others properties of this important financial quantity. Note that for now there is no real financial market in the country and therefore this indicator become very important for study and practical purposes.

2.1. The Effect of the Net Flows of the Money

Some specific analogies between economic and physical models discussed in (Mantegna, 2000) have been implemented up to the thermodynamic level. So, in (Banerjee, 2010) the flow of the money has been identified with the heat, the money per capita was accredited as the temperature and so on. The increment of the entropy is calculated directly from the analogy using the second law of thermodynamics giving

$$\delta\, S = \left(\frac{1}{T_E} - \frac{1}{T_A}\right)\delta M + \ln\left(\frac{T_E}{T_A}\right)\delta N \qquad (5)$$

where M is the total money and N is the population owning it. Here we use the subscripts A for Albania and E for EU. Irregular heat transfer causes the entropy to increase so the expression (5) is assumed positive. In the absence of net emigration ($\delta N = 0$) it results that $sign\,(\frac{1}{T_E} - \frac{1}{T_A}) = -sign(\delta M)$. For our system it results that the money streams inward the country with lower $T \sim GDP_{capita}$ hence the direction of money flows is E→A. This is clearly done in Euro currency, so favoring the Lek strengthens. In general, one have

$$\frac{\delta M}{\delta N} > \frac{\ln\left(\frac{T_A}{T_E}\right)}{\frac{1}{T_E} - \frac{1}{T_A}} \sim \frac{\ln(GDP_c(A) - \ln(GDP_c(E)}{\frac{1}{(GDP_c(E)} - \frac{1}{(GDP_c(A)}} \qquad (6)$$

Taking $\delta N < 0$ due to the net migration A→E and considering that $GDP_c(A) < GDP_c(E)$, one obtains again that $\delta M > 0$. By this qualitative view, the inward net flows of the money in the A-country produces a depreciating term in the ratio Euro/All as long as the inflation in the country is not too high.

2.2. Informal Economy Pressure

From the econometric prospect, the informal economy causes the GDP to appear smaller, which in turn compromises the official price index and purchasing parity which act as key factors in the exchange rate balances. The considerable amounts of money out of the regularized financial system generate irregular transfers working so as interior heats, producing entropy. The regularities are expected to reduce the degrees of freedom of the system which favor the self-organization events, whereas irregularities oppose them. So, the underground economy discourages the self-organization regimes in the exchange rates. From the other part, the money in the informal economy acts as heat reservoir which opposes the cooling of the system during the 'crises'and slow down the warming (GDP_c increase) when the production in the country is healthy. By using MIMIC modeling, we estimated that the informality level in Albania during 2000-2015 has been 35-42% of the GDP. Similar figures are reported by different sources. Considering this significant level of the informality, this bad stuff worked positively at once, preserving in some extends the balance ALL/EURO. However, absorbing and emitting irregularly the money during interior heats exchanging would put liquidities in an intermittent alert causing the system to be in an out of-equilibrium state that would impair or even damage the country's finances and the economy itself in the long run.

2.3. LPP Signature and Extension

We explored the LPP behavior in the Euro/Lek exchange rate series for the period 2000-2019. The verification of the LPP fit is not an easy task due to the nature of the residuals as seen in (Fantazzini & Geraskin, 2011). Several techniques and approaches in this issue have been discussed in (Sornette, 2001), (Yan, 2012), (Wosnittza, 2013) and we have employed them in our previous addresses.

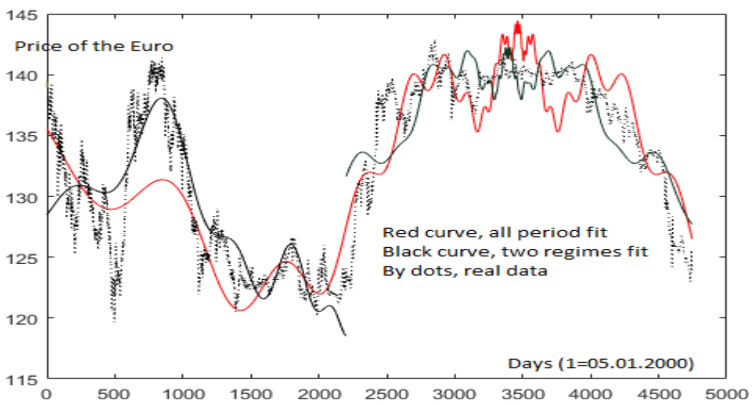

Figure 4. Identification of the Regimes by Using the Modified Log-Periodic Function

We used herein the Lomb period-gram combined with D_{hq} analysis (Zhou, 2002) to argument the parameters obtained by LPP fit. So far, we evidenced LPP signatures in some time windows on the series, but usually they fade off without causing crashes. However, long term fit of the form (5) has not been observed. Considering the specifics of our system, we propose to amend the functional form (5). So, let's suppose that a LPP is being developed in the system at the time t. Assume that some amount of money is injected or withdrawn by a specific factor. It causes the price P to be shifted to another value P' in the LPP curve which correspond to the price at another moment t+τ so P'=P(t+τ). If this activity is persistent, the net effect would produce a similar consequence in the hazard rate as does the herding behavior employed in JLS model. As result, a kind of polarization would be imposed in the "system coordinates" which start oscillating log-periodically with a cyclic frequency ω_1. Next we may assume that this effect is not strong enough to change the (DSI) multifractal structure of the system, so the old LPP regime parameters (t_c, ω) remain intact. By elementary calculation the new dynamics is

$$y = y_0 + A(t - t_c)^m \cos(\omega * \log(t - t_c) + \varphi_1) + \mathrm{B}\cos((\omega - \omega_1)\log(t - t_c) + \varphi_2) + C(t - t_c)^m \cos(\omega + \omega_1)\log(t - t_c) + \varphi_3). \quad (7)$$

We observed that in the long term the form (7) has fitted better the time series behavior in the full range (2000,2019). The term involving ω-ω_1 allegedly describes a "slower" dynamics whereas the term with cyclic frequency ω+ω_0 represent a "faster" dynamics compared to the fundamental behavior. They both contribute in modifying of the initial LPP trend avoiding the crash or bubble. The model (7) needs more arguments to be confirmed in a more general sense but it worked well in describing a long term dynamics of our series.

3. Evidences from the Distribution of the RoR and Multifractality

The econometric quantity measuring the relative price $s = \frac{p_t - p_{t-1}}{p_t}$ called rate of return (RoR) plays the role of the velocity in the statistical mechanics. Similarly with (Borland, 2009), we assume that the distribution of the RoR for exchange rates could be q-Gaussian. Herein we used the explicit form of the q-Gaussian resulting from the optimization of the q-entropy (Tsallis, 2011), (Wilk, 2015) etc.,

$$\rho(x) = \frac{\sqrt{q-1}}{\sqrt{3-q}} * \frac{\Gamma\left(\frac{5-3*q}{2*(1-q)}\right)}{\Gamma\left(\frac{2-q}{1-q}\right)*b)} * \left(1 - \left(\frac{1-q}{(3-q)*b^2} * ((s - \mu)^2)\right)\right)^{\frac{1}{1-q}} \quad (8)$$

Therefore, q-parameter obtained by the fit establishes the functional form and the constant values for q-Gaussian, embodying therefore the fitted object (8) with the right statistical mechanics connotation for our system. Next, according to (Umarov, 2010), the form (8) represents a stationary distribution if q<5/3, and it has the variance defined for q<2. Note that it still represents a distribution object for q<3.

3.1. Remarks about descriptive analysis

By fitting the q-Gaussian to the distribution of the RoR for the series of spot FX prices covering the period [2000, 2019], we obtained q=1.9225 which corresponds to the "infinite variance zone" in the terms of Tsallis theory. Considering the period [2008, 2019] which corresponds to the second regime of the prices themselves as identified by LPP analysis above, we obtained the values q~1.664 which is in the edge of the stationary condition ($q_{stationary} < \frac{5}{3}$). The descriptive analysis in this case would result questionable because q=1.664 is quite proximate to the limit value 1.667. Similar properties have been observed for the interval [2012, today]. Such evaluation for the USD/ALL exchange rates and the prices of Gold give q~1.339, 1.399 respectively. Note that in linear modeling assuming first differences stationary (hence, RoR), Euro/ALL series are not good candidate to be used for this period. Accordingly the measurement of the mean and variance for the variable RoR are practically not possible for this period. In this sense, arithmetic averages and variances do not have representative properties. Opposing result was found for USD/Lek exchange rate and Gold prices for the same period. In the Figure 2 we have used the semi-logarithmic presentation of the distribution to make possible the observation of details on the displayed graphs.

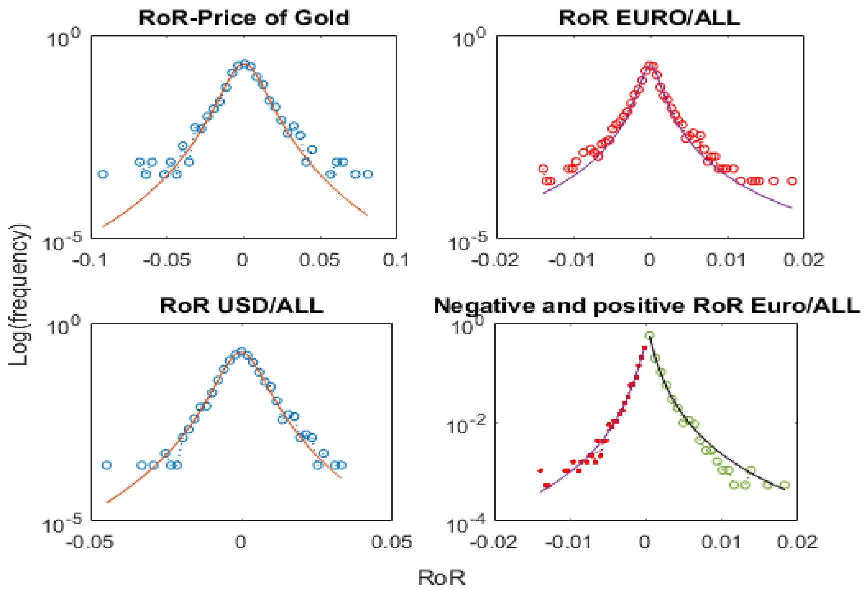

Figure 5. Semi-log presentation: Q-Gaussians fitted with distribution of the return of exchange rate. By marks, real pdf data, solid curves, q-Gaussian fitted.

The statistical analysis of the fitting has supported the q-Gaussians as the best fitted distribution with the optimal histograms of RoR. Therefore the above motioned q-analysis based on the q-Gaussian fit is considered conclusive from the descriptive point of view. We used it in the next stage and for more detailed analysis. So, it resulted that the high magnitude RoR (the tail) were displaced significantly from the fitted q-Gaussian. We qualified this deviance as the outcome of the mixed states and proposed to split it in the sub-states say the negative and the positive return value. We assumed that the states whose RoR's distribution is stationary are proper stat of the system; otherwise we considered them to be a mix of proper states. The classes or categories of the RoR (the bins) obtained by the histogram optimization are considered as microstates in the terms of statistical mechanics. So, it resulted that microstates belonging to the highest values of RoR are responsible in pushing the system out of stationary regime. By removing them we can obtain sub-states where the descriptive analysis can be more acceptable.

3.2. Some properties of the RoR sub-states

Following the analysis for the two branches proposed above, we observed that the distributions for the sub-series of negative and positive return were found stationary for the time intervals [2004, 2019], Figure 3.

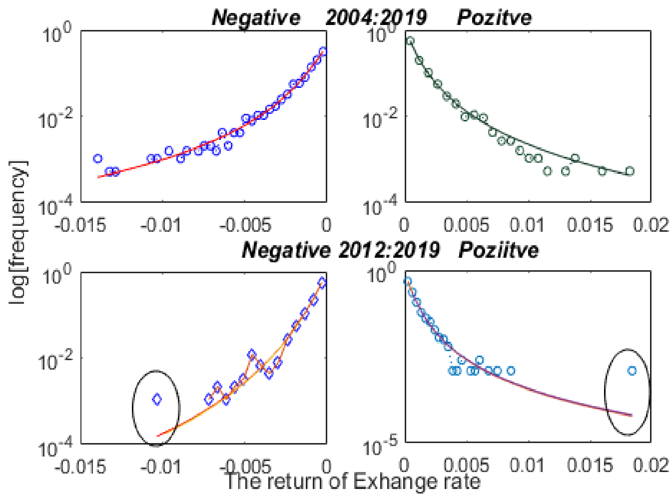

Figure 6. Levels of the RoR According to the Optimal Binning-the Classes

For the period [2012, 2019] that is the time just afterwards the 2008-2010 crises, we observed that again the highest RoR magnitude categories (the bin on the edge) were found separated from the others and significantly out of the tail of the q-Gaussian fitted to the histogram in both branches, Figure 3. Those values represent rare events.

By isolating them and re-assessing the distribution we obtained $q_{entropy}$ ~1.32-1.35 so the remaining part of the histogram belongs to a stationary distribution. For those stationary states a deeper mechanical statistics analysis become possible. Firstly, we obtain that $q_{entropy}^{positive\ band} \neq q_{entropy}^{negative\ band}$ therefore those bands are in different grade of the stationarity. This asymmetry suggests that the positive and the negative returns have been affected from asymmetric effects as well, including different factors. By evaluating the rate of q-entropy production using $q_{sensitive}$ we obtained $q_{sensitive}^{positive\ band} > q_{sensitive}^{negative\ band}$. It signifies that the alteration of the values in the positive branch have been more intensive in the period [2012, 2019]. This position of the relative dynamics for the two branches of the return would signal the tendency for relaxation in the near future providing that the factors would remain the same. Next, more information could be extracted from the multi-fractal structure. So, in (Pavlos, 2019) and (Pavlos, 2015), the asymmetry A given by the formulae (3) is used to identify the level of the degree of the freedom for the state. Similarly, for the RoR series [2004:2019], we observed that smaller singularity exponents (Holder) $\alpha > \alpha_0$, are dominant. Consequently the low fractal dimension is more populated and anti-diffusive processes prevent the system from relaxation toward random walk (highest dimension states). This behavior favors self-organization regimes. However, going down in sub-state hierarchy, we observe that the picture for negative and positive RoR bands shows different properties. For the positive band, we observed that the multifractal asymmetry is considerable (0.92-1=-0.08), Table 1, indicating that high dimension region is more dominant which suggests that the positive returns have been subject of the processes which boost the degree of freedom and reduce the self-organization signature. The fractal character and discontinuities have been not strongly accented for the positive RoR in this period.

Table 1. q-Tsallis and Multifractal Parameters for the Series of RoR [2004, 2019[

	Multifractal symetri A	Q.Entropy_Production: multifractal	Q.Entropy_Production: Fitting Lyapunov	Q_Entrpy-Stationary
Negative band	0.96927	0.62552	0.61717	1.6667
Positve band	0.91714	0.69963	0.68271	1.6667
Total band	0.93577	0.87218	0.86854	1.995

For the negative band, the multifractal asymmetry A is significantly smaller (0.03) than for the positive one, Table 1. Herein, the excess of the population of the high dimension region in phase space is less highlighted than in the positive band. It signifies the presence of more dynamic processes in it as compared to the other sub-state. So, it resulted that DSI structure factors are less noticeable in the negative than for the positive returns. Those differences are likely to contribute to destabilize the self-organization regimes for the exchange rate, once it has started.

4. The Prediction and Forecasting Issues

The neural network (NN) analysis is proven to be very intriguing for modeling and analysis in a large number of systems. In the case of time series it is practical to use associative forecasting mode which simply use to predict future values based on recent ones. Remember that in the NN method, the system of the quantities $\{x_i\}$ affect the responses {y} by the intermediacy of a transfer function that mimics the activation of the reaction in vivid organisms. For the simplest case, the one layer model, the formal equation is $y = f(wx + b)$where w represents the weight for each factor x, b is the bias and f is the analytical form of the transfer function. In short, there are many details and specifics that can be elaborated to attain a good prediction outcome.

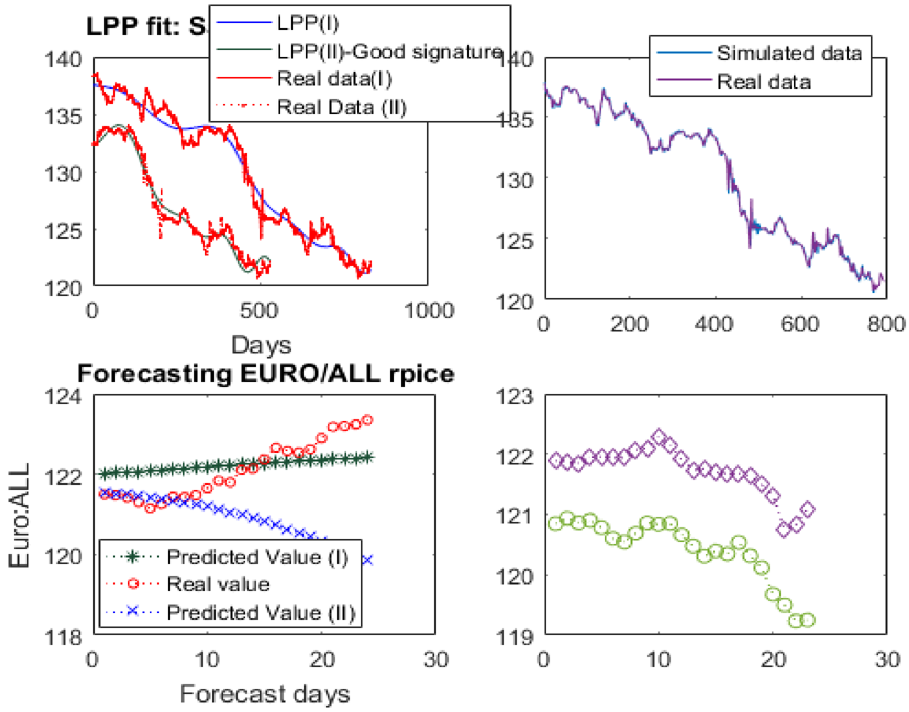

Figure 4. Predicting Exchange Rates Series for 23 'Incoming' Days. Right panel, Log-Periodic, Right Panel Neural Network

Adding to them, we hypothesized that the prediction would work better for states in the low dimension regimes, but necessary far from the critical region (singularity t_c point in the LPP). By running the NN algorithm, we observed that the best prediction in our case corresponded to the series that exhibits a significant LPP behavior. However, those arguments are only qualitatively or even empirical. As we mentioned, the quality of the LPP fit is a disputable issue due to the difficulties of testing it. To overcome some problem of empirical fit we used the approach of near-to-LPP behavior in (Prenga &Ifti, 2011). So far, we made a little bit effort in the assessment of the presence for LPP precursor. Otherwise the outcome of prediction has resulted not satisfactory. In short, by using Lomb period-gram as suggested in (Johansen, 2000), (Graf, 2003), we have localized an acceptable LPP signature for the series in the interval [3100, 3970], corresponding to [May 2016, October 2019]. Next, by performing an ad hoc genetic algorithm we finished the LPP fit and have identified its parameters. The critical time for this LPP precursor is found at the coordinate 1115, which lies far from the end of the series under analysis. Next, we have cut the 23 spot values (one financial month) before the end in this series. We used the NN-tool in Matlab to perform calculation for this session.

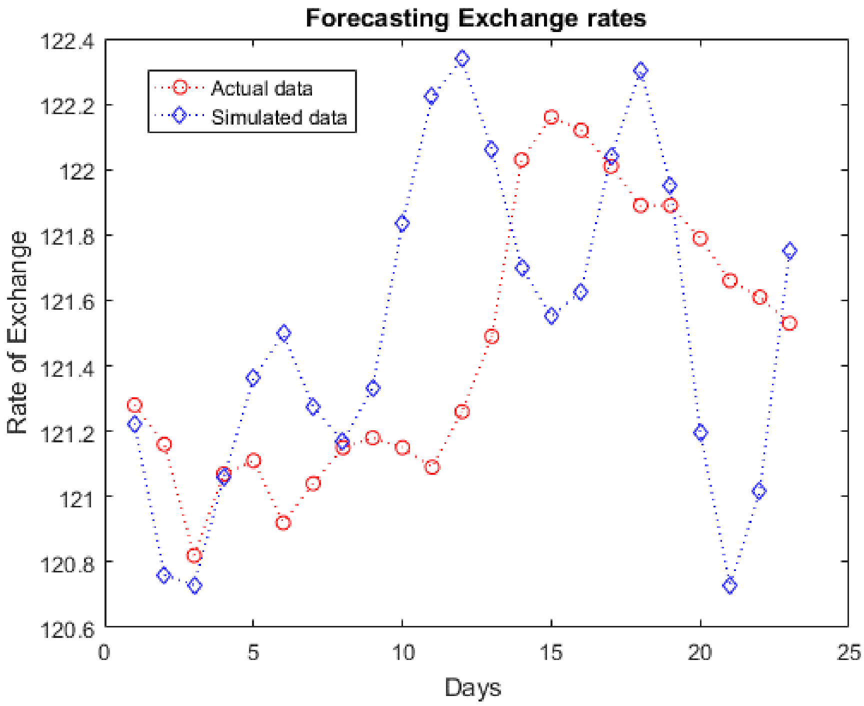

Figure 5. Predicting from Optimal Trained Network

After employing NN training and running, we improvised the forecasting procedure and evaluated it by comparing the simulated and real values. It resulted that the forecasted FX values for the ‘next’ 23 days have been realized within 1.5% uncertainty and the simulated values preserved the trend of the data as well, Figure 4. By exploring, most matched transfer function, regression method, numbers of layers and the number of recent terms constituting the {x} set in the NN modeling, the result has improved significantly, Figure 5. In this realization we used 35 layers, 120 elements in the {x} set, selected the transfer function to be logistic and the regression. This selection is by nature empirical and depends on the actual series but the way we precede can be classified as an optimal in this observation.

5. Conclusions

Econophysics approach and complexity analysis were used as a complementary tool in the study of Euro/Lek exchange rates dynamics for the period 2000-2019. Based on the analogy with thermodynamic systems, in this work we realized that informal economy and the apparent misbalances on economical level between Albanian and EU economy has favored the long term stability for our national currency during [2004, 2019]. An important factor that has acted as bubble-evanescence is the informal economy. It acted as a heat reservoir which release or engulf liquidities amounts modifying therefore the currencies balances and some key parameters of the system. Next, we have identified a long term LPP signature which includes an anti-bubble like deprecation of the Euro until 2004, and a full regime that started at the early 2005 and is likely to conclude in 2019-2020. The best LPP fit has been realized by employing the hypothesis that non-market effects have produced a secondary log-periodic process which modified significantly the initial self-organization regime discouraging the anxious behavior. Next, the stationarity of the state of the system is considered proprietary for the descriptive analysis. The distribution of the rate of return (RoR), were found usually non-stationary. As a result, the measurement and the deterministic approaches and modeling are likely to fail or would contain high deviances. Aside of searching for opportune time interval in the sense of stationarity, we used a physical decomposition strategy to analyze sub-states down to the microstates of the system. So, by using fractal and multifractal analysis we obtained that the negative and positive returns exhibit different dynamics. It signifies that possibly different factors or causes do affected positive and negative move for the RoR. To go deeper in this argument a more careful econometric analysis is needed which we skipped in this work. Finally, we employed NN method to forecast the exchange rates behavior. By combination of the above complexity and econo-physics arguments, we realized a forecast for 23 days lag (one month with good accuracy).

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