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Application of the Phase Analysis of Time Series for the Identification of Macroeconomic Cycles Based on the Dynamics of the Exchange Rates

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The article deals with one of the methods for identifying macroeconomic cycles of economic indicators using the example of the dollar and the euro exchange rates for the period 2000-2016. Time series of economic indicators, especially over a long period of time, contain irregular cyclical fluctuations with unstable amplitudes and periods. The use of traditional methods to study such oscillations, generally speaking, is not suitable. The method of phase analysis of time series allows one to identify hidden long-term macrocycles and, in some cases, make predictions. Since the end of 2008, both currencies started a new cycle, and their phase diagrams make a simultaneous jump up. Then they go into the negative area. From 2010 to early 2015, both phases coincide and are below the trend line of both currencies. But from the beginning of 2015 they make a sharp jump upward, when both currencies have risen above the expected trend value by almost 20 points, which indicates a new strongest wave of the economic crisis.

Key words and phrases: exchange rates, time series analysis, macroeconomic cycles.

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1. Introduction

As a rule, time series of economic indicators, especially over a long period of time, contain irregular cyclical fluctuations with unstable amplitudes and periods. Outwardly, the stochastic nature of these phenomena reflects the cyclical development of the economy under the influence of many random and nonrandom, market and volitional influences, that is, many hidden factors that cannot always be taken into account. Thus, such fluctuations can be a reflection of macrocycles of the development of economic processes.

The use of traditional methods to study such oscillations, generally speaking, is not suitable. For example, the spectral analysis models the motion of a time series by the sum of regular sinusoids. However, it is unlikely that economic indicators have a strict periodicity and constancy of amplitudes due to interference of a huge number of external economic and political influences. Regression analysis approximates the entire series as a whole, not taking into account the local properties of the series. Meanwhile, in the economy, each cycle has its own characteristics, since it is generated by a variety of causes of a very different nature, which can only be inherent in certain time intervals and, as a rule, do not repeat [1]. Therefore, other methods are needed to investigate irregular cyclic oscillations. One such method is phase statistics approach to time series analysis. As mentioned in [2], many studies have indicated that phase patterns can code more information than the amplitude [17–19].

There are different approaches to the phase analysis of time series [1, 2]. Some phase statistics approaches were introduced to study physiological [3] and financial time series [4]. The approach mainly consists of application of the Hilbert-Huang method [5] to decompose an empirical time series into a number of intrinsic mode functions (IMFs). Cross-disciplinary studies on financial systems have attracted much attention in recent decades [1, 6–10]. Note, for example, the wavelet transform modulus maxima approach [11–16].

2. Main section

To present the proposed approach, some definitions are needed. The fluctuation is the amount of deviation of the values of a series from a certain fixed level. As a rule, this is a trend, or a deviation from the average value in case the trend is not significant. The fluctuation power is the absolute value of the fluctuation $|Dy_t|$. The phase is the period of positive or negative fluctuations of the series. When, for example, the dollar or euro exchange rate is above the trend line, this is a positive fluctuation. Otherwise, there is a negative fluctuation. The duration of the phase is the time interval of the corresponding phase. Thus, irregular cyclic oscillations mean the presence of a number of differently directed fluctuations. The power of the i-th phase is the sum of the absolute fluctuations of the series inside the phase:

$$P_i = \sum_{t=t_i}^{t_{i+l_i}} |Dy_t|,$$

where t_i is the moment of the beginning of the i-th phase, t_{i+l_i} is the phase-ending moment, l_i is the phase duration. The average value of the phase is the power averaged over the interval $t_i; t_{i+l_i}$.

The economist, as a rule, deals with a time series containing random fluctuations. In the initial series, each such fluctuation or several neighboring ones can form low-power phases that have no essential content. Therefore, it is desirable to clear the series of random fluctuations and their corresponding phases in order to obtain some significant motions of the series movements that can be interpreted in some way. Typically, this is an iterative process, where at each step there is an aggregation of low-power phases with two neighboring phases with a more significant power. Therefore, it is necessary to specify a criterion for stopping the absorption of low-power phases. What kind of criterium is this? This can be the level of power lost in the series, i.e. a predetermined percentage of the aggregate power of the series that is allowed to lose during the phase aggregation process. In this case, the sum of absolute values is calculated, which is taken as 100 percent.

As a second option, such a criterion can be a predetermined number of phases. The choice depends on the nature of the problem being solved [1].

After the iterations are completed, a phase diagram is constructed, where each moment of time corresponds to the mean value of the phase with the corresponding sign.

Let's consider an example. Figure 1 shows the dynamics of the dollar for the period 2000-2016 citekurs.As fluctuations, we use deviations of the initial values from the trend. The trend of the ruble exchange rate (in Fig. 1 it is depicted by a dotted line) for the period 2000–2016 is statistically insignificant, therefore the 0X axis corresponds approximately to the average value of the dollar for the indicated period, which was 28.75 rubles.

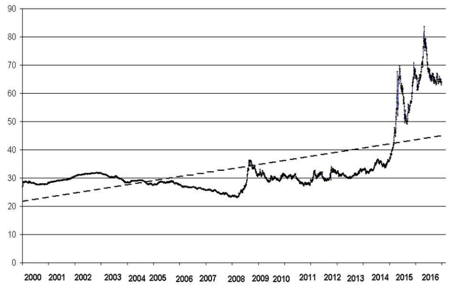

Figure 1. The dollar exchange rate for the period 2000-2016

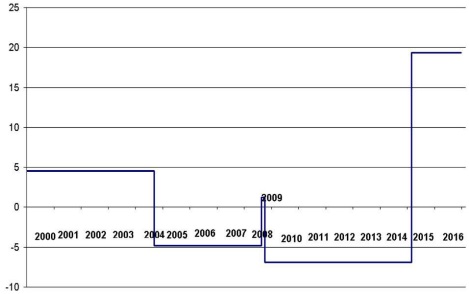

Figure 2. The phase diagram of the dollar exchange rate for the period 2000-2016

Figure 2 shows the phase diagram of the dynamics of the dollar exchange rate for the specified period. Each phase is matched with the average dollar rate corresponding to each phase. As a criterion for stopping the iterative process, the level of the lost power of the elements of the series, 5%, was adopted here. However, after the third iteration, there was no point in continuing the process of combining low-power phases. The level of power loss of the series was only 4.5%.

Four macrocycles are clearly distinguished here: 2001–2004, 2004–2008, 2008–2014 and a cycle beginning in early 2015.

Similarly, the euro was analyzed for the period 2000-2016. The dynamics of the euro is shown in Figure 3. Unlike the dollar, the euro's time series contains a significant trend. As fluctuations, deviations of the initial values from the trend were also considered here. The lost power level of the series is 2.75%. Figure 4 shows the phase diagram of the dynamics of the euro exchange rate and the same four macrocycles are also clearly visible here.

Figure 3. The euro exchange rate for the period 2000-2016

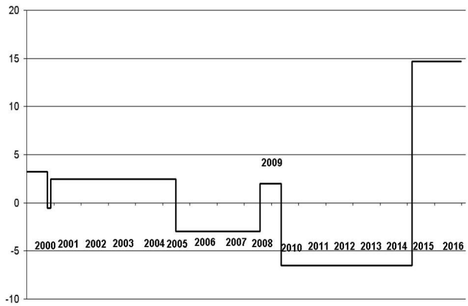

Figure 4. The phase diagram of the euro exchange rate for the period 2000-2016

To compare the phase diagrams of the dynamics of the euro and the dollar, they were plotted on a single graph (Fig. 5). Note that since the end of 2008, both currencies started a new cycle, and their phase diagrams make a simultaneous jump up. Then they go into the negative area. From 2010 to early 2015, both phases coincide and are below the trend line of both currencies. But from the beginning of 2015 they make a sharp jump upward, both currencies have risen above the expected trend value by almost 20 points, which indicates a new strongest wave of the economic crisis. Such a situation remains unchanged for two years, which indicates the possible duration of this economic crisis.

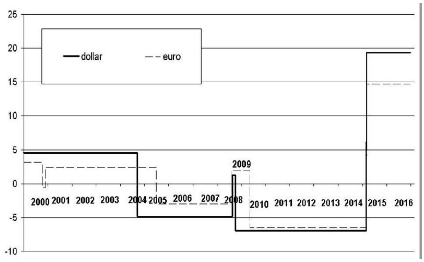

Figure 5. Phase diagrams of the dollar and euro exchange rates for the period 2000-2016

Similar calculations were made for the exchange rates of the yuan and the yen (Fig. 6 and Fig. 7). The corresponding phase diagrams are shown in Fig. 8 and Fig. 9. Here you can watch macrocycles that are more similar to each other than to the corresponding diagrams for the dollar and euro.

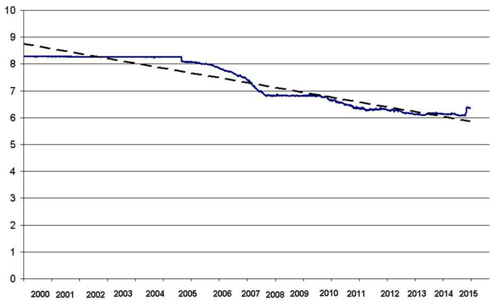

Figure 6. The yuan exchange rate for the period 2000-2015

Figure 7. The yen exchange rate for the period 2000-2015

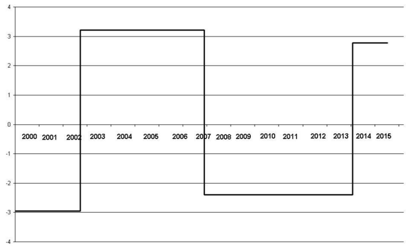

Figure 8. The phase diagram of the yuan exchange rate

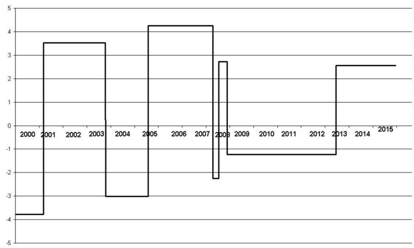

Figure 9. The phase diagram of the yen exchange rate

3. Conclusions

Thus, the method of phase analysis of time series allows one to identify hidden long-term macrocycles in them and, in some cases, make predictions. Of great interest are multidimensional generalizations of the method, which are supposed to be carried out in subsequent works.

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