The Analysis of Customs Mirror Statistics of Foreign Trade of Russia, Represented by Time Series

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Abstract—**The article presents the results of the analysis of mirror statistics of Russian foreign trade carried out by methods of predicative analytics. A comparative analysis of the exponential smoothing models and ARIMA time series was carried out on the example of two product groups and four countries with the highest share of imports in foreign trade with Russia. The study was based on statistics from the International Trade Centre for the 18-year period of observation.**

I. Introduction

Foreign trade in Russia represents a significant portion of budget revenues. Some experts are of the opinion that the actual volume of imports is inconsistent with the data of customs statistics, which leads to budget losses. Mirror statistics seek to identify such deviations by comparing the data provided by the exporting country with the data specified by the importing country.

II. Overview

In Russia, mirror statistics are analyzed using two methodologies. Scientists at the Institute of Market Problems at the Russian Academy of Sciences have developed an econometric model [1] based upon data on customs-banking currency control from the Central Bank of Russia, data on foreign trade activity from the Federal Customs Service of Russia (FCS), the Eurasian Economic Commission, the Ministry of Finance and other organizations. The analysis revealed discrepancy between Russian foreign trade statistics and those of its trading partners. Authors then determined the average level of tolerance caused by the methodological reasons, and determined the level of discrepancy caused by potential violations of customs legislation. Ultimately, they calculated magnitude of possible losses for the Russian budget. This technique has been criticized by the FCS as incomplete [2].

The primary sources of information for the second technique, which was developed by the FCS [3], are the databases of the International Monetary Fund (IMF) and the FCS. The IMF database was developed using world trade dynamics for a 16-year period (on a yearly, quarterly, and monthly basis) and represents the value of exports and imports for each country in its trade with other countries, for the world in a whole, and for various groups of countries.

The obvious disadvantage of both methods is that the data is taken from organizations and offices that are not comparable in profile and scale of activity, and the estimates are based on the interpretation of aggregated data.

After more than five years since development of these methods, the possibilities of modern databases have grown significantly. In the field of trade research big data is presented in the Trade Map, developed by the UNCTAD/WTO International Trade Centre (ITC) with the objectives of facilitating strategic market investigations. By transforming the large volume of primary trade data into an accessible and interactive Web-based format, Trade Map provides users with indicators on country or product performance, demand, alternative markets and the role of competitors. It allows queries based on product, group of products, country and regional country groupings for exports or imports [4]. The size of data can be estimated as following: number of countries is about 200, information is presented for export and import of any country in any other country or from it. Products are covered according to the Harmonized commodity description and coding system (HS). The HS comprises approximately 5300 product descriptions that appear as headings (four-digit level) and subheadings (six-digit level), arranged in 96 chapters (two-digit code), grouped in 21 sections. The Trade map search engine allows users to map information about imports of one country (Russian Federation in the case of our investigation) that should mirrors and can be compared with the data of corresponding export from the trade partner country at the six-digit level of the HS code during the same time period. These new capabilities allow researchers to determine whether there are differences in mirror statistics and analyze them in two ways: by country and by product.

According to the Analytical Department of the FCS, the problem of data discrepancies exists in nearly all countries. Despite the fact that over the last fifteen years such divergences in Russia have significantly decreased, the problem persists and requires further study [5].

This study's objective is to use modern databases to analyze a sampling of two representative HS headings to determine whether there are meaningful discrepancies in mirror statistics in Russian foreign trade.

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III. THE OBJECTS OF STUDY

We consider the structure of Russia's foreign trade. To obtain reliable results, we estimated the trade in goods with largest import volumes (https://trademap.org/Index.aspx). In 2018, the main five imported products by value were of HS chapters 84, 85, 87, 30, and 39. For each of these chapters we determined three main exporters (exporter 1, 2 and 3). Trade with each trading partner in the section headings (four-digit code) was analyzed by mirror statistics (import of RF from exporter 1 was compared with the export of exporter 1 to the RF and the same for exporters 2 and 3). At this stage we identified the four-digit heading with the largest discrepancy in mirror statistics. It is usually so that main supplier by two-digit chapter (for example, chapter 39 – plastics) is not the same as the main supplier by certain four-digit heading of this chapter (for example 3918 – floor coverings). That is why we had again to identify two main exporters for chosen headings. If for both exporters there was an excess of exports over imports in 2018, a time series were constructed. Analysis of the chapters 84, 85, 87, 30 and 39 (having 87, 48, 16, 6 and 26 headings respectively) revealed just two headings, where sought discrepancy was determined. These data are given in Table I.

TABLE I. CHARACTERISTICS OF DATA FOR ANALYSIS

Heading	Countries
Floor coverings of plastics. 3918	Belgium, China
Special purpose motor vehicles. 8705	USA, Germany

We analyzed time series with a year step for the period 2001 - 2018. Fig. 1 shows imports from China of floor coverings (3918) and exports of these products from China to RF [5].

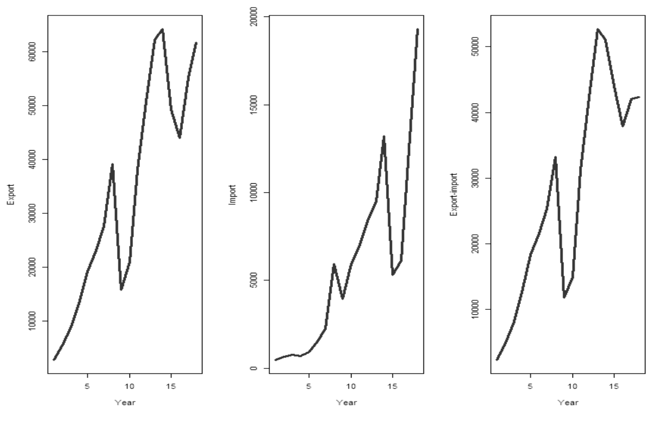


Fig. 1. Diagram of time series for heading 3918 showing imports from China and exports from China to RF.

The diagram shows that:

- There is a positive trend for each of the analyzed time series. The volume of imports from China increases.
- There is a substantial difference between the data provided by customs authorities in China and those in Russia.
- The differences between the data of the exporting country and the importing country increases.

At the Fig. 2. the results of the mirror statistics comparison for both main trade partners - China and Belgium - are presented.

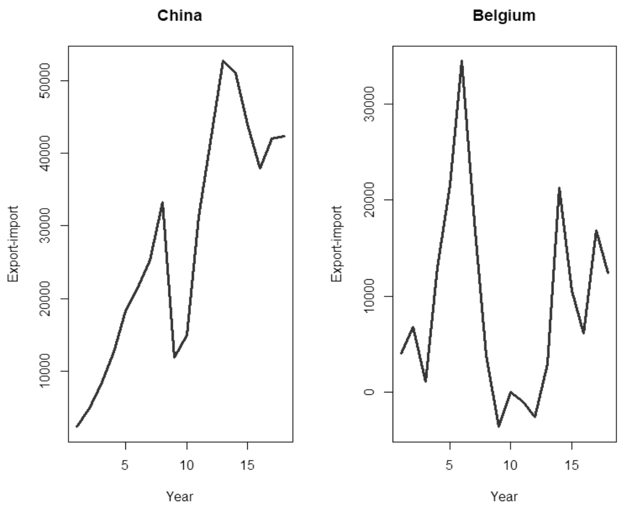


Fig. 2. Diagram of time series for heading 3918 showing mirror statistics in trade with China and Belgium

In most periods, the exports to Belgium exceeded imports; however, unlike with China, the discrepancy in trade statistics with Belgium did not grow over time.

Fig. 3 shows the diagram for special vehicles (heading 8705) as a result of statistics comparison of Russia with the United States and Germany. There were 18 reviewed periods overall, exports of trade partners did not exceed corresponding imports of RF in trade with the US during 9 years and Germany during 5 years.

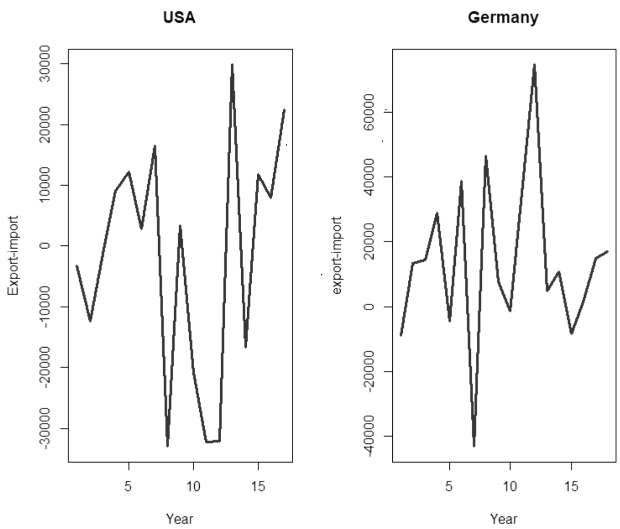


Fig. 3. Diagram of time series for heading 8705 showing mirror statistics in trade with the US and Germany

Based on these initial observations, the study formulates the following hypotheses to be tested:

- Discrepancies in mirror trade statistics concerning floor coverings (heading 3918) are significant.

• Discrepancies in mirror trade statistics concerning special vehicles (heading 8705) are insignificant.

IV. Methods

For confirmation or rejection of these hypotheses on the analyzed countries and product groups, the study will use methods based on the theory of time series. Existing research methods are based on the assumption of stationarity or non-stationarity of the time series, the presence of harmonic fluctuations caused by seasonality, and assumptions on the nature of the random component. We will continue to investigate the series of differences of a number of exports and imports to verify coincidences in the data of mirror statistics.

To analyze the hypothesis of stationarity, we will use the correlogram of the autocorrelation functions, as well as the Dicky-Fuller statistical criterion [6, 7]. This criterion is based on checking the unit root in the time series. The null hypothesis assumes that there is a unit root and the series is non-stationary. Under the assumption of autoregression of the first order three types of autoregressive models are considered:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t;$$
$$\Delta y_t = b_0 + \gamma y_{t-1} + \varepsilon_t;$$
$$\Delta y_t = b_0 + b_1 t + \gamma y_{t-1} + \varepsilon_t.$$

where $\Delta y_t = y_t - y_{t-1}$; y_t, y_{t-1} are levels of the analyzed time series for time points t and t-1;

b_0, b_1, γ are parameters of the model;

ε_t is the value of the random component at time t.

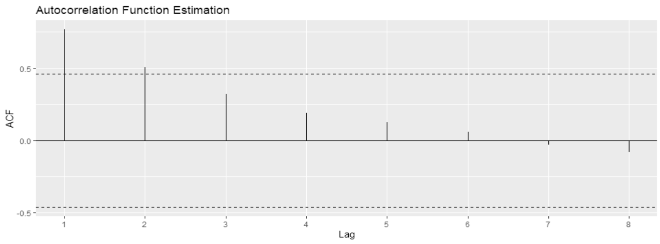
We will consider the first of the following three models assuming that the time trend is missing. However, there is autocorrelation of time series levels. It has a unit root and belongs to the category of integrated time series (DS series). The construction of differences in series can remove non-stationarity.

Table II shows the values of the Dickey-Fuller statistical test and significance level of the p-value for the three time series in the analyzed countries.

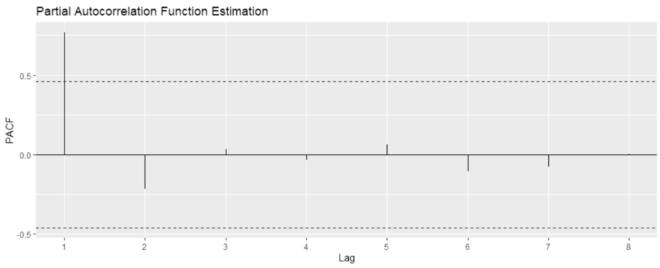
TABLE II. DICKEY-FULLER (DF) CRITERION AND P-VALUE

Time Series	Country							
	China		Belgium		USA		Germany	
	DF	p-value	DF	p-value	DF	p-value	DF	p-value
export	-3.05	0.17	-2.76	0.28	-1.94	0.60	-1.62	0.72
import	-3.94	0.025	-1.27	0.85	-1.69	0.69	-1.31	0.84
Delta = export - import	-2.81	0.26	-2.37	0.43	-1.26	0.85	-2.41	0.42

Thus, all of the time series except one are DS series, i.e., non-stationary series, since for them the p-value < 0.05. The correlogram autocorrelation functions ACF and PACF support this conclusion. Fig. 4 shows example of it for a number of differences between the data on exports of plastic coverings from China.



a)



b)

Fig. 4. Correlogram: a) autocorrelation function estimation; b) partial autocorrelation function estimation.

The given correlograms show that there is significant autocorrelation of the first and second order. The time series model can be represented by the autocorrelation function.

The studied series are unsteady, have single roots, as well as a stochastic trend, identified by the criteria of Dickey-Fuller, as well as Kvyatkovsky-Phillips-Schmidt-Shin. Because the least squares estimate is not asymptotically normal. To study them, we will use smoothing methods and the ARIMA methodology [8,9,10].

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V. Results

The assumption about the presence of non-stationarity and the presence of a linear trend (see Fig. 2) will use the filter exponential smoothing [11,12, 13] ETS of the form "AAN," implying the presence of an additive random component (first letter A) and an additive linear trend (second letter A), as well as the absence of a seasonal component (third letter N). When building the model, we use the Box-Cox transformation parameter, which is chosen with the aim of improving the quality of the smoothing model.

The initial smoothing model has the following forms:

For China:

$$y_{t+h} = 130{,}3 + 16{,}2h.$$

For Belgium:

$$y_{t+h} = 1131 - 10{,}6h.$$

For the United States:

$$y_{t+h} = 61 - 8{,}7h.$$

For Germany:

$$y_{t+h} = 69936 + 5167{,}7h.$$

General model smoothing given this initialization has the form:

$$s_t = \alpha y_t + (1-\alpha)(s_{t-1} + b_{t-1});$$
$$b_t = \beta(s_t - s_{t-1}) + (1-\beta)b_{t-1},$$

where α, β are filter settings;

s_t, s_{t-1} are smoothed values that match the time series for time points t and t-1;

b_t, b_{t-1} are smoothed values of the trend parameter of the time series for time points t and t-1.

The predicted values of the levels of the series are found using the relationship:

$$y_{t+h} = s_t + b_t \cdot h,$$

where y_{t+h} represents the forecast values of the levels of the series at time $t+h$.

Figure 5 shows the diagram of the prediction of levels of time series for the four countries.

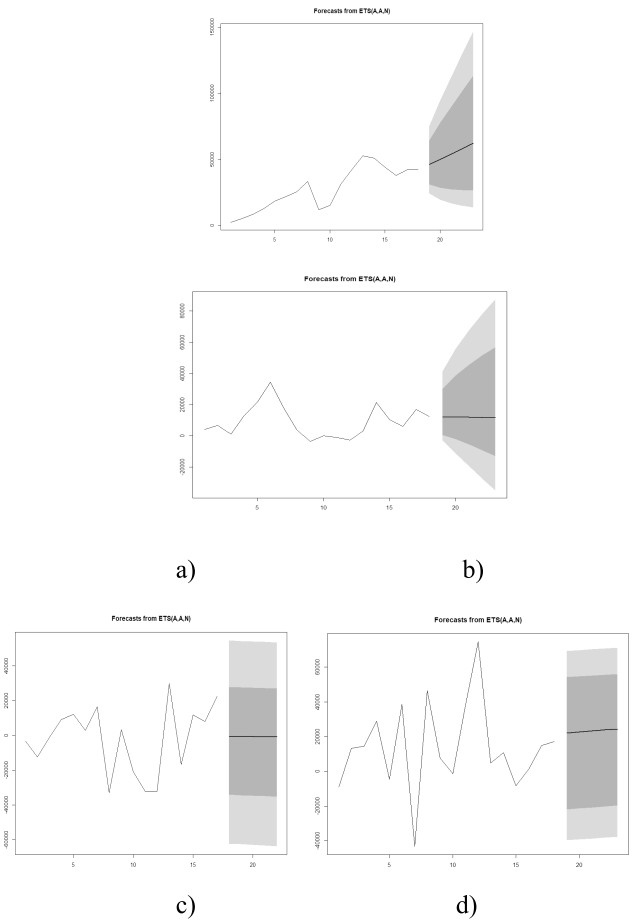

Fig. 5. Forecast diagrams: a) China; b) Macedonia; c) USA; d) Germany

This figure shows that for China there is a projected growth of discrepancies between the data of the exporting country and the data of the customs authorities of Russia as the importing country. Such a consistent pattern indicates a need for additional search the causes of discrepancies in mirror statistics of China and Russia for this group of goods.

For the other three exporting countries, this trend is practically absent. However, there are differences in the data provided by the customs authorities. Table III lists the figures for the ETS models for the four tested countries.

Both Fig. 3 and Table III have extremely large error estimates (σ) for two time series: United States and Germany. Therefore, the obtained results of smoothing cannot be used for analysis and forecasting because of their poor quality.

TABLE III. ETS MODELS

Indicator	Country			
	China	Belgium	USA	Germany
λ, Box-Cox	0.49	0.71	0.67	1.2
α	0.9999	0.9999	0.026	$1 \cdot 10^{-4}$
β	$2 \cdot 10^{-4}$	$1 \cdot 10^{-4}$	$1 \cdot 10^{-4}$	$1 \cdot 10^{-4}$
σ	56	771	1189	260820
AIC	203	297	294	506
AICc	208	302	300	511
BIC	207	301	299	511

The filter model for China is:

$$s_t = 0{,}9999\, y_t + 0{,}0001(s_{t-1} + b_{t-1});$$
$$b_t = 0{,}0002\,(s_t - s_{t-1}) + 0{,}9999 b_{t-1}.$$

For Belgium, the model is almost identical:

$$s_t = 0{,}9999\, y_t + 0{,}0001(s_{t-1} + b_{t-1});$$
$$b_t = 0{,}0002\,(s_t - s_{t-1}) + 0{,}9999 b_{t-1}.$$

According to the models, smoothing almost does not occur, because the smoothing parameter α ≈ 1. This fact also suggests that the filter exponential smoothing allows for a qualitative solution of the problem of forecasting. One have to use other methods and models. Currently, the most popular forecasting models are ARIMA. The study solves the problem of constructing ARIMA models for the studied datasets. With this purpose, we apply the function auto.arima statistical language processing R [14], [15]. The forms of the obtained models for each of the four series of differences are shown in Table IV.

TABLE IV. ARIMA MODEL

Country	China	Belgium	USA	Germany
ARIMA-model	ARIMA (0,1,0)	ARIMA (0,0,1) with non-zero mean	ARIMA (0,0,0) with zero mean	ARIMA(0,0,0) with non-zero mean
AIC	358	382	385	420
AICc	358	383	386	421
BIC	359	384	386	422
MASE	0,94	0,78	0,76	0,59

Consider the first group of products: floor coverings (heading 3918).

The results show that the model time series of differences in mirror statistics for China is a model of random walks:

$$y_t = y_{t-1} + \varepsilon_t,$$

where y_t, y_{t-1} are levels of the analyzed time series for time points t and t-1;

ε_t is the value of the random component at time t.

Consequently, the non-stationarity of the time series is not caused by the presence of a deterministic trend. The series is not TS and represents the difference-stationary DS series. So, it can be used for prediction only for a small period. Table V shows the forecast values with the horizon equal to five years.

TABLE V. FORECAST FOR CHINA

Year	Lower bound 95%	Upper bound, 95%	The predicted value
2019	25708	59022	42365
2020	18808	65922	42365
2021	13513	71217	42365
2022	9050	75680	42365
2023	5118	79612	42365

For Belgium, the model of moving average is of the first order. This series is a stationary series with nonzero. The model has the following form:

$$y_t = 8973 + \varepsilon_t + 0.56\varepsilon_{t-1}.$$

The estimation error in the average level of the series is 2931. The error coefficient estimate in the random component εt-1 is equal to 0.16. Therefore, the coefficients of this model are significantly different from zero at 0.05. Forecast values for this model are given in Table VI. A non-zero expectation value, possibly determined by different approaches, is mirrored in the statistics of different countries.

TABLE VI. FORECAST FOR BELGIUM

Year	Lower bound 95%	Upper bound, 95%	The predicted value
2019	-8376	19628	8556
2020	-10391	28338	8973
2021	-10391	28338	8973
2022	-10391	28338	8973
2023	-10391	28338	8973

For the US, the model has zero mathematical expectation. Forecast values for this model are given in Table VII.

TABLE VII. FORECAST FOR THE US

Year	Lower bound 95%	Upper bound, 95%	The predicted value
2019	-37298	37298	0
2020	-37298	37298	0
2021	-37298	37298	0
2022	-37298	37298	0
2023	-37298	37298	0

For Germany, the model is of white noise with nonzero. The model has following form:

$$y = 13568 + \varepsilon_t.$$

With error estimates of the average response rate equal to 5906, this supports the hypothesis that it has a significant difference from zero at 0.05. The forecast values for this model are given in Table VIII.

TABLE VIII. FORECAST FOR GERMANY

Year	Lower bound 95%	Upper bound, 95%	The predicted value
2019	46612	37298	13568
2020	46612	37298	13568
2021	46612	37298	13568
2022	46612	37298	13568
2023	46612	37298	13568

Due to the fact that the considered model contains only a random component, and the model for the United States and Germany is a model of white noise, we will formulate the hypothesis that the analyzed time series can be considered as spatial sampling, which allows them to explore methods of the theory of random variables. Check the statistical hypothesis of insignificant difference from zero and mathematical expectations of the difference between the data of mirror statistics. We use a simple t-test to test the null hypothesis. The results of its audits for the three random variables are shown in Table IX.

TABLE IX. ONE SAMPLE T-TEST

Indicator	Country		
	USA	Germany	Belgium
t	-0.45	2.23	3.83
p-value	0.6585	0.039	0.001
mean	-2128	13567	9203
Confidence interval, 95%	[-12151;7893]	[745;26389]	[4137;14269]

The data show that at the significance level 0.001 for all random variables, the null hypothesis is accepted. At a significance level of 0.01, the null hypothesis is confirmed for the second group of goods - special vehicles of heading 8705. For the first group of products at this level of significance iy is impossible to make such a conclusion.

VI. CONCLUSION

The simulation results with the theory of time series show that the relevance and results of various methods of predictive analytics depends on the quality of the original data and variance levels of the time series. The current study uses the most popular methods: exponential smoothing and autoregression-moving average. In the case of step time series of less than one year, the appearance of seasonal components such as weekends, holidays, etc. is possible, the complexity of the study will increase.

The obtained simulation results show that there is a very large variation in levels of time series for the analyzed countries and product groups. Therefore, the generated models lead to large errors of estimation and forecasting. They can be considered as a tool for the rapid assessment of the state of affairs in the customs statistics.

The mirror statistics are based on the results of the analysis of different groups of goods and countries. In some cases there is a difference between the data of exporters and that of importers. The reasons for this difference vary. Therefore, further research should be conducted, taking into account various factors.

Despite the non-stationarity of time series, established in this work, a deterministic trend was not found. Though estimation errors for the 80 and 95% reliability level are big, it has been proven that no trends associated with the distortion of mirror statistics, at least for the studied countries and the studied product groups, are revealed. Naive "tomorrow will be like today" prediction models can be used to predict future values.

As a result of constructing time series models and verifications of statistical hypotheses, it was established that discrepancies in mirror trade statistics concerning floor coverings (heading 3918) are significant, and the differences in mirror trade statistics for special vehicles (heading 8705) are insignificant. The resulting output shows that the methods of predictive analytics has enabled confirmation of the formulated hypotheses.

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