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Predicting customer churn based on changes in their behavior patterns

Yury A. Zelenkov[a]
E-mail: yzelenkov@hse.ru

Angelina S. Suchkova[b]
E-mail: assuchkova_1@edu.hse.ru

[a] HSE University
Address: 20, Myasnitskaya Street, Moscow 101000, Russia

[b] HSE University – Saint Petersburg
Address: 16, Soyuza Pechatnikov Street, Saint Petersburg 190121, Russia

Abstract

Customer retention is one of the most important tasks of a business, and it is extremely important to allocate retention resources according to the potential profitability of the customer. Most often the problem of predicting customer churn is solved based on the RFM (Recency, Frequency, Monetary) model. This paper proposes a way to extend the RFM model with estimates of the probability of changes in customer behavior. Based on an analysis of data relating to 33 918 clients of a large Russian retailer for 2019–2020, it is shown that there are recurring patterns of change in their behavior over a single year. Information about these patterns is used to calculate the necessary probability estimates. Incorporating these data into a predictive model based on logistic regression increases prediction accuracy by more than 10% on the metrics AUC and geometric mean. It is also shown that this approach has limitations related to the disruption of behavioral patterns by external shocks, such as the lockdown due to the COVID-19 pandemic in April 2020. The paper also proposes a way to identify these shocks, making it possible to forecast degradation in the predictive ability of the model.

Keywords: customer churn, customer churn prediction, RFM model, RFM model extension, customer behavior patterns, predictive analytics

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Introduction

The concept of customer relationship management (CRM) implies the acquisition and retention of the most profitable customers based on an understanding of their values and the motives that determine behavior [1]. The costs of retention are much lower than those of attracting new customers, and the loss of a customer means the loss of all purchases that he could make during the life cycle [2]. Since not all customers are equally attractive to the company financially, it is extremely important to first determine their profitability, and then appropriately allocate resources to retain them [3].

The problem of optimizing customer retention costs is solved in two stages: the first is customer segmentation, and the second is the prediction of changes in their behavior. For segmentation, clustering methods are usually used, which allow us to divide a set of clients into internally homogeneous groups (classes) which at the same time differ greatly from each other [4]. The goal of models that solve the second problem is to identify customers who can change their group, for example, move from the class of active buyers to the class with low purchasing [5]. This approach is called customer churn prediction. This problem can be reduced to a binary classification problem: using customer data for periods 1, ..., t, train a classifier h that predicts the probability that in period $t + 1$ a customer will remain in the same group, move to a group that generates more income (class label 0), or move to a group with an aggregate lower income (class label 1). Based on these forecasts, companies develop differentiated marketing strategies aimed at retaining customers belonging to class 1 [2].

The most widely used approach to the analysis of customer behavior is the RFM model, which combines data on the time passed since the last activity of the customer (Recency), the number of his purchases for the period t (Frequency) and the total amount of money spent (Monetary) for the same period [6]. According to the traditional approach, the customer database for each of the three RFM dimensions is divided into five equal segments (quantiles). The top 20% of customers get label 5, the next 20% get label 4, and so on. As a result, each customer is associated with a label containing three numbers corresponding to quantiles according to RFM measurements, for example, 534 or 231. Thus, 125 groups of customers with potentially different behavior are allocated. It is obvious that this approach has drawbacks, since it does not guarantee that the selected groups, firstly, are internally homogeneous, or secondly, that they differ greatly from each other. Therefore, recently cluster analysis methods (k-means, self-organizing Kohonen maps, etc.) are more often used; they allow us to divide the customer database using formal metrics [7].

Many authors consider variations of the RFM model, expanding it with additional dimensions, including using the dynamics of customer behavior. For example, a model that considers discounts is proposed in [8], and the duration of a client's stay in a certain cluster is considered in [9].

In the context of the task of predicting the outflow of customers, the discovery of patterns that describe stable trajectories of consumer movement between clusters is one of the most important areas of research. For this, various dynamic models based on pattern identification with such methods as clustering [10, 11], association rules [12], and hidden Markov models [13] are used.

The purpose of this study is to develop a method that allows us to predict a change in customer behavior (i.e., their movement from one class to another) considering information on consumer flows between groups accumulated over previous periods. According to our hypothesis, the intensity of the transition of clients from one class to another varies throughout the year, but there is a stable pattern that repeats from year to year. Thus, we can consider the observed rates of flows of clients from class to class as estimates of the probability that the client will leave the cluster in which he is currently located. The inclusion of this information in the predictive model should significantly increase the accuracy of the prediction.

1. Data and task formalization

To test the formulated hypothesis, a data set was used that includes information on purchases made by customers of a large Russian retail chain in 2019–2020. The data was consolidated monthly, and for each customer the following values were calculated:

- R – the number of days that have passed since the last purchase until the beginning of the current month,
- F – the number of purchases in the current month,
- M – is the total amount of the client's expenses (retail network income) in the current month.

Other data often used in customer churn forecasting tasks (age, gender, marital status, etc.) were not used in this case, since they contain a significant number of gaps and unreliable values. After removing outliers and incomplete data, a set was obtained containing information about 33 918 customers who made at least five purchases in two of the studied years.

At the next stage, stable user clusters were identified. To do this, the data were divided into periods of one month and grouped as follows. Customers who did not make purchases in the month under

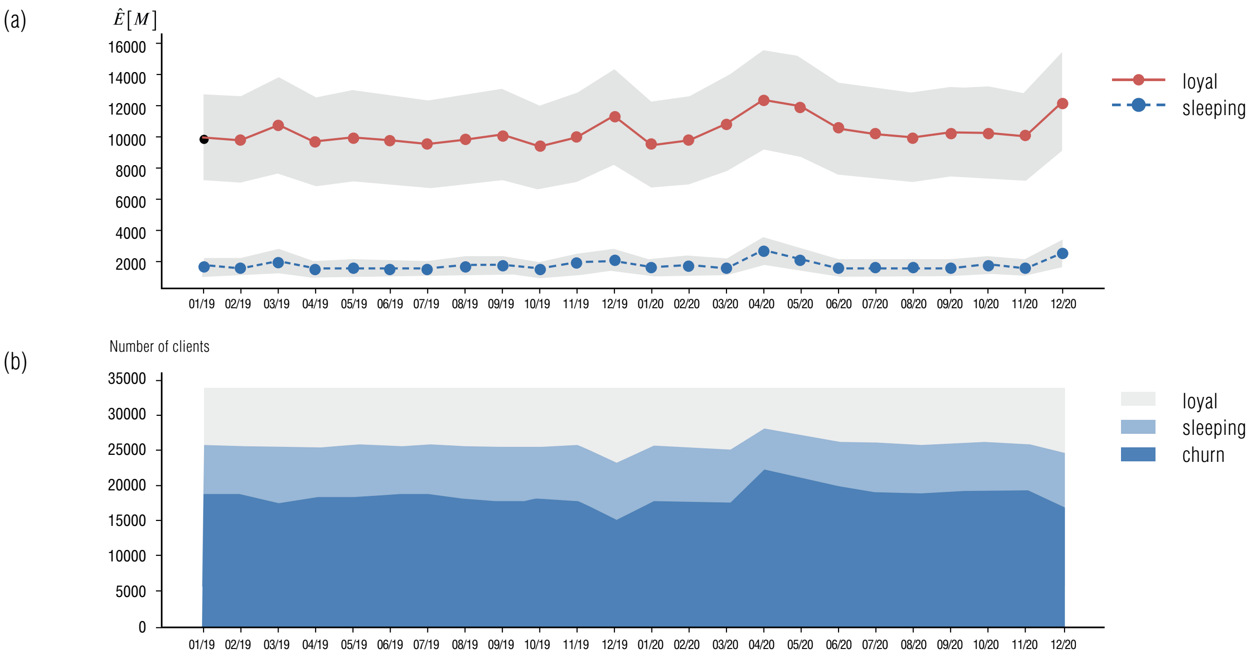

Fig. 1. (a) – average income and 95% confidence interval for clusters of customers who make purchases; (b) – change in the number of clients by clusters.

consideration (obviously, for them $F = 0$ and $M = 0$) were considered to belong to the same cluster and were excluded from the analyzed data set; customers with $F > 0$ and $M > 0$ were segmented using the algorithm k-means. The quality of the resulting separation for a different number of clusters was evaluated using the silhouette score [14]. The maximum values were obtained for splitting into three clusters (one including customers without purchases in the current month, and two identified by the k-means algorithm among customers with purchases). The average value of the silhouette score for 24 months is 0.708, the minimum is 0.649 for December 2019 and the maximum is 0.779 for April 2020.

Figure 1(a) shows the change in the average retail chain income $\hat{E}[M]$ from a customer and the corresponding 95% confidence interval for two clusters of buyers making purchases. A cluster that gives a higher average income brings together buyers who can be defined as "loyal," while a cluster of customers that generate less income can be called "sleeping". The third cluster, which unites customers without purchases, we called "churn". *Figure 1(b)* presents the change in the number of clusters.

Analyzing the presented graphs, we can conclude that there are certain patterns that repeat from year to year. For example, in December, the size of the loyal cluster increases and the income generated by it increases simultaneously; this is associated with seasonal holidays (New Year and the corresponding holidays).

An analysis of the significance of exogenous variables was also performed using a method based on measuring the decrease in the accuracy of the model when mixing the values of the attribute of interest (permutation importance [15]). Logistic regression was used as the base classifier because this model is robust to perturbations, and the accuracy of the model was estimated using the area under the receiver operating characteristic curve (AUC) because this metric is not sensitive to class imbalance [16]. The results obtained show that the most significant features (in descending order of significance) are R_t, M_t, F_t, preceding the predicted period $t + 1$, i.e., the process of changing customer behavior under study is Markovian. Data from earlier periods does not affect the quality of the prediction. This is consistent with the results of other researchers [4, 17, 18].

Thus, the formulation of the customer churn prediction problem can be refined as follows. Let X be the set of customer descriptions and $Y = \{0, 1\}$ the set of class labels. We must build an algorithm h: $X \rightarrow Y$, capable of classifying an unknown object $x \in X$ according to a known finite training sample $D = \{[R_t, M_t, F_t]_1, y_1, \ldots, [R_t, M_t, F_t]_m, y_m\}$, where $y \in Y$, and the vector $(R_t, M_t, F_t) \in X$ is a feature description of the object.

2. Modeling customer flows

As noted above, many researchers focus on expanding the feature vector including additional features in it, which improves the accuracy of the classification algorithm. In this paper, it is proposed to use information about the dynamics of customer flows between clusters.

This idea was inspired by epidemiological models (EM), which consider the movement of people between different groups: susceptible, infectious, recovered, etc. [19]. The intensity of movement from group A to group B is determined by the transition rate α^{AB}, which determines the proportion of members of group A who moved to B. In most EMs, these rates are considered as exponentially distributed random variables, but in our case, their exact values can be calculated, since the number of all groups is always known. The second difference is that EMs usually assume a limited number of possible trajectories of movement between groups; in our case, the client can move from his group to any other. Considering all the above, the dynamics of customers can be represented by the following difference equations:

$$L_{t+1} = L_t + \alpha_{t+1}^{SL} S_t + \alpha_{t+1}^{CL} C_t - [\alpha_{t+1}^{LS} + \alpha_{t+1}^{LC}] L_t$$
$$S_{t+1} = S_t + \alpha_{t+1}^{LS} L_t + \alpha_{t+1}^{CS} C_t - [\alpha_{t+1}^{SL} + \alpha_{t+1}^{SC}] S_t$$
$$C_{t+1} = C_t + \alpha_{t+1}^{SC} S_t + \alpha_{t+1}^{LC} L_t - [\alpha_{t+1}^{CL} + \alpha_{t+1}^{CS}] C_t.$$

Here L_t, S_t, C_t are the number of clients in the "loyal", "sleeping" and "churn" clusters, respectively, at time t;

α_{t+1}^{AB} is the flow coefficient that determines which part of the clients who are in group A at time t will move to group B in period $t + 1$.

The index $t + 1$ in this case means that the value of this coefficient will become is known only after the moment $t + 1$.

The coefficient α_{t+1}^{AB} can be calculated as

$$\alpha_{t+1}^{AB} = F_{t+1}^{AB} / A_t,$$

where F_{t+1}^{AB} is the number of clients (flow) who moved from group A to B in the interval between t and $t + 1$; is the number of clients in group A at time t.

A comparative analysis of the flow coefficients is shown in *Figs. 2–4*. The top graphs in each figure represent the values of the coefficients for the months of 2019 and 2020 (in this case, the subscript of the variable means the year), as well as the difference between them. Areas shaded in different shades represent different seasons (winter, spring, summer, and autumn). It can be seen that there is no seasonality associated with the time of year. The vertical dotted line corresponds to December, when, as noted above, there is an increase in the number of purchases. It follows from these graphs that the values of the coefficients for different years are quite close, and the difference between them tends to zero (marked with a horizontal dotted line). The only exception is observed in April. This is because a lockdown was introduced in April 2020 due to the COVID-19 pandemic, which led to a decrease in the activity of buyers.

The bottom pair of graphs in each figure shows the distribution of the values of the respective coefficients for both years under study, as well as the kernel den-

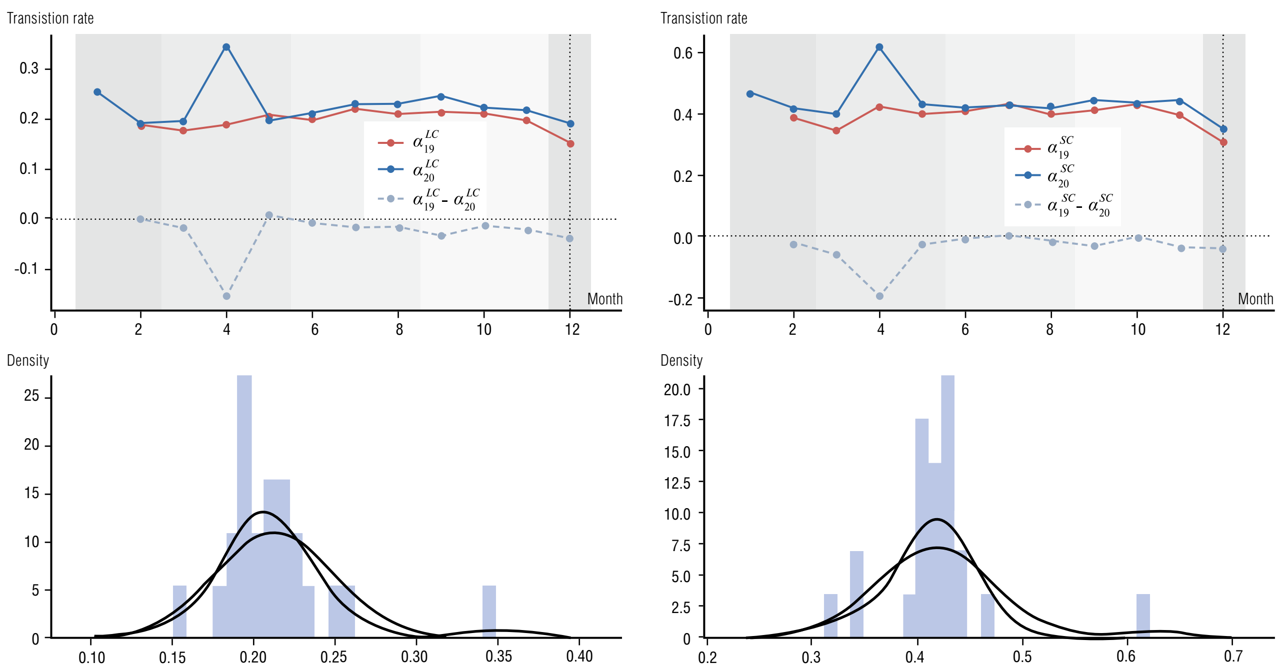

Fig. 2. Flow coefficients to cluster C (churn).

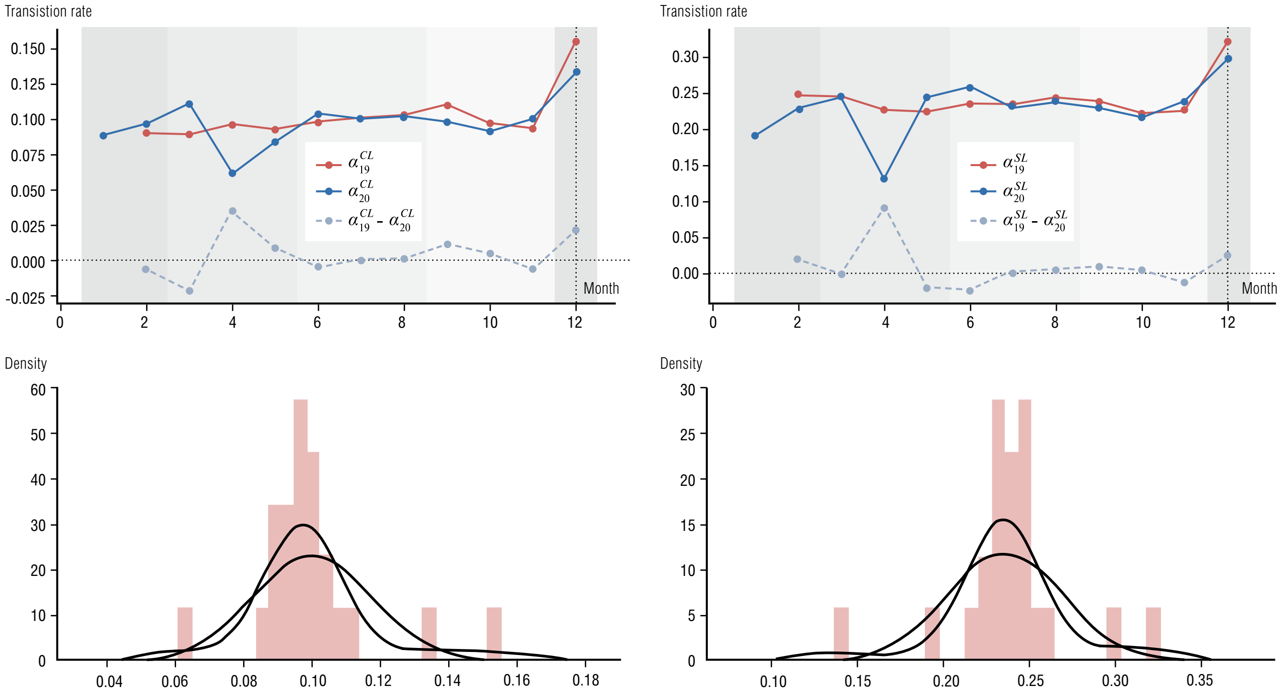

Fig. 3. Flow coefficients to the cluster L (loyal).

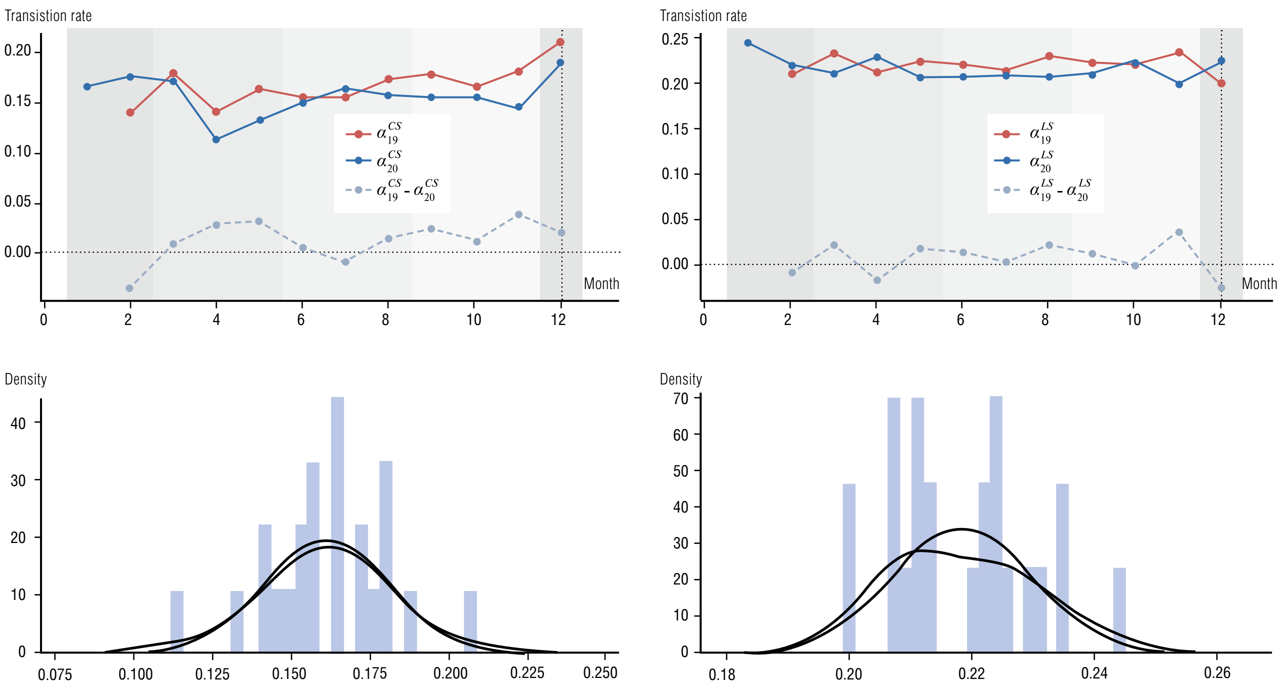

Fig. 4. Flow coefficients to the cluster S (sleeping).

sity estimation (KDE) of this distribution and the normal distribution with the mean and variance calculated from the observed values. It can be seen from these graphs that the distribution of the values of the flow coefficients is close to normal. Also, based on the information presented, it can be assumed that the time series representing the values of the coefficients for both years are stationary.

To test the assumption of stationarity of time series, an Augmented Dickey-Fuller test (ADF) was performed. The values of the corresponding statistics are presented in *Table 1*, column ADF. The results obtained prove that the null hypothesis about the presence of unit roots and, consequently, the non-stationarity of the series is rejected for all coefficients except α^{CL} and α^{LS}. However, if we exclude the observation corresponding to April 2020, which introduces the greatest disturbances, then all the series become stationary (column ADF_{-4}).

In addition, to assess the similarity of the coefficients for the two years studied, two measures were calculated (*Table 1*): cosine similarity (CS) and mean absolute percentage error (MAPE)

$$CS(P,N)=\frac{\sum_{i=1}^{n}P_iN_i}{\sqrt{\sum_{i=1}^{n}P_i^2}\sqrt{\sum_{i=1}^{n}N_i^2}},$$

$$MAPE(P,N)=\frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{P_i-N_i}{P_i}\right|.$$

In this case, P and N are vectors of flow coefficients for 2019 and 2020, respectively.

Cosine similarity is the cosine of the angle between two vectors in n-dimensional space, where n is the number of values in the sequence. As follows from *Table 1*, the angle between vectors of the flow coefficients is almost zero, i.e., the directions of the vectors coincide. Relatively high *MAPE* values are also explained by the results of the lockdown due to the COVID-19 pandemic. This is proved by comparing the *MAPE* (%) and $MAPE_{-4}$ (%) columns calculated respectively on all data and the data from which April was excluded.

Thus, it can be assumed that the inclusion of information about flows between groups in the number of features when solving the problem of predicting the outflow of customers will improve the accuracy of classification. Using the coefficients α, we can calculate

Table 1.

The results of testing for stationarity and similarity measures of coefficients α for 2019 and 2020

Coefficients		ADF	ADF_{-4}	*CS*	*MAPE* (%)	$MAPE_{-4}$ (%)
Flows to cluster C	α^{LC}	–5.088*	–4.121*	0.982	16.0	9.2
	α^{SC}	–4.594*	–4.855*	0.993	10.4	6.8
Flows to cluster L	α^{CL}	–2.777**	–7.968*	0.990	10.9	8.3
	α^{SL}	–5.367*	–6.612*	0.992	8.4	5.0
Flows to cluster S	α^{CS}	–1.431	–10.757*	0.992	12.4	11.7
	α^{LS}	–0.995	–5.649*	0.997	7.5	7.5

* $p<0.01$; ** $p<0.1$.

Table 2.

The value of the *TNR*, *TPR*, *AUC* и G_{mean} metrics for logistic regression

Period	$D_1 = [R, F, M]$		$D_2 = [R, F, M, \hat{p}, \hat{v}]$		$\frac{G_{mean}(D_2)}{G_{mean}(D_1)}$	$\frac{AUC(D_2)}{AUC(D_1)}$
	G_{mean}	*AUC*	G_{mean}	*AUC*		
04/20	0.811	0.812	0.856	0.863	1.055	1.063
05/20	0.739	0.745	0.741	0.747	1.004	1.003
06/20	0.781	0.781	0.000	0.500	0.000	0.640
07/20	0.767	0.767	0.846	0.854	1.102	1.113
08/20	0.750	0.750	0.750	0.750	1.000	1.000
09/20	0.733	0.734	0.839	0.850	1.145	1.158
10/20	0.758	0.758	0.841	0.853	1.109	1.125
11/20	0.743	0.743	0.842	0.854	1.134	1.148
12/20	0.742	0.742	0.831	0.839	1.120	1.131

an estimate $\hat{p}$ of the conditional probability $p(y = 1|X)$ of moving a customer from a group with high purchase costs to a cluster with lower costs, i.e., from the loyal cluster to the sleeping or churn clusters and from the sleeping cluster into the churn cluster. In accordance with the conditions formulated above, the assessment of the probability that the client belongs to class 1 is defined as

$$\hat{p}_t = \alpha_t^{LS} + \alpha_t^{LC}, \ \textit{if cluster} = \textit{loyal}$$
$$\hat{p}_t = \alpha_t^{SS}, \quad \textit{if cluster} = \textit{sleeping}.$$

Since the estimate of $\hat{p}_{t+1}$ for the forecast period is unknown, we introduce an additional variable $\hat{v}_t$, that considers potential changes in $\hat{p}_{t+1}$ based on the data of the previous year

$$\hat{v}_t = \hat{p}_{t+1-q} - \hat{p}_{t-q},$$

where q is the time lag corresponding to the duration of the pattern of repetitive customer behavior. In this case $q = 12$.

3. Results and discussion

To test the effectiveness of the proposed approach, a numerical experiment was conducted to predict the outflow of customers based on a logistic regression model. The model was trained on two data sets: the first one included the metrics $D_1 = [R, F, M]$; the second one was extended by the variables рен за счет предложенных здесь переменных $D_2 = [R, F, M, \hat{p}, \hat{v}]$ proposed here. The task of the model was to determine the class of the object in the period $t + 1$ from the data in period t. Training, respectively, was carried out on the data set $[(R, F, M, \hat{p}, \hat{v})_{t-1}, y_t]$.

The results of serial testing of the model on validation samples over different periods are presented in *Table 2*. The metrics used are the area under the receiver operating characteristic curve (AUC) and the geometric mean

$$G_{mean} = \sqrt{TPR \cdot TNR},$$

where *TPR* and *TNR* are the proportion of correctly classified objects of true positive rate ($y = 1$) and true negative rate ($y = 0$), respectively. The choice of this metric in addition to AUC is justified by the fact that, other things being equal, the geometric mean has a higher value for balanced predictions for both classes [16].

As follows from *Table 2*, the inclusion of variables $\hat{p}$, $\hat{v}$ provides an increase in the accuracy of the predictive model (in most cases, more than 10%) during periods when there are no external shocks. Thus, the proposed approach can be used to develop individual strategies for retaining users in a relatively stable time.

At the same time, the model turns out to be useless when the influence of external disturbances is catastrophic, and this influence manifests itself with a delay (see results for the period 06/20). In this case, the predictive ability of the model corresponds to random guessing ($AUC = 0.5$), and all predicted objects are classified as belonging to class 0. This is quite understandable, since to predict the period $t = 6$ based on data from period $t = 5$, a model is used that is trained to classify objects at time $t = 5$ on data $t = 4$, when the behavior of customers has changed dramatically due to the lockdown. This means that in April 2020 there was a violation of the customer behavior pattern based on which estimates of the probability of behavior change are built. However, this situation is not critical since the decrease in the predictive ability of the model due to external shocks is quite foreseeable and can be taken into account when using it.

A signal warning about a potential decrease in the accuracy of the model is a significant deviation at the moment t of the current values of the coefficients α^{AB} from the values recorded for this moment in previous years. This deviation can be detected by analyzing the graphs presented in *Figs. 2–4* or by statistical methods. If there is such a deviation for the forecast at $t + 2$, it is advisable to use a model trained on the data $D_1 = [R, F, M]$.

Conclusion

The paper shows that in the analyzed retail network there is a repeating pattern of customers moving between groups with the same behavior lasting one year. Using information about customer flows between these groups allows you to assess the likelihood of a change in their behavior. Compared with the traditional RFM model, the forecasting accuracy is increased by more than 10%.

It also demonstrates the limitations of the proposed approach, which are associated with a violation of the behavior pattern due to external shocks. A method for identifying such a violation is proposed, making it possible to predict the degradation of the predictive ability of the model.

In conclusion, we also list possible ways to improve the efficiency of the proposed method:

- Using a sample spanning more than two years. This will make it possible to more accurately determine the average values of the α^{AB} coefficients, as well as consider their trends.
- Selection of periods of shorter duration (for example, a week). Potentially, this can make it possible to detect patterns of behavior change of higher frequency, which will increase the accuracy of forecasting in the short term.
- Use of more complex models than logistic regression. ■

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About the authors

Yury A. Zelenkov

Dr. Sci. (Tech.);

Professor, Department of Business Informatics, Graduate School of Business, HSE University, 20, Myasnitskaya Street, Moscow 101000, Russia;

E-mail: yzelenkov@hse.ru

ORCID: 0000-0002-2248-1023

Angelina S. Suchkova

Student, BSc Program «International business and management», Saint Petersburg School of Economics and Management, HSE University – Saint Petersburg, 16, Soyuza Pechatnikov Street, Saint Petersburg 190121, Russia;

E-mail: assuchkova_1@edu.hse.ru

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Dynamics of investments in Russia under the conditions of sanction restrictions: Forecast based on an agent-based model

Alexandra L. Mashkova
E-mail: aleks.savina@gmail.com

Orel State University named after I.S. Turgenev
Address: 95, Komsomolskaya Str., Orel 302026, Russia

Central Economics and Mathematics Institute of the Russian Academy of Sciences
Address: 47, Nakhimovsky Prospect, Moscow 117418, Russia

Abstract

The situation of a trade war between Russia and Western countries is unprecedented in recent history, both in terms of the scale of the restrictions being introduced and because of their mutually dangerous nature, as a result of which the entire world economic system is experiencing difficulties. An urgent task is to develop an economic policy for Russia that will allow for a quick reorientation to Eastern markets and the use of new growth drivers. Evaluation of the effectiveness of the measures taken should be carried out using modern tools, one of which is agent-based economic models. Since Russia is not considered as a key player in the models of international trade relations developed in a number of countries, in order to assess the sanctions imposed against it, it was necessary to develop a new tool – an agent-based model of trade wars between Russia, the USA, China and the European Union. The purpose of the study presented in this article is to assess the need of the Russian economy for additional investments in various industries for large-scale import substitution of products till now supplied from unfriendly countries. To achieve this, the agent-based model reproduces the sectoral structure of the considered economies of the countries and trade relations among them that existed before the start of the special military operation, compiles scenarios of possible sanctions, and simulates the corresponding changes in international trade relations. As part of the scenario calculations, three series of experiments were carried out. In the first series, for each scenario the expected dynamics of Russia's GDP in 2022 was estimated in the context of organizing import substitution programs in key industries, and the cost of these programs was calculated. In the second series, the dependence of GDP dynamics on the volume of investments was studied. The third series simulated the dynamics of trade relations for the period up to 2025 for two investment policy options in each scenario. The results of the experiments also show that the impact of investments on the economy is stronger, the more severe the sanctions are, and under these conditions, the implementation of investment programs can accelerate economic recovery on average by 0.5% of GDP per year.

Keywords: trade wars, agent-based model, sanctions, scenario calculations, investment

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Introduction

Since the start of Russia's special military operation in Ukraine, the world has faced the imposition of economic sanctions that are unprecedented in many respects. Firstly, this is the scale of restrictions, affecting more than half of the trade turnover in a number of industries with countries that are not directly involved in the military conflict and are not in agreements on military cooperation with the conflicting countries; in some cases, they completely block this turnover. Secondly, we see the mutually dangerous nature of the restrictions introduced, as a result of which not only the Russian economy suffers, but also the economies of the United States, the EU and neutral countries, due to global shortages of fuel, food and metals provoked by the sanctions, as well as inflation, suspension of production and related unemployment. In the current conditions, the low-income segments of the population suffer the most. Even in developed countries, they are under the threat of hunger, and the question arises, what is it: underestimation of the consequences of the measures being introduced, or deliberate neglect of their impact on the lives of ordinary citizens? History can shed light on the motives of the governments of countries that are now introducing these restrictions, and the task of the current moment is to develop an economic policy for Russia that will minimize the damage caused, and in the future even lead to emerging growth drivers.

To solve this problem, computer models of the economy that integrate the available data on production, employment, and economic relations between countries can serve as an effective tool. The most famous project in the field of developing tools for quantitative assessment of trade wars is The Global Trade Analysis Project (GTAP), which brings together scientific researchers from different countries [1, 2]. GTAP uses a generic modeling methodology based on computable general equilibrium (CGE) models. GTAP has developed a number of model complexes, including:

1. WorldScan, which simulates the trade of 29 products among 30 countries that have the largest weight in world GDP, and enlarged regions that include several states. Goods and services in the model are produced using labor, capital and intermediate products, the contribution of which is determined by the parameters of the corresponding production function. Supply and demand for a particular product in a particular country is formed taking into account supply and demand of this product in other countries, and the price depends on substitution opportunities, transport costs, trade barriers and other factors. Using WorldScan, the impact of tariff increases on certain types of products and on the industry as a whole was assessed, both for individual countries sequentially and for all at the same time. Based on the results of these calculations, the sectors most sensitive to trade wars in the United States and China were identified. Based on the simulation results, it was concluded that in the case of bilateral symmetrical impacts between the US and China, the latter bears the greatest losses, but in the event of a large-scale trade war, China also suffers the most [3].

2. The GLOBE multisectoral model [4], developed by specialists from the University of Hohenheim and the US Naval Academy, was used to assess the consequences of trade wars among the countries of the North American Free Trade Area, regulated by the North American Free Trade Agreement.

3. Multi-country multi-sector model MIRAGRODEP, developed at the International Food Policy Research Institute (Washington, USA), based, in addition to the GTAP methodology, on MIRAGE model (modeling of international relations under applied general equilibrium). The focus of this model is on trade in goods between the US, China, and Mexico [5].

4. The Center for International Trade and Economics and the Institute of World Economics and Politics of the Chinese Academy of Social Sciences have developed a global model for assessing the consequences of a trade war between the United States and China [6].

The models listed above focus on consideration of the world's largest players, most often the United States and China, sometimes also the EU countries. Despite the fact that in some of the presented model complexes Russia stands out as a participant, the available publications do not provide any assessments of the impact of economic sanctions on Russia which have been regularly imposed against it since 2014. At the same time, the world's leading agencies began very quickly to give negative forecasts for the Russian economy: JP Morgan on February 28 predicted a 20% drop in GDP in the second quarter, the World Bank in April suggested an annual drop of 11.2%, and Bloomberg in May spoke of a drop of 12%. To counteract such a negative informational impact on public opinion, it is necessary to have our own model complexes that can quickly update forecasts in changing conditions, and include Russia as one of the key participants in world trade. This task is being implemented by the CEMI RAS team using an agent-based approach [7–11]. The model developed simulates trade interactions among Russia, the USA, China, the European Union and the united rest of the world [12]. The series of calculations carried out in 2021 did not assume the scenario of such a global trade war against Russia, which we are currently witnessing, so the adaptation of the model to new realities becomes an urgent task. In particular, the purpose of this work is to assess the needs of the Russian economy for additional investments in various industries for large-scale import substitution of products hitherto supplied by unfriendly countries.

The processes of investment in the Russian economy have been studied from various points of view: the impact of the investment and state monetary policy [13–15], foreign investment [16], and distribution of investment between old and new technologies [17]. Despite the relatively lower efficiency of public investment compared to private investment, as shown in [13], under the current conditions, the role of public investment in the affected sectors of the economy is increasing.

Calculations on the model developed will make it possible to assess not only the required investment volumes, but also their impact on the reorganization of supply chains and dynamics of the country's domestic product, as well as the risks associated with insufficient investment activity of organizations and the state.

1. Methods

Agent-based modeling was chosen as the main research method. This makes it possible to evaluate the dynamics of the global system as a result of the interaction of various agents: countries, organizations and residents [18, 19]. Compared to such a widespread approach to building computer models of the economy as computable general equilibrium models (CGE), agent-based models have a number of features that determine their ability to reproduce complex socio-economic processes:

1. Heterogeneity of agents and their characteristics, which allows us to use different behavior models for them.

2. Direct interaction between agents that influences their decisions.

3. Bounded rationality of agents.

Based on these principles, agent-based economic models (ACE) can serve as a kind of computer laboratory for assessing the impact of policies on macroeconomic dynamics [20]. The ACE approach is used to model tax [21], monetary [22, 23] and macroprudential policy [24, 25], as well as regulation of the labor market [26].

In the model developed for trade wars, the interaction between agents determines the direction and structure of commodity-money flows between countries and their change under the influence of demand and government regulation. The study presented in this paper was carried out in accordance with the following methodology:

1. Reproduction in an agent-based model of the existing sectoral structure of the economies of the countries under consideration and trade relations between them (modeling "as is"). In conditions that are constantly changing at the moment, it seems correct to clarify that the existing structure is understood as the structure that existed before the start of the special operation and the international sanctions that followed.

2. Drawing up scenarios for the external economic situation, taking into account both packages of sanctions already introduced and those planned.

3. Modeling structural changes in trade relations between countries under conditions of the scenarios developed on the assumption of unlimited investment opportunities for organizations.

4. Estimating the amount of investment required to increase output in the sectors affected by the sanctions, based on the output of the simulation.

5. Modeling changes in trade relations in the context of limited investment opportunities for organizations and countries.

2. Structure of the model

The use of an agent-based approach makes it possible to achieve a high degree of detail in the model and reflect their consequences for the budgetary system, production, employment and incomes of residents in the model of trade wars. For each country considered in the model, the population is recreated in accordance with its gender and age structure (*Fig. 1*). The created agents-residents participate in the processes of production (like employees at workplaces) and consumption of products produced by agents-organizations.

Organizations in the model are enlarged and represent a group of organizations in the same industry in the country for which their indicators are aggregated: output, number of workplaces and volume of fixed assets characterizing production capacities.

Trade relationships in the model are defined through the supply chain of organizations, while export and import supplies form the international trade exchange. Supplies in the model are divided into three types:

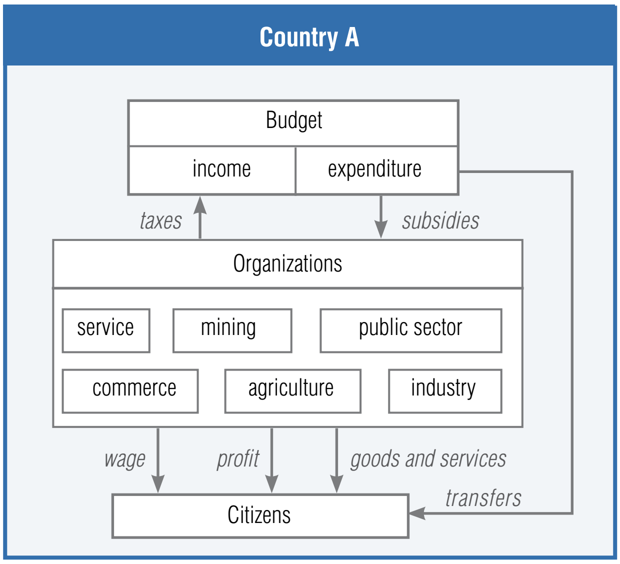

Fig. 1. Relationships between model objects within one country.

- intermediate supplies of raw materials and components to other organizations, for the convenience of further calculations, are divided into current (directly dependent on output volumes) and static;
- investment supplies of fixed assets, in which the main (purchase of machinery, equipment and buildings) and additional (purchase of products of other industries, reflected in the accounting as investments) are distinguished;
- supplies of final products, the buyers of which are agents-residents.

Supply of each type can be realized (in the past period) and planned (calculated for the next period). Planned deliveries are used to regulate and calculate changes in trade relations. For each supply, the identifier of the supplier and buyer, date, delivery volume, sale and purchase price are specified. The sale price is set in the currency of the state where the supplier agent-organization is located, without taxes. The purchase price consists of the sale price, sales taxes, export and import taxes (for international supplies), and is converted into the currency of the state in which the buying agent-organization is located.

States have a national currency, the rate of which is set relative to the currencies of other countries. The budgetary system of each state receives revenues through the tax system and makes expenditures, including paying benefits to the population and subsidies to organizations, and also finances the public sector of the economy. For the states, a budget is built for each model year; this includes revenue and expenditure parts presented in aggregated form (*Table 1*). Furthermore, the functions of the state in the model involve the introduction of restrictions on the import and export of products of certain industries.

Table 1.

Budget structure in the model

Income	Expenditure
Wage taxes	Public sector financing
Domestic production taxes and excises	
Export taxes and excises	Subsidies for the national economy
Import taxes and excises	
Government loans	Government loan servicing
Other income	Other expenditures

The developed model of trade wars considers the dynamics of trade relations among a number of countries and their associations: Russia, the USA, China, the European Union and the rest of the world (*Fig. 2*). Trade among countries is determined, on the one hand, by the needs of their economies, and, on the other hand, by the current sanctions restrictions on imports and exports. In light of recent events, the countries in the model can be divided into three groups:

1. The initiators of the economic war which introduced the largest number of sanctions: the US and the European Union (in *Fig. 2* on the left).

2. Sub-sanctioned countries with large economies: first of all, Russia, against which the largest number of restrictions apply, as well as China, against which the United States has imposed economic sanctions since 2018 (in *Fig. 2* on the right).

3. The rest of the world (ROW), which is considered to be a conditionally neutral enlarged country in the model, although it includes both countries that also imposed sanctions against Russia, and countries that did not support the imposition of restrictions, as well as countries under Western sanctions.

The software structure of the agent-based model of trade wars includes algorithms for the formation of the population and organizations, the dynamics of the economic environment, and the implementation of sanctions restrictions. In the first group of algorithms, the initial generation of resident agents, organizations (with the definition of output volumes, supplies, fixed

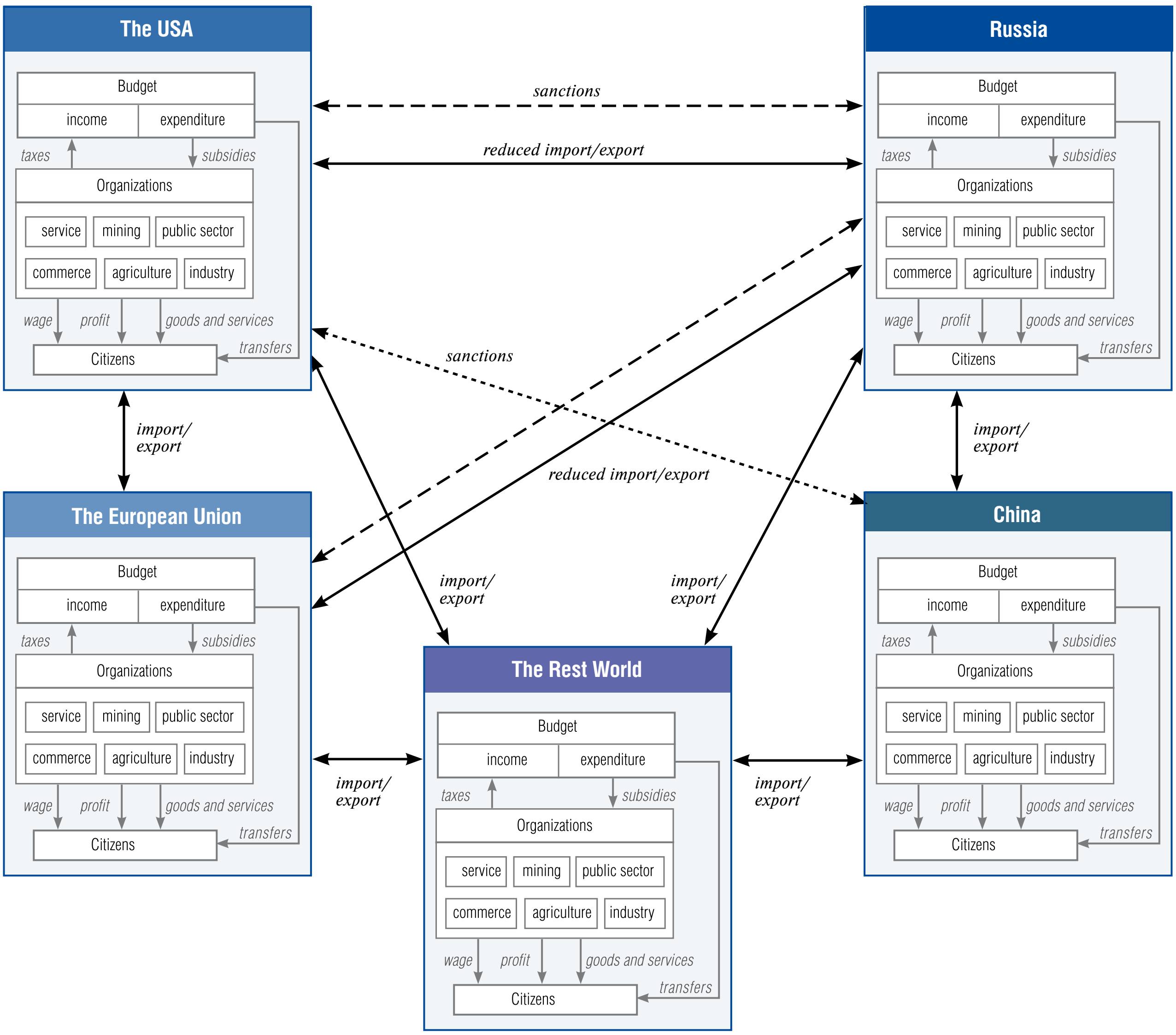

Fig. 2. Conceptual structure of the agent-based model of trade wars.

assets) and jobs are created, where resident agents are fixed. These issues are considered in detail in [27, 28]. The second group of algorithms includes implementation of the following processes:

- production: purchase of raw materials, production delay, wholesale of products;
- consumption: receiving wages and purchasing final products;
- public administration functions: payment of benefits to the population, financing public sector organizations and investments in the national economy through organizations of agriculture, mining and manufacturing industries;
- change in the supply chain as a result of sanctions restrictions;
- calculation and planning of necessary investments.

Model events in the sphere of production and consumption of products in the model of trade wars are considered in [12]; functions of the budgetary system are presented in [29].

Trade restrictions in the model are considered from two sides: restrictions on the import of certain types of products from a number of countries and restrictions on exports to other countries. Each restriction is presented by the following data set:

$$TR = \langle S_1, S_2, t, i, r, y \rangle,$$

where S_1 – country in the model;

S_2 – trade partner country of S_1;

t – type of trade relationship subject to restrictions (import or export);

i – industry whose products are subject to restrictions;

r – the value of the trade restriction in shares relative to the volume of trade relations in the previous period;

y – model year in which the trade restriction was introduced.

To adjust the existing structure of trade relations in the context of introduction of new sanctions, an assessment is made of the availability of import supplies for purchasing organizations from each country and supplier organizations from trading partner countries. If new restrictions are introduced in the pair of countries and industry under consideration, then the volume of supply is reduced, and the difference is entered into the array of missing supplies for the supplier's industry. After considering all supplier countries, the formed array of missing supplies is distributed between domestic suppliers and suppliers from countries that did not impose trade restrictions. The algorithm for implementing trade restrictions is presented in more detail in [7]. The implementation of this algorithm leads to a change in sales and output of organizations from countries involved in a trade war, and an increase in trade flow with friendly and neutral countries.

3. Modeling investment dynamics

The planning of the necessary investments of organizations consists of regular costs for maintaining the fixed assets (FA) fund and the costs of increasing production capacities in accordance with the expected dynamics of output (*Fig. 3*). The cost of maintaining the fixed asset fund is assumed to be equal to the depreciation allowance known from country and industry statistics.

To estimate the costs of increasing production capacity, data on the cost of fixed assets of the organization of the industry i in the country j E_i^j are used. As a result of the algorithms described above for adjusting sales volumes, the output growth coefficient for each organization KV_i^j is known. The volume of investments for the increase of production is calculated as:

$$IP(t+1)_i^j = E_i^j \cdot KV_i^j,$$

where $IP(t+1)_i^j$ – investments in the increase of production in the period $(t+1)$.

The growth rate of the organization's investments in the next period is calculated relative to the investments of the current period :

$$KI(t+1)_i^j = \frac{IP(t+1)_i^j + IA(t+1)_i^j}{IP(t)_i^j + IA(t)_i^j},$$

where $KI(t+1)_i^j$ – the growth rate of investments of the organization of the industry i in the country j in period t;

$IA(t)_i^j$, $IA(t+1)_i^j$ – depreciation charges in periods t and $(t+1)$;

$IP(t)_i^j$ – investments in the increase of production in the period t.

According to the calculated coefficient $KI(t+1)_i^j$ the plan of investment supplies of organizations is corrected, then the sequential processing of supplier organizations takes place, within which the values of their sales and intermediate supplies are adjusted. The procedure for checking supplier organizations is determined by their industry affiliation: first, organizations producing final products (light industry), then intermediate (production of fuel, materials and chemical products) and finally – raw materials (agriculture and mining).

To exit the algorithm from the recursion of recalculation of mutual deliveries, an assumption is introduced into the model that separates current (depending on the volume of output) and static intermediate supplies by industries of suppliers and buyers. Supplies are divided in such a way that in the terminal sectors of the algorithm (agriculture and mining) all intermediate supplies are static. This assumption makes it possible to avoid looping the algorithm, since the organizations of industries that do not need to adjust the circulating supplies of raw materials from other industries after output changes are processed last.

4. Initial data

The information content of the agent-based model of trade wars is carried out on the basis of data from official statistical agencies: the All-Russian State Statistics Service [30], the US Bureau of Economic Analysis [31], the National Bureau of Statistics of China [32] and Eurostat [33], as well as the World Bank [34]. In all the sources presented, selections by key parameters and their download in Excel document format are available, with the exception of the National Bureau of Statistics of China, which publishes statistical yearbooks in the form of pictures of the corresponding pages.

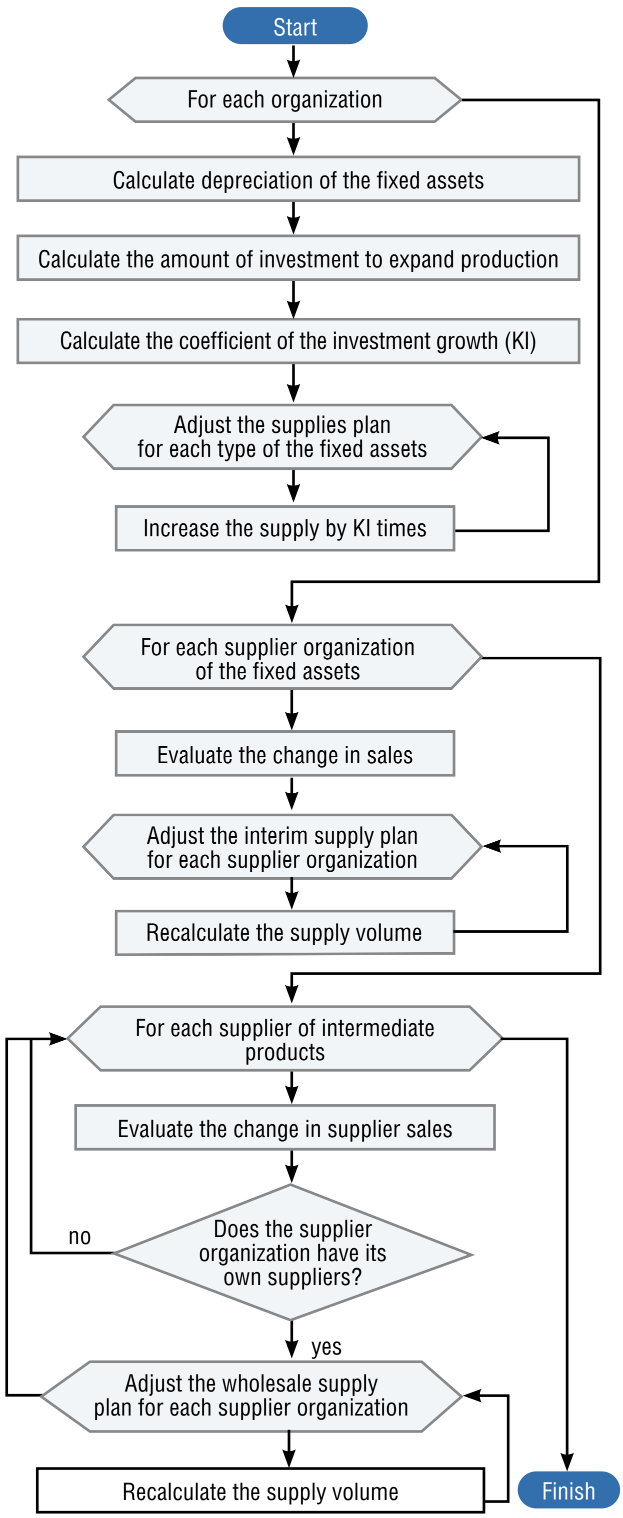

Fig. 3. Algorithm for calculation of investments.

The greatest difficulty at the stage of information content of the model is the collection and unification of data on the economic relationships of organizations in different countries, including intersectoral supplies, imports and exports of various types of products. An indispensable source of such data are input-output tables, which are published for each of the countries represented in the model (Russia, China, USA), as well as the countries of the European Union, considered as a whole. There are two difficulties in using official input-output tables to generate simulation input tables. First, the industry classifiers used to generate input-output tables vary from country to country, and therefore direct comparison of industries and products is not possible. While the classifiers of the European Union (63 industries) and Russia (60 industries) are quite similar, the United States (71 industries) and China (17 industries) have significant differences from

Table 2.

Value added of consolidated industries in various countries, in units of the national currency

Industry in the model	Country in the model				
	Russia, billion rubles	USA, billion dollars	EU, billion euro	China, billion yuan	ROW, billion dollars
Agriculture, food production	5865.7	441.3	511.8	10755.6	4015.6
Mining	12622.5	293.3	42.2	3194.1	1192.5
Fuel production	2545	157.4	60.6	2486.1	928.2
Public sector	13827.5	4522.7	1384.8	8947.6	3340.6
Chemical production	2080.6	534	433.2	4586.8	1712.5
Production of the materials	3993.9	383.8	393.1	3831.9	1430.6
Production of transport and equipment	3166.9	860.4	874.9	7558.7	2822
Light industry	432.9	136.8	168	3983.9	1487.4
Service	35350.8	10503.9	8275.7	27388.2	10225.3
Commerce	12737.8	1934.9	1642.4	13941.8	5205.1
Construction	5340.6	890.6	852.1	6241.6	2330.3
Total in national currency	97964.2	20659.1	14638.8	92916.3	34690.1
Total in USD	1687	20659.1	15689	14280	34690.1

Calculated by the author on the basis of data from the FSSS, the US Bureau of Economic Analysis, Eurostat, the National Bureau of Statistics of China and the World Bank.

them. To solve this problem, the model creates 11 aggregated industries, each of which corresponds to one or more industries from the input-output tables of countries (*Table 2*). Also, the industries of the model are compared with the Standard International Trade Classification (SITC) to aggregate countries' imports and exports.

Secondly, the time periods for which input-output tables are presented differ: data for 2019 are available for all countries, with the exception of China, for which the latest input-output tables refer to 2017. To ensure that the most up-to-date information for all countries is used, industry output and supply data are updated to 2019 using China's GDP growth rates available on the World Bank website [34]:

$$a_{kl} = \sum_{i=1}^{n}\sum_{j=1}^{m} a_{ij} \cdot \frac{va_i^{2019}}{va_i^{2017}},$$

where k – an aggregated industry in the model that includes a number of industries of the economy $i = \overline{1,n}$;

l – an aggregated industry in the model that includes a number of industries of the economy $j = \overline{1,m}$;

a_{kl} – supplies of the organization of an aggregated k from the organization of an aggregated l;

Table 3.

Information on fixed assets (FA) of organizations in Russia

Industry in the model	Cost of FA, billion rubles	Commissioning of new FA, billion rubles	Depreciation of FA, billion rubles
Agriculture, food production	9948.1	1045.2	408.8
Mining	29774.9	3085.4	1115.1
Fuel production	3532.9	340.7	237.3
Public sector	23560.3	1348.3	2847.9
Chemical production	3460.8	333.7	255
Production of the materials	6388.7	616.1	420.7
Production of transport and equipment	5289.8	510.1	482.9
Light industry	744	71.8	70.1
Service	258369.6	14136.8	6005.5
Commerce	5567.8	560.9	2288.7
Construction	3094.1	459.9	138.2
Total:	349731	22508.9	14270.2

Calculated by the author on the basis of data from the FSSS.

a_{ij} – supplies of industry i from the organization of industry j according to the data of the input-output balance;

va_i^{2019} and va_i^{2017} – value added of industry i in 2017 and 2019 respectively.

The GDP of the rest of the world is calculated based on the World Bank data as the difference between the global GDP ($87 trillion) and the GDP of the countries considered in the model ($52.3 trillion). We consider the sectoral structure of the economy of the rest of the world to be similar to that of China, which is the largest among developing countries. The results of the calculations are presented in *Table 1*.

Information about fixed assets available to organizations, their depreciation and commissioning of new ones is also presented for aggregated industries in the model (*Table 3*).

5. Scenarios

Until 2020, when building forecasts for the development of the Russian economy, the price of Urals oil, the exchange rate of the ruble against the US dollar, inflation, GDP dynamics, exports and imports of goods were taken into account as the main scenario parameters [35]; at the same time, the decline in energy prices and the depreciation of the ruble against the US dollar were considered traditional risk factors.

Serious adjustments to the formation of forecast scenarios were made due to the coronavirus pandemic, which caused such difficulties as a slowdown in the global economy; decrease in demand for raw materials, goods and services; decline in trade, tourism, public catering. The maintenance and introduction of epidemiological restrictions has become a new risk factor in the global economy, affecting the volume and structure of final demand and, as a result, output and employment in a number of industries. In this context, two scenarios have been developed: an optimistic one, which assumes the stabilization of the epidemiological situation, and a pessimistic one, in which bursts of incidence are regularly repeated, causing the introduction of new restrictions [12]. At the moment, a conservative epidemiological scenario seems more likely, in which the repetition of waves of coronavirus infection does not lead to a further slowdown in the global economy, and the epidemiological restrictions introduced affect only certain regions.

After the start of Russia's military special operation in Ukraine, the formation of forecast scenarios for the global economy became an even more difficult task. The United States and the European Union are introducing unprecedented sanctions, the consequences of which affect not only Russia, but the whole world. The phenomena observed in recent months show the need not only to consider new risk factors for the Russian and global economy, but also their new combinations; in particular, the ruble exchange rate has shown stability which was not observed earlier in crisis periods. At the same time, one of the significant risk factors is inflation, which arose against a background of fluctuations in the ruble exchange rate; but after its stabilization, prices did not return to their original level due to pressure from the supply side, a break in international supply chains and an expected shortage of various goods and components.

In these conditions, within the framework of calculations on the agent-based model of trade wars, the exchange rate of the ruble to the US dollar, the dynamics of energy prices and expected inflation are taken into account as scenario parameters. In the context of the political situation, three scenarios are proposed:

1. Reinforcement of US and EU sanctions up to limiting their trade exchange with Russia by 70–90%.

2. Preservation of sanctions with a decrease in trade exchange with unfriendly countries by 40–60%.

3. Reduction of sanctions up to 20–30% of imports and exports.

The proposed values of the scenario parameters are presented in *Table 4*. World energy prices are in direct correlation with the sanctions imposed, since they are growing against the background of a shortage and an increase in the cost of logistics, while in the case of reinforced sanctions, the price at which Russia can sell them decreases, due to a limited number of possible buyers. Despite the fact that the measures taken by the Bank of Russia to stabilize the ruble exchange rate have shown their effectiveness, the forecast exchange rate of

75 and 90 rubles per dollar, respectively, is used to make calculations in the context of preserving and reinforcing sanctions. If the ruble exchange rate shows its stability in the long term, then scenarios for preserving and reinforcing sanctions will require adjustments to this parameter.

The restriction of trade exchange between countries is set in the form of restrictions on imports and exports as a percentage of their volume in the previous year (in *Table 4* – as a percentage of the values of 2021). The dynamics of countries' GDP and international trade volumes are calculated based on the results of the simulation output.

6. Results and discussion

The agent-based model of trade wars was programmed in C# MicrosoftVisualStudio based on the developed algorithms. The choice of a software tool is due to the need to work with a large amount of data and the related optimization of procedures and functions, which is difficult in standard modeling environments. The scaling of the model was set at the level of 1:10 000; thus, in total, about 800 000 residents were created in five countries (Russia, the USA, China) and their associations (the EU and the enlarged rest of the world). The information support of the model is presented in the form of a database using initial data loaded in Excel format (the procedure for converting statistical data from various countries to a common format is discussed in the corresponding section). The database of the model of trade wars is managed using the PostgreSQL DBMS. Scenario parameters are also loaded from the table, and the corresponding modeling parameters (inflation, trade restrictions between countries, exchange rates) are reset.

The purpose of calculations based on the developed model is not so much to build forecasts of the dynamics of the Russian economy, which is an extremely difficult task in the current conditions, as to analyze scenario deviations with various possible combinations of external factors and control influences. The first series of experiments consisted of three calculations aimed at modeling structural changes in trade relations between countries and the increasing need for the Russian economy to invest in import-substituting projects. According to the scenario parameters, the trade turnover between Russia and Western countries (the USA and the EU) decreases by 30%, 50% and 80% year-on-year with the reduction, preservation and reinforcing of sanctions, respectively, which is partially compensated in monetary terms by price increases. Based on the output data of the first series of experiments, an assessment of the volume of investments required to increase output in industries affected by sanctions is carried out, and the cost of organizing new import-substituting production capacities is taken into account while the costs of maintaining the fixed assets of organizations

Table 4.

Scenario parameters

Scenario parameter	Scenario		
	Reinforcement of sanctions	Preservation of sanctions	Reduction of sanctions
Dynamics of energy prices, %	–20	15	20
Ruble to US dollar exchange rate	90	75	60
Restriction of trade exchange between Russia and unfriendly countries, %	80	50	30

(depreciation charges) and annual budgetary costs for the national economy are excluded. The estimates obtained for various scenarios are presented in *Table 5*.

In the second series of calculations, an assessment was made of the impact of investment volumes on the economic situation in Russia. To do this, within each scenario, six investment policy options were considered, where option #1 assumes the absence of additional investments for the implementation of import substitution programs, and option #6 – investment of the entire required estimated amount presented in *Table 5*. Intermediate options reflect options for partial additional investment: 20, 40, 60 and 80 percent of the required estimated amount in each scenario.

The graphs presented in *Fig. 4* reflect the results of 18 experiments carried out, the output of which was the forecast of the dynamics of Russia's GDP in 2022 relative to the values of the base year 2021. An analysis of the results of the second series of experiments shows that the impact of investments on the dynamics of GDP is stronger, the more severe the sanctions imposed by Western countries.

An increase in investment becomes critically important in the context of scenario No. 3 (reinforced sanctions), in which the implementation of a full range of import substitution programs makes it possible to reduce the decline in GDP from 12% to 10%. Under scenario No. 1 (sanctions reduction) in the current year, the Russian economy shows a weak dependence on the implementation of investment projects (less than 1% of GDP).

To conduct the third series of experiments within each scenario, two investment policy options were selected: option #2 (investing 20% of the required estimated amount) and option #5 (investing 80% of the required estimated amount) and modeling of trade relations for the 3-year period was carried out. The dynamics of Russia's GDP was also chosen as the output parameter of the simulation, and on the graph it is presented on an accrual basis relative to the values of the base year, which makes it possible to estimate the speed of economic recovery to pre-crisis values.

Figure 5 shows the forecast of GDP growth in the context of reducing international sanctions. After the fall in the current year, the Russian economy shows

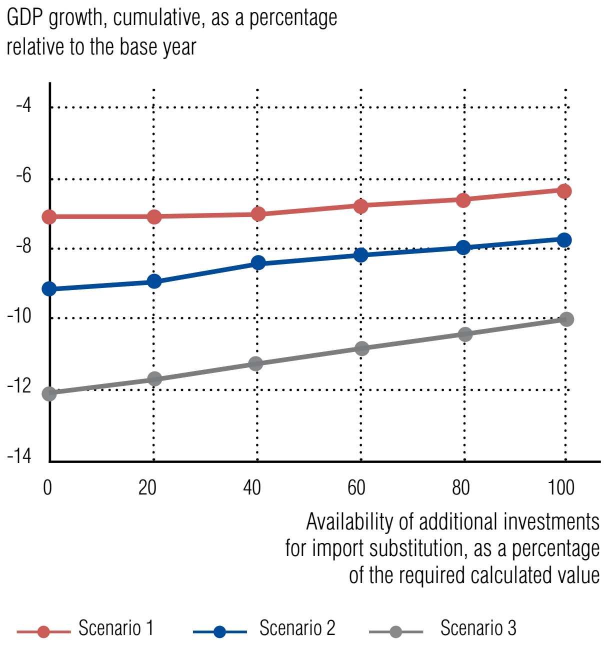

Fig. 4. Forecast of Russia's GDP dynamics under the conditions of various shares of additional investment from the required calculated values.

Table 5.

The need of the Russian economy for additional investments in 2022, billion rubles

Parameter	Scenario 1	Scenario 2	Scenario 3
Additional investments	183	300	453

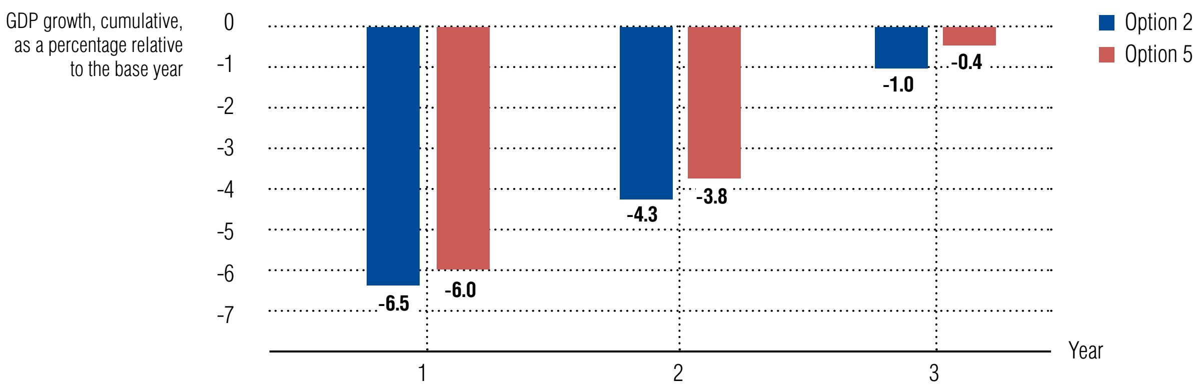

Fig. 5. Forecast of Russia's GDP dynamics in the context of the reduction of sanctions (scenario No. 1).

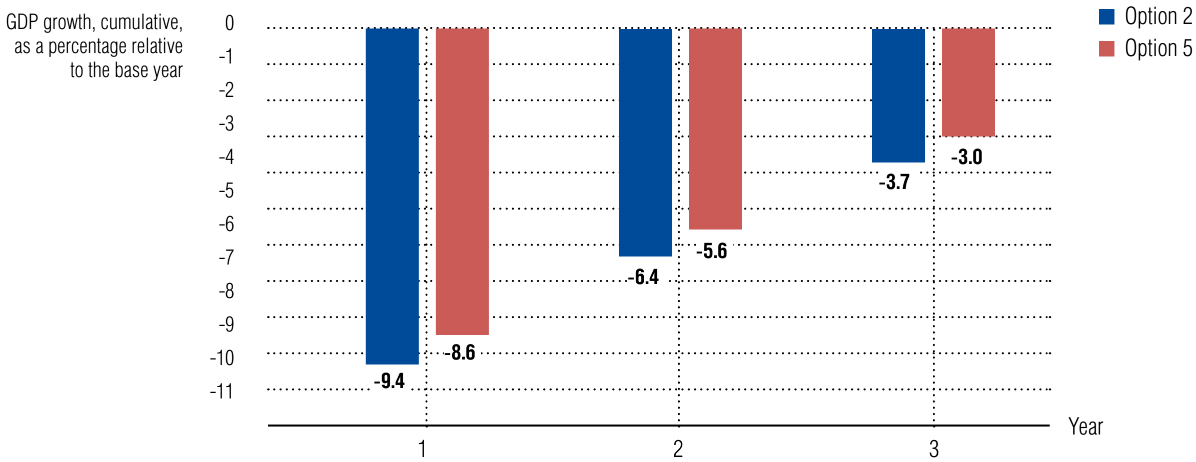

Fig. 6. Forecast of Russia's GDP dynamics in the context of preservation of sanctions (scenario No. 2).

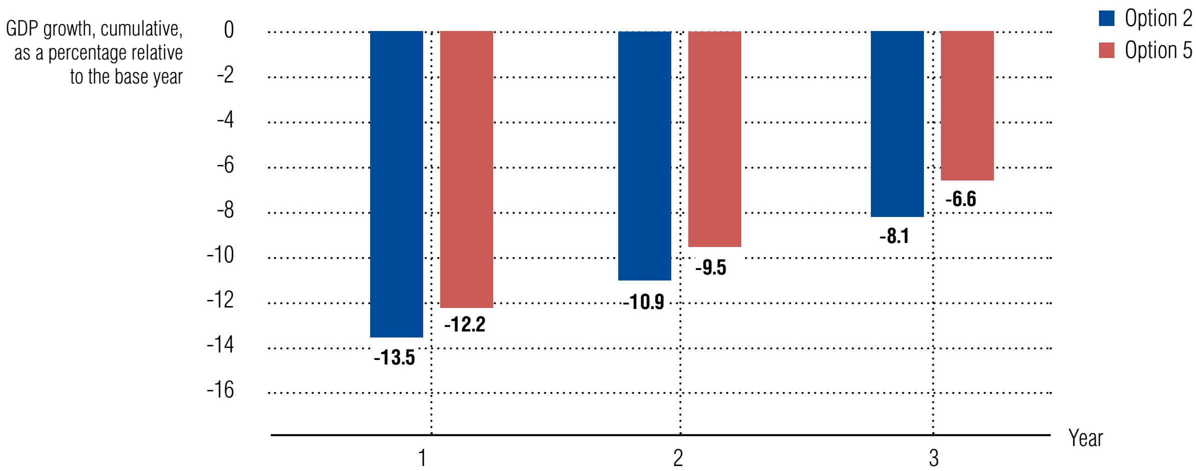

Fig. 7. Forecast of Russia's GDP dynamics in the context of reinforced sanctions (scenario No. 3).

moderate growth, and for the 3-year period it is almost returning to pre-crisis values, while the change in the volume of the import substitution program does not significantly contribute to this process (the difference is 0.6% of GDP for 3 years).

According to the calculations carried out, under the conditions of preservation of sanctions, the Russian economy is not recovering to pre-crisis values for the 3-year period, while the contribution of import substitution programs to GDP dynamics is also not very significant: the final increase over 3 years is 0.7% more when investing 80% of the required calculated value compared to investing 20% of it (*Fig. 6*).

The economic recovery is slowing down even more in the face of tougher sanctions, but the impact of investment volumes is increasing: for the 3-year period the implementation of import substitution programs by 80% of the required calculated value makes it possible to weaken the overall decline to 6.6%, which is 1.5% higher than the GDP growth relative to the expected values when implementing 20% of the investment program (*Fig. 7*).

Thus, the series of calculations we conducted show that the impact of investments on the economy, estimated through the forecast of GDP dynamics, is the strongest with the preservation and reinforcing of sanctions by Western countries. Under these conditions, the implementation of import substitution programs can accelerate the recovery of the economy and its growth rate after overcoming the crisis by an average of 0.5% per year compared to the forecast version, where investment programs are implemented on a smaller scale.

The results obtained are based on a number of assumptions embedded in the agent-based model of trade wars at the stage of its development. Firstly, it is an assumption about the complete substitutability of products of one industry, thanks to which goods and components that have fallen under sanctions can be replaced with domestic analogues or supplies from neutral and friendly countries. Secondly, logistical problems and delays that arise when changing suppliers are not taken into account, though they are especially serious due to the geographical remoteness of friendly Asian compared to unfriendly European countries; due to this assumption, production downtime is not taken into account when waiting for materials and components. Thirdly, it is assumed that there are countries in the world that have not joined the sanctions against Russia, and that they are willing and able to supply the required types of products, which in the conditions of the most negative foreign policy scenario may not be feasible. Also, due to the large number of uncertainties, the time horizon of the calculations carried out was limited to 3 years, although for a comprehensive assessment of the effect of the implementation of large-scale investment projects, it should be extended to at least 10 years.

Conclusion

This paper presents a computer model of trade wars, including Russia, the United States, China, the European Union and the united rest of the world as key participants in world trade. The model is using the agent-based approach and reflects the interaction of three types of agents: countries that introduce and remove trade restrictions, organizations that purchase and manufacture products both for the domestic market and for export, and residents living in countries working in organizations and consuming their products. The arrays of initial modeling data were formed on the basis of information from official statistical agencies of Russia, China, the USA, the European Union and the World Bank. All data loaded into the model, including inter-industry supplies, output, import and export of various types of products, were unified to 11 aggregated industries. To make forecasts, three scenarios of the external economic situation were formed: reduction of the imposed sanctions, their preservation and further reinforcement, while inflation, world currency rates and the share of trade turnover between countries falling under the imposed restrictions are set as scenario parameters.

The purpose of computer experiments on the model of trade wars in this work was to assess the need of the Russian economy for additional investments in various industries for large-scale import substitution of products hitherto supplied by unfriendly countries. To solve this problem, three series of calculations were carried out. The first series of three experiments was aimed at modeling structural changes in trade relations between countries in the current year under the conditions of the developed scenarios, assuming unlimited investment opportunities of the state and organizations. Based on the results of this series, an estimate of the volume of investments required to increase output in the industries affected by sanctions was obtained: 183 billion rubles in the scenario of reducing sanctions; 300 billion rubles while preserving sanctions; 453 billion rubles with their further reinforcement. In the second series of 18 experiments, the impact of investment volumes on the dynamics of Russia's GDP in in the current year was assessed; for this purpose, six investment policy options with different volumes of investments in import-substituting industries were considered within each scenario. The results of the second series show that the dependence of GDP on investment is quite strong in the conditions of reinforcement of sanctions and relatively weak when they are reduced. To conduct the third series of experiments, two of the considered options were selected for each scenario, and simulation was carried out for the 3-year period. The results of the third series of experiments also show that the impact of investments on the economy is strongest when sanctions are maintained and tightened. Under these conditions, the implementation of import substitution programs in industry allows acceleration of the economic recovery by an average of 0.5% of GDP per year.

Calculations based on the model developed allow us to assess changes in trade turnover among countries under changing restrictions, the impact of this process on the production of various types of products, as well as the relationship between investment activity and the overall economic situation in different countries. In this paper, the constructed forecasts for the Russian Federation were presented, but an important area of further research is analysis of the consequences of the sanctions imposed on the Western countries that initiated this process, as well as consideration of the scenario of strengthening the trade confrontation between the United States and China under conditions of a possible new military conflict. ■

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About the author

Alexandra L.Mashkova

Cand. Sci. (Tech.);

Associate Professor of the Department of Information Systems and Digital Technologies, Orel State University named after I.S. Turgenev, 95, Komsomolskaya Str., Orel 302026, Russia;

Senior Researcher at the Laboratory of Computer Modeling of Socio-Economic Processes, Central Economics and Mathematics Institute of the Russian Academy of Sciences, 47, Nakhimovsky Prospect, Moscow 117418, Russia;

E-mail: aleks.savina@gmail.com

ORCID: 0000-0003-1701-5324

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Diffusion of digital technologies in the face of external shocks: The case of the COVID-19 pandemic

Roman A. Shcherbakov
Email: rashcherbakov@hse.ru

Sofya G. Privorotskaya
E-mail: sprivorotskaya@hse.ru

Konstantin O. Vishnevskiy
E-mail: kvishnevsky@hse.ru

HSE University
Address: 20, Myasnitskaya Street, Moscow 101000, Russia

Abstract

This paper investigates the impact of external shocks on the spread of digital technologies. Using the example of the COVID-19 pandemic, we identify and describe four patterns that reflect the uneven response of different digital technologies to external conditions undergoing transformation. The patterns differ in both the magnitude of the pandemic's impact and the timing of the resulting effects. Video conferencing, business continuity and telemedicine services showed a dramatic increase in demand at the beginning of COVID-19 and a gradual decline in the later stages. A more moderate response in the early weeks of the pandemic is typical of e-commerce and online entertainment. Delayed effects are seen in digital logistics services and digital currencies, which reacted much later than other technologies. Finally, a slow decline in significance after the pandemic began has been observed for biometrics and cybersecurity technologies. Similar patterns may describe the transformation of the spread of digital technologies not only under the influence of COVID-19, but also in the face of dramatic economic and social changes of other origins.

Keywords: digital transformation, digital technology, digital diffusion, economic shock, market adaptation, COVID-19

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Introduction

The COVID-19 pandemic has accelerated the spread of digital technology across economic and social spheres. Many companies, organizations and government agencies have been forced to move to a more intensive digital transformation of key business processes. In particular, due to lockdown restrictions, certain operations have been switched to a remote format [1–3]. The ability to successfully implement and adapt digital technologies has become one of the competitive advantages of business during the crisis [4]. The innovative potential of companies was partly redirected to create effective solutions to combat the social and economic consequences of COVID-19. Thus, during the pandemic, the use of digital solutions (including the spread of online education, remote employment, e-commerce, telemedicine, etc.) significantly increased [5].

The external shock triggered by the pandemic led to shifts in the supply and demand for digital products and services, many of which were already widespread before the pandemic (e.g., streaming or conferencing platforms). Under these kinds of shocks, changes are heterogeneous and may be characterized by different market patterns (e.g., immediate, or delayed demand response, long-term or temporary nature of changes, etc.) [6–7].

Empirical evidence on the impact of COVID-19 on digital diffusion formed the analytical basis for the study. This allowed us to draw conclusions about the possible types of market reactions and their corresponding characteristics of technological directions (including the level of maturity, consumer demand, sensitivity to external factors, etc.).

1. Technology diffusion: theoretical background

The diffusion of new technologies is influenced by a set of factors. The intensification of entrepreneurial activity, the development of international trade and the accompanying economic growth contribute to greater adoption of digital technologies [8]. In addition, the use of digital platforms and the strengthening of network effects contribute to the deepening of cooperation among companies and the creation of partnerships, all of which stimulates the spread of technology, for example, in e-commerce, education, finance, health, agriculture, transport, energy, industry, etc. [9, 10]. The quality of human capital (including the level of managerial competence, technical skills of employees and the general level of education) has a significant impact on the speed and depth of adaptation of new technologies [11].

The process of technology diffusion under the influence of the aforementioned factors is described by various models. Epidemiological models (epidemic models) associate it with the transmission of information from one user to another by analogy with the process of disease transmission [12, 13]. In such models, the spread of information about technologies is described by an S-curve, emphasizing its non-linear nature [14]. Other approaches, such as probit models, describe the factors that affect the adaptation of a new technology at the level of an individual company or person [15]. If the significance of a factor (for example, such as profit from the technology's implementation), exceeds a certain limit, it leads to its successful implementation [16]. However, such models take into account long-term trends and exclude the influence of external shocks – events that can radically change the demand or the way the technology is used. This kind of transformation is the key subject of this study.

2. The impact of the COVID-19 pandemic on digital technologies

The emergence of external shocks in the economy distorts the trajectories of technology diffusion and greatly increases the level of uncertainty, making it difficult to predict its future development. The COVID-19 pandemic has had a significant impact on the level of use of technological solutions already widely available on the market, as well as less mature ones. In particular, the rapid proliferation of technologies that enable the support of remote working formats is considered one of the most significant effects of the pandemic, which overcame a few negative consequences [4, 17]. At the same time, the increased demand for such solutions led to increased data security risks, which also stimulated an increased need for cybersecurity technologies [18, 19].

The impact of COVID-19 on the digital transformation of particular industries (especially those most affected by the pandemic) has received considerable attention in scientific literature. The most tangible effects have been observed in health care [3, 20, 21]. In particular, the pandemic has increased the demand for telemedicine and accelerated its adoption [21]. The disruption of traditional supply chains has also been a driver for the introduction of technologies related to transportation and logistics. The restructured supply chains have actively involved solutions that had previously been used on a smaller scale, in particular drones [22, 23]. For example, drones have been actively used to ensure the delivery of medicines, medical devices, and essential goods, especially in areas that are difficult to reach by conventional transport [24].

The spread of technology in a pandemic has been extensively researched in the academic field. However, there are a few gaps in this field. There are virtually no studies comparing the response of individual digital solutions, including products and services, to the effects of the pandemic. There is also a lack of attention to the changing patterns and nature of digital diffusion under the influence of the pandemic.

In order to fill the existing gaps, the following research objective was set: to identify possible patterns of digital diffusion under the influence of external shocks by analyzing the dynamics of digital diffusion under the COVID-19 pandemic.

3. Methodology

We applied statistical methods to evaluate and interpret quantitative metrics derived from intelligent analysis of big data. This approach allows one to answer the questions posed, since it makes it possible to measure metrics that characterize technological trends and their dynamics. Descriptive empirical research provides an opportunity to present an integral picture of the development of digital technology in the context of the pandemic, as well as to complement existing scientific works on this topic.

To collect empirical data, we used the system of intellectual foresight analysis of big data developed at the Institute of Statistical Studies and Economics of Knowledge of the National Research University Higher School of Economics (HSE) – iFORA (Intellectual foresight analytics) [25]. We used the indicators of *significance and dynamics* of a particular topic in professional English-language media for two periods:

2018–2019 (pre-pandemic period) and 2020–2022 (pandemic and post-pandemic period) to assess the dynamics of digital technologies. The media corpus includes 548,000 sources. The corpus includes news publications in professional business and specialized industry media, as well as official press releases from digital technology companies.

The following indicators were calculated based on the results of intelligent analysis of big data.

Significance is the relative frequency of occurrence of the topic in the documents on the analyzed area:

$$FREQ = \sum\nolimits_{i=1}^{T} f_i, \quad (1)$$

where *FREQ* is the frequency index;

f_i – occurrence of the term in the *i*-th year;

T – length of years interval, $i = 1, ..., T$.

Dynamics is the average annual growth rate of frequency of mentions:

$$AAGR = \frac{1}{T}\left(\frac{\sum\nolimits_{i \geq T/2} f_i}{\sum\nolimits_{i \leq T/2} f_i} - 1\right), \quad (2)$$

where *AAGR* is the indicator of the growth rate;

f_i – occurrence of the term in the *i*-th year;

T – length of years interval, $i = 1, ..., T$.

The indicators are calculated based on selected keywords (*Appendix 1*) by technology areas (clusters), which include digital solutions that have become relevant in use during the pandemic. The technology areas were selected based on the OECD OPSI COVID-response Tracker database, which compiles digital solutions applied to mitigate the pandemic effects in various countries and reflect the technology agenda during the pandemic period [26]. The study is based on an analysis of nine clusters, including: video conferencing, business continuity services, telemedicine, digital logistics services, digital currencies, e-commerce, online entertainment services, cybersecurity and biometrics. Based on the OECD database, a compilation of key terms reflecting the most common digital solutions, grouped into nine clusters, was formed. Terms missing from the corpus of texts, as well as outliers (terms with a frequency of mention close to zero and general terms with an inflated frequency) were removed from the list of keywords.

The selected toolkit allows tracking current changes in digital dynamics with little delay, which is achieved by constantly updating the iFORA document database. Thus, it becomes possible to obtain data for 2021 and early 2022, which cannot be achieved with traditional statistical metrics. Moreover, normalized metrics evaluated from big data analysis allow one to compare different technology trends using a single scale. In contrast to traditional studies based on the analysis of internet search data from an unspecified list of sources, the analysis using iFORA is based on a corpus of digital-specific documents from a professional media database (including industry and business media, company press releases on digital topics, etc.).

A similar approach, based on the analysis of the significance of topics in the media in the iFORA system, is widely used by researchers to identify and describe market trends in various economic sectors (agriculture and food sector [25]; mobile commerce [27]; extractive industries [28, 29].

4. Results and discussion

The results of the analysis demonstrated that the pandemic has had a highly uneven impact on the spread of individual technology areas (*Table 1*). Business continuity and videoconferencing services, digital currencies, and telemedicine showed the sharpest growth in 2020. At the same time, the dynamics for several clusters, including biometrics and cybersecurity, was negative in the same period. In 2021, there is a slowdown in pandemic effects: the level of dynamics for business continuity services, digital currency videoconferencing, and telemedicine is significantly lower than in 2020. For other clusters, less dramatic changes are observed during this period – there is a gradual adaptation of markets.

An analysis of the spread of technology areas from 2018 to early 2022 revealed four patterns of digital diffusion in the COVID-19 pandemic: (1) shock effect, (2) moderate effect, (3) delayed effect, (4) negative effect.

Table 1.

Dynamics of the spread of technology areas in 2019–2021

Technology areas (clusters)	Significance growth rate (dynamics), in % to the previous year		
	2019	2020	2021
Business continuity services	1.4%	214.8%	1.6%
Video conferencing services	10.1%	156.8%	–11.5%
Digital currencies	17.9%	120.2%	52.4%
Telemedicine	3.3%	74.4%	23.9%
Digital Logistics	2.7%	28.4%	10.2%
E-commerce	–10.8%	15.0%	6.1%
Online Entertainment	25.5%	9.5%	–4.0%
Biometrics	1.0%	–17.2%	10.2%
Cybersecurity	3.0%	–19.5%	21.9%

Source: the authors' calculations based on the results of intelligent analysis of big data in the iFORA system.

Pattern 1: Shock effect

The pattern is characterized by a sharp increase in significance in the short term (at the beginning of the pandemic) and a gradual downward trend during the rest of the observation period.

This kind of trend trajectory during the COVID-19 pandemic is typical of such technological areas as business continuity services, video conferencing and telemedicine. A surge in significance for all services in this group occurred between March and mid-April 2020 (*Fig. 1*). However, after peaking in April, the clusters showed a sharp decline in significance until September–October 2020, indicating a weakening of the effects during this period.

The shock response is primarily due to the fact that all of the technologies in this cluster were directly used to deal with the effects of the pandemic. The results of the present study are consistent with previously published findings of a shocked increase in demand for telemedicine in the early weeks of the pandemic [30]. At the same time, despite a gradual decline in relevance across these clusters by early 2022, it remains at higher levels than before the pandemic, suggesting a profound, long-term impact.

At the same time, the trajectory of development in telemedicine differs from the other two clusters: the significance indicators achieved in March–April 2020 (shock period) turn out to be more stable and do not decrease as significantly as the pandemic recedes. Such trend behavior may indicate gradual adaptation of telemedicine technologies to conditions after COVID-19 pandemic and gradual expansion of their application. A few studies have found a qualitative change in the status of telemedicine, which has gained greater acceptance among both healthcare profession-

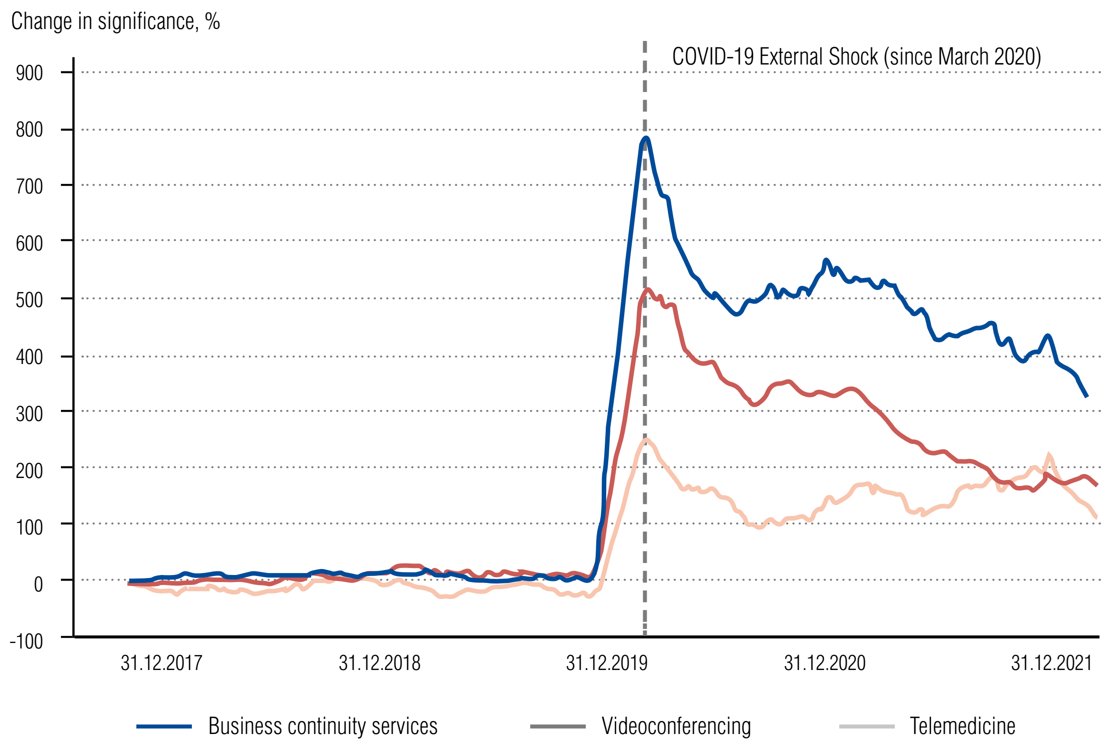

Fig. 1. Pattern 1: Change in significance in 2018–2022 (in percentage to the level as of December 31, 2017).
Source: authors' calculations based on iFORA big data mining.

als and patients [31]. At the same time, further growth in demand in this area, as confirmed by other authors, is limited by barriers related to data privacy, immaturity of technology, etc. [32].

Pattern 2: Moderate effect

The pattern is characterized by a moderate increase in the significance of technological areas at the beginning of the pandemic. In contrast to the first pattern, there is no sharp decrease in significance after the period of external shock (March–April 2020).

Since March 2020, the significance for e-commerce and online entertainment clusters has increased sharply. Just as in the previous pattern, high values were achieved in April 2020, but the scale of the changes does not allow us to conclude on their shock nature (*Fig. 2*). In particular, the change in significance for March–April 2020 was 30–35 percentage points (p.p.), while for the video conferencing, business continuity and telemedicine clusters the increase was over 100 p.p. Meanwhile, the April 2020 figures do not demonstrate peak values for these clusters. Overall, there is weak growth in the initial period of the pandemic (*Table 1*), which also indicates that there are no signs of shock changes as in the case of the previous pattern. At the same time, growth rates for both clusters declined after 2021.

The more moderate response to the pandemic may be due to the fact that technologies in the two clusters analyzed were not used directly as a response to the pandemic, like telemedicine or video services. More-

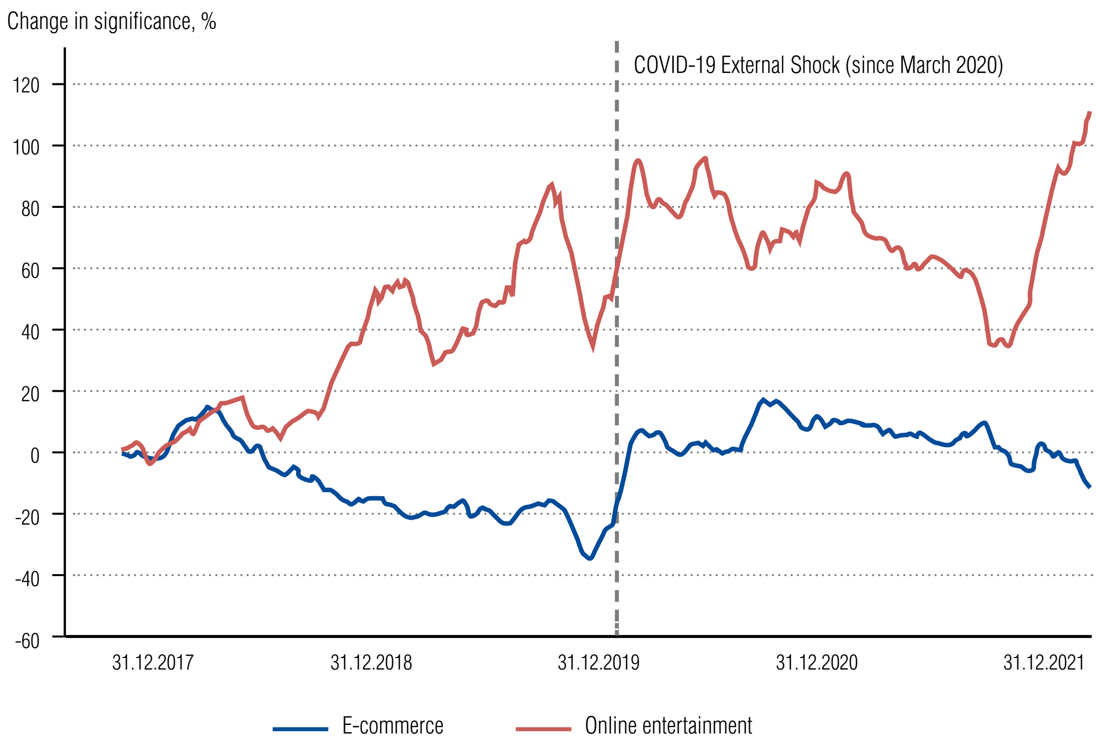

Fig. 2. Pattern 2: Change in significance in 2018–2022 (in percentage of the level as of December 31, 2017).
Source: authors' calculations based on iFORA big data mining.

over, several studies show that disruptions in global supply chains have also negatively impacted supply in e-commerce, in the presence of high demand, confirming its limited growth over the observed period [33]. In addition, in the online entertainment sector, despite the increased demand for digital platforms during the pandemic, supply and demand for other services changed, such as exhibitions, festivals, limited film production, etc. became impossible. [34]. As a result, in the case of these clusters we can conclude there was a less visible response to the impact of the pandemic.

Pattern 3: Delayed effect

The pattern is characterized by a much later attainment of peak significance over the observed period, as well as a lack of shock response at the beginning of the pandemic, indicating a delayed nature of the transformational effects.

The delayed nature of the pandemic effects on the spread of these technological areas is related to the need to adapt technologies to the new conditions. For example, the significance of digital logistics reached its highest levels only by the end of 2020 (*Fig. 3*). A similar trajectory over the same period was demonstrated by the significance indicators for digital currencies.

Deferred pandemic effects have also been mentioned in earlier studies. According to several authors, only in the long term will innovative supply chains play an important role in meeting the demand for certain products, which helps to reduce the negative effects of the pandemic [23]. At the same time, the growth of

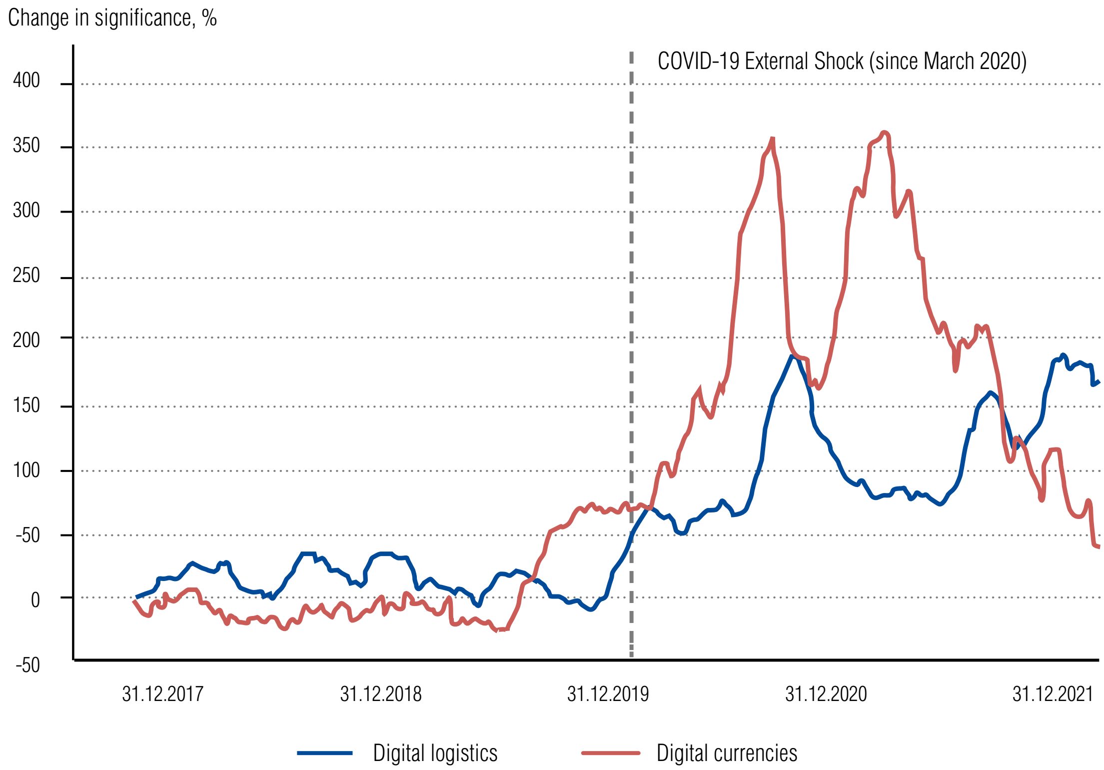

Fig. 3. Pattern 3: Change in significance in 2018–2022 (in percentage to the level as of December 31, 2017).
Source: authors' calculations based on iFORA big data mining.

digital currencies is justified by the gradual adaptation of financial regulation to the pandemic and the use of digital currencies to stimulate economic recovery. Other studies also confirm the positive stimulative effect of digital currencies on e-commerce in China, which has made them subject to financial regulation and led to accelerated diffusion [35, 36].

Pattern 4: Negative effect

This pattern is characterized by a lack of significant growth after the pandemic began and a persistence of negative dynamics throughout the observation period.

The significance of biometrics and cybersecurity technologies, unlike the others, demonstrated a smooth downward trend throughout the entire observation period (*Fig. 4*). At the beginning of the pandemic (March–April 2020), a decline in the significance of both technological areas was observed, which, however, was not sharp and amounted to about 15–20 p.p. At the same time, despite positive growth rates in 2021 (*Table 1*), the significance of both technological areas did not return to pre-pandemic levels. We can say that after the pandemic their significance in the business agenda did not fall significantly, but at the present rate of increase in significance there was no return to pre-pandemic levels. It will only be possible to draw conclusions about the depth of the pandemic's impact on these clusters in the longer term.

At the same time, the results of this study do not confirm the results of previously published works. In particular, a number of authors have concluded

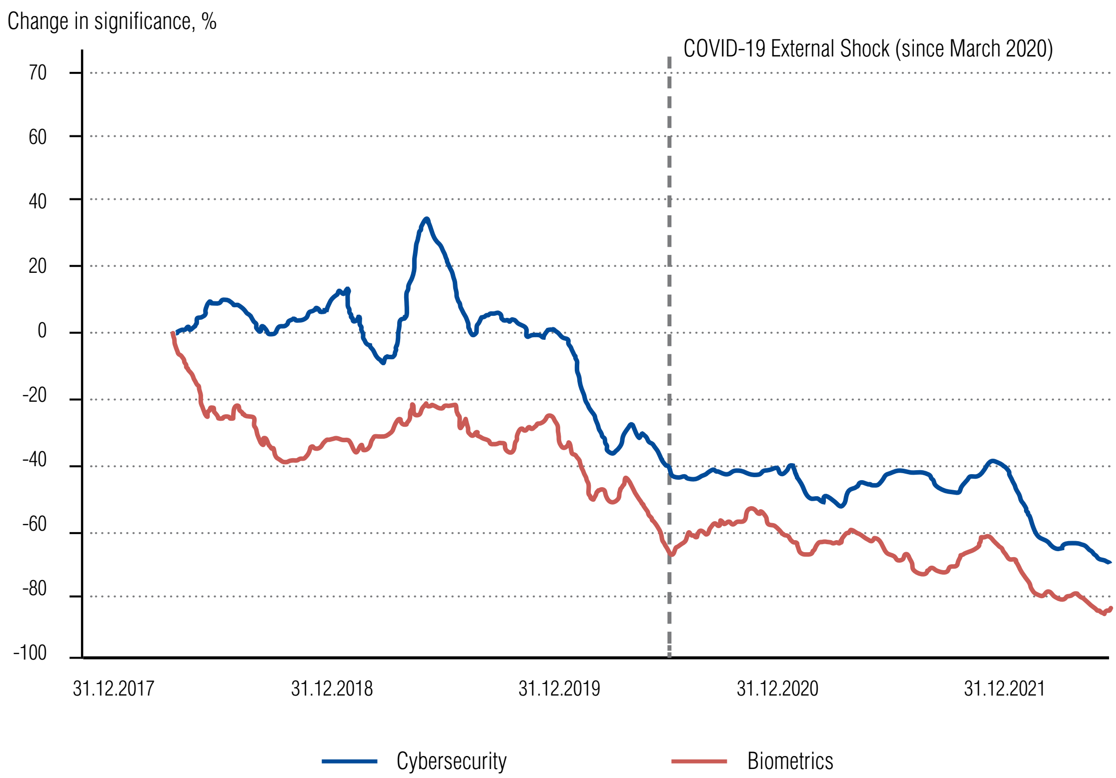

Fig. 4. Pattern 4: change in significance in 2018–2022 (in percentage to the level as of December 31, 2017).
Source: authors' calculations based on intelligent analysis of big data in the iFORA system.

that there was increasing need for cybersecurity services after the beginning of COVID-19 [18, 19]. This study demonstrates a gradual recovery of the positive dynamics of the significance of cybersecurity by the end of 2020 and 2021, which may be due to the gradual adaptation of society to the increased use of other digital technologies and the growing demand for cybersecurity solutions.

Thus, in the face of an external shock, there have been significant shifts in the markets of all the analyzed technological areas, with tangible differences in their nature. The "behavior" of each individual cluster is determined by the specifics of the technologies included in it, including their level of maturity, the breadth of application in industries, the degree of influence of the pandemic on key areas of their application, etc. Similar patterns may describe changes in the trajectories of spread of digital technology under conditions of turbulence in the external environment caused by various kinds of economic and social shocks.

Conclusion

Dramatic conjuncture changes and an increase in the level of uncertainty significantly complicate the decision-making process for economic actors. The approach proposed in this paper reveals regularities in the response of digital products and services markets to external shocks and, thus, makes it possible to increase the predictability of possible changes.

Empirical observations during the COVID-19 pandemic (2020—2022), obtained using big data mining, allowed us to systematize the possible types of digital technology responses to external shocks. Due to its versatility, the proposed approach can be applied to assess the effects of external shocks of different origins. First, metrics reflecting the significance in the agenda allow us to quantify the scale of response of different technological trends and to compare them with each other. Second, access to the most up-to-date information makes it possible to quickly track and respond to such changes. Third, as a result, it becomes possible to identify certain patterns and further classify them.

The analysis results reflect the highly uneven impact of shocks on the trajectories of digital diffusion. The four patterns identified differ both in the strength of the transformational impact (from moderate to pronounced) and in the timing of the resulting effects (from immediate to delayed long-term response).

A sharp growth "in the moment" and a subsequent slowdown while maintaining the overall positive trend are characteristic of the technological solutions of the first pattern. For clusters in this group, we can conclude that there are deeper structural changes that persisted in the post-pandemic period. Less pronounced or delayed effects in the medium term are characteristic of the second and third patterns. This reaction is associated with a less pronounced sensitivity of technologies to changes in the conjuncture and the presence of a certain time lag for adaptation to the changed situation.

As the influence of COVID-19 wears off, there is an inverse process of "de-digitalization" for those areas where the costs of accelerated digitalization were too high. Within the fourth pattern, there are negative dynamics in response to external changes. In this context, temporary external shocks may not lead to long-term structural transformation, but only accelerate the existing trend (with a possible subsequent "rollback").

Identification of such patterns is an important element of forecasting economic and social development both for the state and for business. The results we have presented can be generalized for a comprehensive analysis of the factors contributing to changes in business processes, restructuring of value chains, shifts in digital products and services markets, and the breakdown of relevant technological trends. ■

Acknowledgements

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Appendix 1.

List of keywords for technology clusters

Clusters	Keywords
Videoconferencing	Video conferencing app
	Video conference
	Video conferencing tool
	Video conferencing solution
	Video conferencing
	Video conferencing platform
	Cisco webex

Clusters	Keywords
Videoconferencing	Video conferencing service
	Video conferencing software
	Video meeting
	Microsoft teams
	Zoom
	Teleconferencing
	Video communication

Clusters	Keywords
Videoconferencing	Video conferencing service
	Video conferencing software
	Video meeting
	Microsoft teams
	Zoom
	Teleconferencing
	Video communication
	Virtual conference room
	Virtual conferencing
	Online conferencing
	Videoconferencing solution
	Videoconferencing software
Business continuity services	Business continuity plan
	Business continuity
	Remote workforce
	Business solution application
	Remote collaboration
	Remote worker
	Real time intelligence
	Remote employee
	Business continuity tool
	Remote work
	Remote collaboration tool
	Virtual workspace
	Virtual collaboration
	Online collaboration tool
	Virtual collaboration platform
	Collaboration software

Clusters	Keywords
Business continuity services	Digital work environment
	Collaboration technology
	Virtual whiteboard
	Cloud base collaboration
	Cloud base communication
	Online collaboration platform
	Enterprise collaboration platform
Digital logistics	Logistic supplier
	Logistical arrangement
	Logistic centre
	Logistical challenge
	Logistic app
	Supply chain AND digital service
	Transport AND digital service
	Logistic AND digital service
	Supply chain AND digital solution
	Management tool AND supply chain
	Logistics AND digital solution
	Logistic hub
	Digital logistics
Telemedicine	Telehealth vendor
	Telehealth service
	Telemedicine service
	Telehealth visit
	Telehealth platform

Clusters	Keywords
Telemedicine	Telehealth provider
	Telehealth company
	Virtual doctor
	Telehealth consultation
	Telehealth program
	Telehealth solution
	Virtual care
	Telehealth
	Telemedicine
	Remote consultation
	Mobile telehealth
	Telehealth policy
	Telehealth policy
	Telemedicine consult
	Online care
E-commerce	Online delivery service
	Pickup and delivery service
	Grocery delivery service
	Food delivery service
	Delivery service
	Delivery service
	Home delivery service
	Online shopping
	Food delivery
	Google pay
	E commerce
	E commerce platform
	Ecommerce business
E-commerce	Ecommerce store
	Last mile delivery
	Digital commerce
	E commerce delivery
	Virtual marketplace
Online entertainment	Home broadcast
	Virtual museum
	Online entertainment
	Streaming service
	Streaming platform
	Virtual sport
Online entertainment	Virtual tourism
	Digital entertainment
	Streaming content
	Virtual gallery
	Virtual tour
	Virtual travel
	Virtual entertainment
	Virtual fashion
Cybersecurity	Cybersecurity policy
	Cybersecurity concern
	Cyber risk
	Cyber criminal
	Cyber threat
	Cybersecurity company
	Cybersecurity service
	Cybersecurity strategy
	Cybersecurity industry

Clusters	Keywords
Cybersecurity	Cybersecurity tool
	Cybersecurity product
	Cyber defense
	Zero trust
	Information security
	Critical infrastructure protection
	Cybersecurity solution
	Cybersecurity technology
	Cybersecurity innovation
	Information security solution
	Data security
Digital currency	E krona
	Digital fiat currency
	Digital dollar
	Digital euro
	Digital yuan
	Central bank digital currency
	Digital fiat
	Bank issue digital currency
	Digital ruble
	Bank digital currency
	Digital renminbi
	CBDC
	Digital RMB
	DFC

Clusters	Keywords
Biometrics	Face recognition
	Biometric identification
	Fingerprint biometric
	Biometric data
	Retina scan
	Face biometric
	Biometric technology
	Voice biometric
	Biometric solution
	Iris recognition
	Biometric research
	Mobile biometric
	Biometric application
	Biometric method
	Facial biometric
	Biometric reader
	Biometric identification system
	Biometric device
	Biometric information
	Multimodal biometric

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About the authors

Roman A. Shcherbakov

Research Assistant, Laboratory for Science and Technology Studies, Institute for Statistical Studies and Economics of Knowledge, HSE University, 20, Myasnitskaya Street, Moscow 101000, Russia;

E-mail: rashcherbakov@hse.ru

ORCID: 0000-0002-5054-3869

Sofya G. Privorotskaya

Cand. Sci. (Econ.);

Head of the Digital Technologies Research Unit, Digital Economics Centre, Institute for Statistical Studies and Economics of Knowledge, HSE University, 20, Myasnitskaya Street, Moscow 101000, Russia;

E-mail: sprivorotskaya@hse.ru

ORCID: 0000-0002-4552-4938

Konstantin O. Vishnevskiy

Cand. Sci. (Econ.);

Director of Digital Economics Centre, Institute for Statistical Studies and Economics of Knowledge, HSE University, 20, Myasnitskaya Street, Moscow 101000, Russia;

Senior Research Fellow, Laboratory for Science and Technology Studies, Institute for Statistical Studies and Economics of Knowledge, HSE University, 20, Myasnitskaya Street, Moscow 101000, Russia;

E-mail: kvishnevsky@hse.ru

ORCID: 0000-0003-3621-0504

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Entropy approach to the analysis of banks' balance sheets

Valentin V. Matokhin [a]
E-mail: vmatokhin@tekora.ru

Anatoliy V. Sigal [b]
E-mail: ksavo3@cfuv.ru

[a] Joint-stock company "TEKORA"
Address: of. 19-23, fl. 15, 56, Profsoyuznaya Str., Moscow 117393, Russia

[b] V.I. Vernadsky Crimean Federal University
Address: 4, Prospekt Vernadskogo, Simferopol 295007, Russia

Abstract

Accounting ensures the collection and systematization of documented information about the facts of the economic life of enterprises and organizations. The information collected is systematized and formalized in various forms of reporting. One of the key forms of reporting is the balance sheet. The balance sheet is based on the principle of double entry, according to which each change in the financial resources of the organization is reflected in at least two accounts related assets and liabilities. Thus, the condition of the balance of the volumes of the generalized values of assets and liabilities is realized. The control element of the balance sheet is the equality of the values of assets and liabilities. However, this control element does not allow us to identify the systemic difference (diversity) of balance sheets with equality of distributed funds. Namely, the equality condition is integral in nature and its fulfillment is not related to the specific nature of item-by-item distributions, since, at a given size of the total cost of the balance sheet, the condition can be fulfilled by various options for the distribution of financial resources by assets and liabilities. Therefore, within the framework of this article, an attempt has been made to introduce a new control element of the balance sheet, taking into account the uneven distribution of financial resources by assets and liabilities of credit and financial organizations.

Keywords: modeling, entropy, balance sheet, assets, liabilities

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Introduction

In the practice of managing credit and financial organizations, the problem of "mortality" of banks is known. According to the data of the Central Bank of the Russian Federation for the period from 2001 to 2022, the number of operating banks decreased by more than 70% (*Fig. 1*).

As the number of active players in the banking sector of the economy decreases, it becomes an increasingly urgent task to identify negative changes in the state of each particular bank.

In order to solve this problem constructively and objectively, we will consider the bank as a managed system and the system of spending financial resources on ensuring the bank's vital activity as a manager (*Fig. 2*).

The approach to the totality of expenses as a management system is based on the simple fact that each expense has a dual nature of influence on the state of the bank. On the one hand, each expense reflects the bank's need for a specific economic resource. On the other hand, each expense makes a change in the state of the control system as a whole, since it changes the values of the cost shares for various items. This prop-

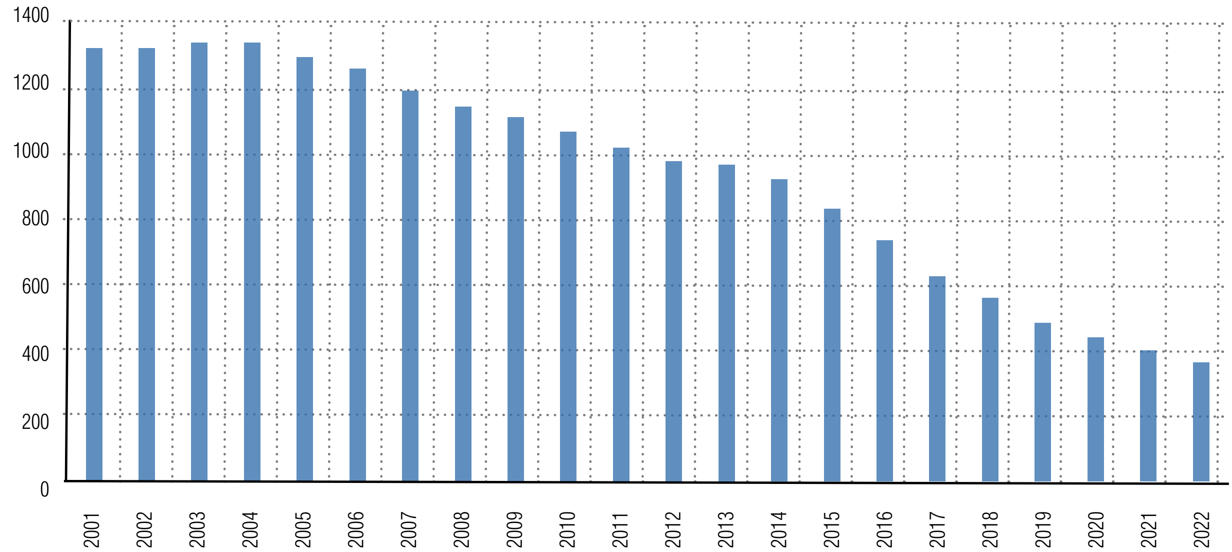

Fig. 1. The number of operating banks.

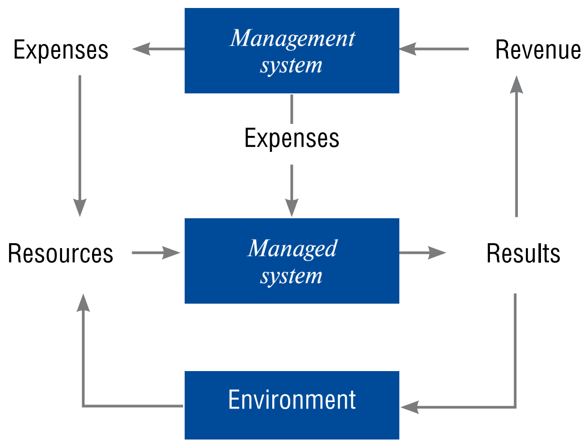

Fig. 2. The scheme of division of the control system into two parts: management and managed system.

erty of the totality of expenses allows you to manage the state of the bank as a single economic system. In the theory and practice of managing complex systems (see, for example, [1–3]) such fundamental concepts as entropy and a variety of state variants of control systems are widely used [4]. It is the variety of states of the control system that makes it possible to respond appropriately to changes in the state of the controlled system. However, in the theory and especially in the practice of balance sheet analysis, the use of the diversity property of the totality of expenses is limited by the lack of suitable methodological approaches. In this regard, the use of entropy as a measure of the diversity of the balance sheet and its application in modeling decision-making processes in the economy (see, for example, [5–14]) allow you to explore a wide variety of aspects and features of the state of the control system.

The purpose of the study is to substantiate the possibility of applying an entropy approach to assessing the diversity of assets and liabilities of the balance sheet, which may reveal the presence of an imbalance in the state of the bank.

1. The diversity of states and entropy of the management system

In order to move from “diversity” as a concept to “diversity” as a parameter of the state of the bank’s management system, let us consider as a first approximation the number of options for managerial decisions on item-by-item financial expenditures. To this end, we present the totality of expenses in tabular form (*Table 1*), in the left part of which there is a list of expenditure items $\mathbf{N} = (n_1; n_2; \ldots; n_N)$, and in the right – the corresponding amounts of expenditure of financial resources $\mathbf{G} = (G_1; G_2; \ldots; G_N)$.

Table 1.

Tabular form of representation of the state of the control system

Item of expenses	The amount of funds
n_1	G_1
n_2	G_2
…	…
n_N	G_N

The tabular form (*Table 1*) allows you to enter the parameter of the diversity of the state of the control system as the number of options W, which can be implemented by a state with fixed values of the number (number) of articles N and the amount of funds S_N.

Let’s explain what has been said with a simple example. Let the number of volumes of distributed funds be a vector $\mathbf{G} = (5, 20, 75)$. Then, changing the order of comparison of the elements of the numerical series $\mathbf{G}$ and the list of articles $\mathbf{N}$, we get $W = 6$, since for $N = 3$ the number of variants is equal to the number of permutations: $W = N! = 3! = 1 \cdot 2 \cdot 3 = 6$ (*Table 2*).

Table 2.

The variety of management solutions

The amount of funds		Variant "1-2-3"	Variant "1-3-2"	Variant "2-1-3"	Variant "2-3-1"	Variant "3-1-2"	Variant "3-2-1"
$G_1 = 5$	⇔	n_1	n_1	n_2	n_2	n_3	n_3
$G_2 = 20$	⇔	n_2	n_3	n_1	n_3	n_1	n_2
$G_3 = 75$	⇔	n_3	n_2	n_3	n_1	n_2	n_1

Further, it is easy to establish that any coincidence of values in the series $\mathbf{G} = (G_1, G_2, ..., G_N)$ reduces the value of the parameter W. In the limit, when the values of all components of the vector $\mathbf{G}$ are equal to each other ($G_1 = G_2 = G_3 =...= G_N$), all variants of the state of the control system are identical to each other, since the permutation of articles in this case no longer plays any role. This feature of the parameter W indicates the importance of studying precisely the unevenness of the distribution of cost values. That is, it is advisable to use a system parameter that would allow us to distinguish numerical series (vectors) $\mathbf{G}$ by the nature of the distribution of the values of their components. In fact, this will answer the question, what is the difference between numerical series with equal values of the parameters N and S_N. Such a system parameter could be the entropy of arbitrary numerical series, which can be used to quantify the diversity (distinctness) of the states of the control system. For example, what is the systemic difference between specific numerical series (vectors) $\mathbf{G'} = (3, 7, 10, 20, 60)$ and $\mathbf{G''} = (5, 10, 15, 20, 50)$, corresponding to different states of the control system? To do this, we first represent the coordinates of the vectors in the form of piecewise linear graphs constructed using a modified Lorentz diagram construction technique. Then, approximating the Lorentz diagram with a special one-parameter function, we determine the parameter of the uneven distribution α (alpha) and calculate entropy as a measure of the diversity of the state of the control system.

2. Lorentz's diagram of arbitrary numerical series

In economics, the method of visual representation of the uneven distribution of income by population groups in the form of a piecewise linear graph is well known [15]. We apply a simplified method of constructing a Lorentz diagram for an arbitrary numerical series. Let us say, for example, the original number series (vector) has five elements (components) $\mathbf{G'} = (3, 7, 10, 20, 60)$ and $\mathbf{G''} = (5, 10, 15, 20, 50)$. Calculate a number of accumulated partial sums $\{S_n\}$ using the following formulas:

$$\begin{gathered} S_1 = G_1,\ \ S_2 = G_1 + G_2 = S_1 + G_2,\ ..., \\ S_n = G_1 + G_2 + ... + G_n = S_{n-1} + G_n,\ ..., \\ S_N = G_1 + G_2 + ... + G_N = S_{N-1} + G_N. \end{gathered} \tag{1}$$

We get the following new series (vectors) $\mathbf{S'} = (3; 10; 20; 40; 100)$ and $\mathbf{S''} = (5; 15; 30; 50; 100)$. Next, we divide each of the accumulated sums Sn by the sum of all the numbers in the original series: $S_N = 100$. As a result, we get a series of numbers (vector) $\mathbf{Y'} = (0.03; 0.1; 0.2; 0.4; 1)$ and $\mathbf{Y''} = (0.05; 0.15; 0.3; 0.5; 1)$, which are the Y_n values of the ordinate axis of the Lorentz diagram. The values of the coordinates along the abscissa axis are calculated by the formula: $X_n = n/N$, where n is the number in order for the example under consideration and $N = 5$, that is, $\mathbf{X} = (0.2; 0.4; 0.6; 0.8; 1)$. And finally, we note on the X–Y coordinate plane the points with coordinates $(X_n; Y_n)$ inside a square with sides equal to one. As a result, we obtain Lorentz diagrams in the form of piecewise linear graphs (*Fig. 3*), which make it possible to visually distinguish $\mathbf{Y''} = (0.03; 0.1; 0.2; 0.4; 1)$ и $\mathbf{Y''} = (0.05; 0.15; 0.3; 0.5; 1)$.

Obviously, Lorentz's diagrams allow you to visually represent the uneven distribution of the values of elements of any numerical series that differ in the number of N elements and the total sum of S_N numbers. In addition, this approach positions any particular distribution between two extreme variants (*Fig. 3*): uniform ("A" – all numbers are equal to each other) and extremely uneven ("M" – one number is significantly larger than the others). For clarity, *Fig. 3* shows two Lorentz diagrams constructed for $\mathbf{G}_\mathbf{A} = (20, 20, 20, 20, 20)$ and $\mathbf{G}_\mathbf{M} = (1, 2, 3, 9, 85)$.

Using the approximation of Lorentz diagrams by a family of one-parameter functions $L(x, \alpha)$ in the form

$$L(x,\alpha) = 1 - \sqrt[\alpha]{1 - x^{\alpha}}, \qquad (2)$$

we introduce the parameter α as a measure of the unevenness of the distribution of values of a particular numerical series (*Fig. 4*) [16, 17].

3. The entropy of a numerical series

In nonequilibrium statistical mechanics, knowledge of the statistical density of the distribution provides complete knowledge of the state of the system [18]. The introduced one-parameter function (2) for the approximation of Lorentz diagrams allows us to obtain an expression for the statistical probability distribution function (probability density) in the following form [16]:

$$\rho(g,\alpha) = \frac{1}{\alpha - 1} \frac{g^{\frac{2-\alpha}{\alpha-1}}}{\left(1 + g^{\frac{\alpha}{\alpha-1}}\right)^{\frac{\alpha+1}{\alpha}}}, \qquad (3)$$

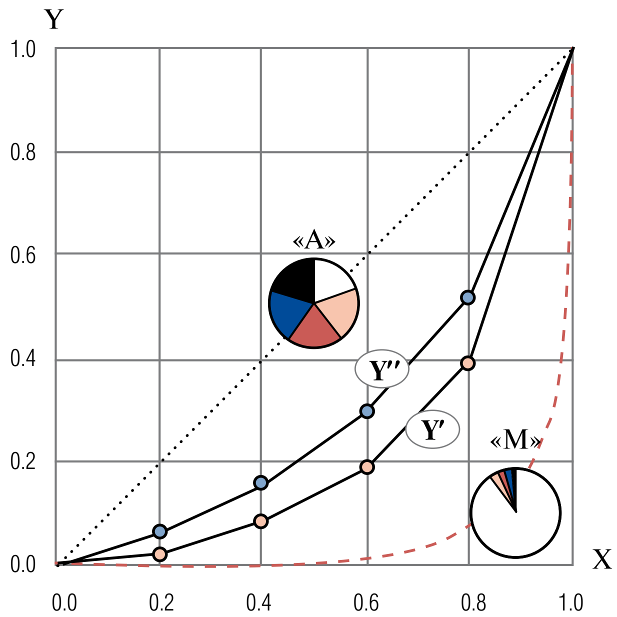

Fig. 3. Lorentz's diagram.

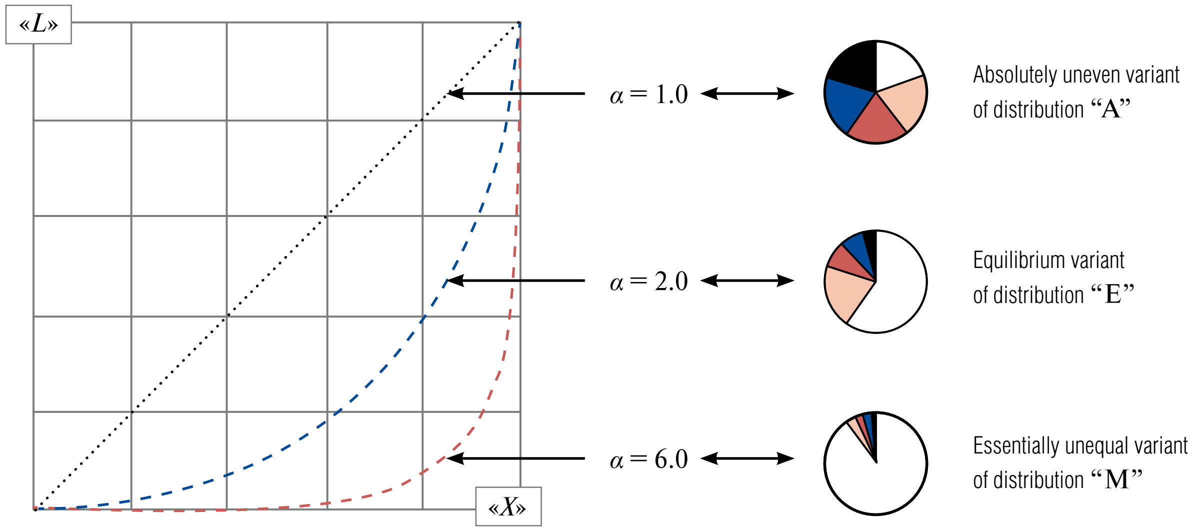

Fig. 4. The family of approximating functions $L(x, \alpha)$.

where g is the value of the flow rate G, normalized (divided) by the value of the average flow rate S_N/N.

And finally, the obtained one-parameter density of the probability distribution (3) allows us to calculate the entropy $V(\alpha)$ for an arbitrary numerical series (vector) **G** [19–21]:

$$V(\alpha) = -\int_0^{\infty} \rho(g,\alpha) \cdot \ln[\rho(g,\alpha)]\, dg. \qquad (4)$$

Figure 5 shows a graph normalized by the maximum value of entropy $V(\alpha)$, obtained by numerical integration of formula (4) [20]. The graph shows the entropy values for the numerical series used in the article: $\mathbf{G}_\mathbf{A}$, $\mathbf{G}_\mathbf{M}$, $\mathbf{G}' = (3,\ 7,\ 10,\ 20,\ 60)$, $\mathbf{G}'' = (5,\ 10,\ 15,\ 20,\ 50)$, $\mathbf{G}_\mathbf{A} = (20,\ 20,\ 20,\ 20,\ 20)$ und $\mathbf{G}_\mathbf{M} = (1,\ 2,\ 3,\ 9,\ 85)$.

In order to give quantitative properties to the description of our approach, it has become quite productive to use a unimodal analytical function $V(\alpha)$, approximating the graph of the entropy of the number series [22]:

$$V(\alpha) = \alpha^{-\sqrt{2}} \cdot \ln \alpha. \qquad (5)$$

As a result, having the function $V(\alpha)$, it became possible on the basis of physical entropy (4) to quantitatively formulate an entropic approach to the analysis of banks' balance sheets.

4. Entropic approach to the analysis of the balance sheet

We apply an entropic approach to the analysis of budgets of various levels [22] to analyze the equilibrium of the item-by-item distributions of assets and liabilities of the balance sheet of banks.

The concept of "balance sheet" has existed for almost six hundred years. The basis of the balance sheet is the Italian mathematician, Franciscan monk Luca Bartolomeo de Pacioli, who laid down in his work [23], published in 1494, the basic principles of accounting. He proposed the principle of double entry, according to which every change in the organization's funds is reflected in at least two accounts related to the corresponding group items of assets and liabilities.

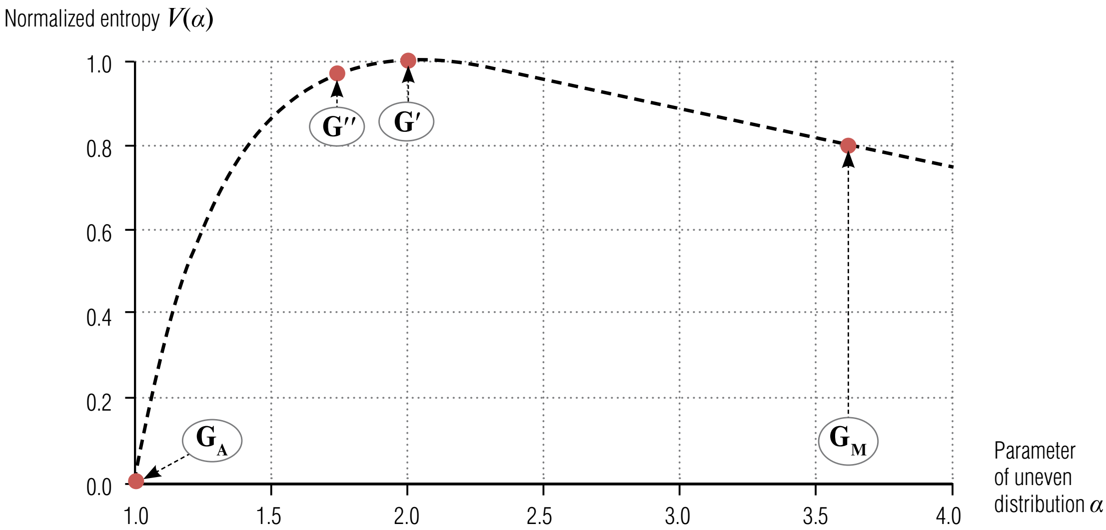

Fig. 5. The entropy of a numerical series with a different parameter of the uneven distribution.

Currently, the balance sheet is a generally accepted financial statement. The control element of the balance sheet is the equality of the value of assets and liabilities. However, the condition of equality of the value of assets and liabilities can be fulfilled by various options for the item-by-item distribution of funds. But it is the item-by-item allocation of funds that are the most important management decisions that affect the state and activities of enterprises and organizations. In this regard, a control element is needed that is directly related to the distribution of funds.

The authors tried to solve the problem by focusing on the productivity of using physical metaphors and concepts in the analysis of nonequilibrium states of macroeconomic systems [24, 25]. A convenient metaphor explaining the essence of the entropy approach to the separate assessment of the entropy of assets and the entropy of liabilities is the comparison of a credit and financial institution with a controlled section of the river. The only difference is that instead of a water flow through a controlled section of the river, we will consider the flow of entropy through a credit and financial institution. At the same time, the entropy flow control system through the organization is figuratively represented as a "gateway" in which the incoming entropy flow (V_A) is determined by the item-by-item distribution of assets (α_A), and the outgoing (V_L) is determined by the item-by-item distribution of liabilities (α_L). As a result, adjusting the distribution of assets and liabilities and calculating the corresponding entropy values (V_A) and (V_L), using formula (5), we implement entropy flow control. Entropy flow control allows us to avoid undesirable entropy "floods" (($\Delta V = V_A - V_L > 0$)) and "dehydration" ($\Delta V = V_A - V_L < 0$) in the control system. Thus, the condition of zero equality of the entropy flow $\Delta V = 0$ serves as a control element of the balance sheet, characterizing the equilibrium ("E") of the item-by-item distributions of assets and liabilities of the balance sheet.

In our opinion, the condition of equality of entropy flows is integral in nature and its fulfillment is associated with the specific nature of item-by-item distributions, since at a given size of the total cost of the balance sheet, the condition can be fulfilled by various options for the distribution of financial resources by assets and liabilities.

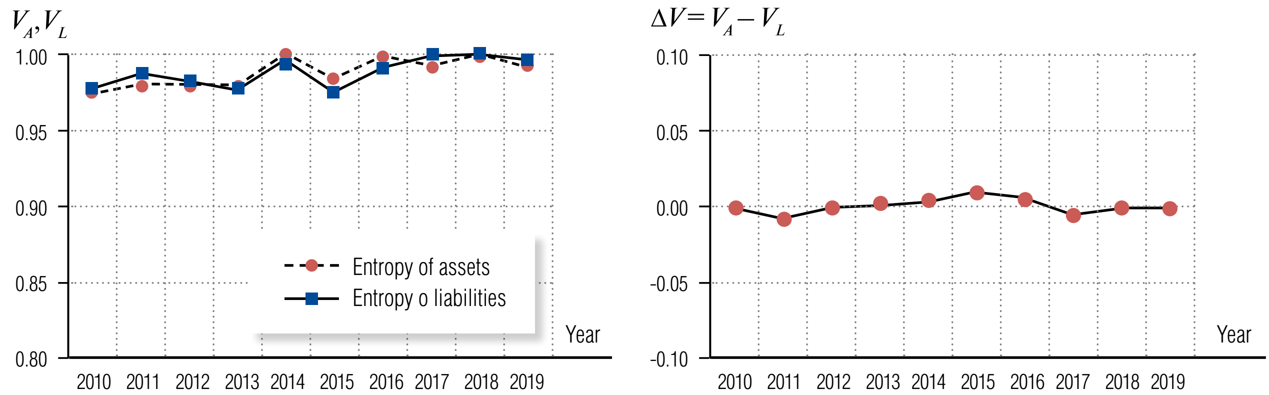

Fig. 6. Entropy of assets (V_A) and entropy of liabilities (V_L) of VTB Bank.

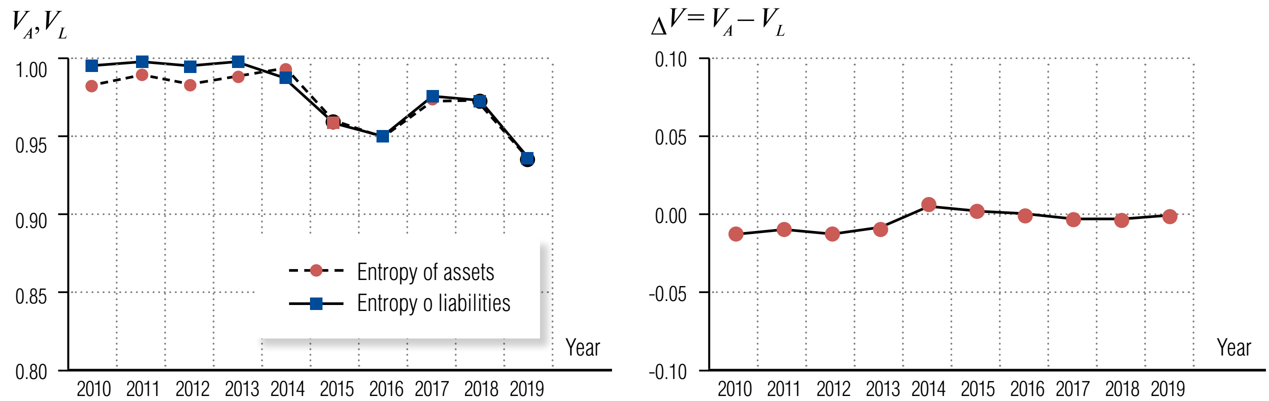

Fig. 7. Entropy of assets (V_A) and entropy of liabilities (V_L) of SberBank.

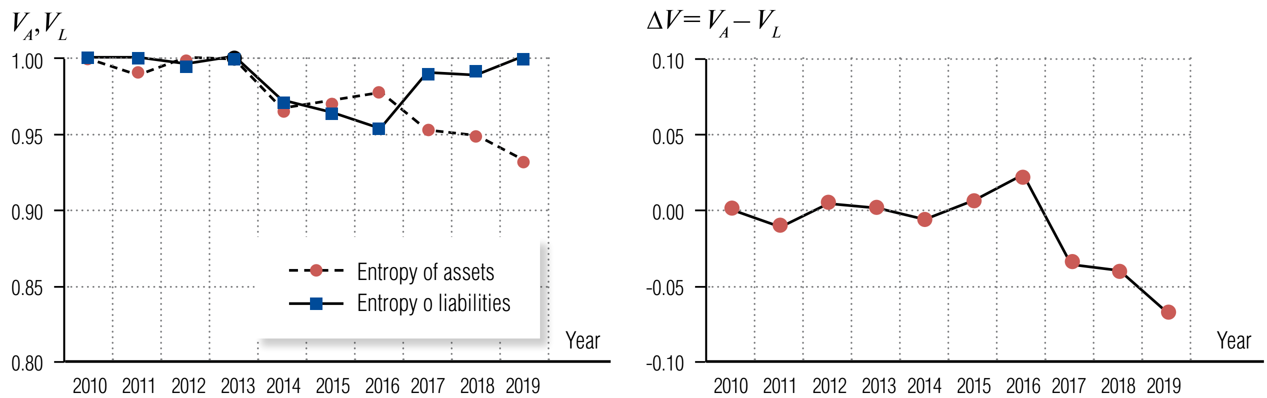

Fig. 8. Entropy of assets (V_A) and entropy of liabilities (V_L) of Promsvyazbank.

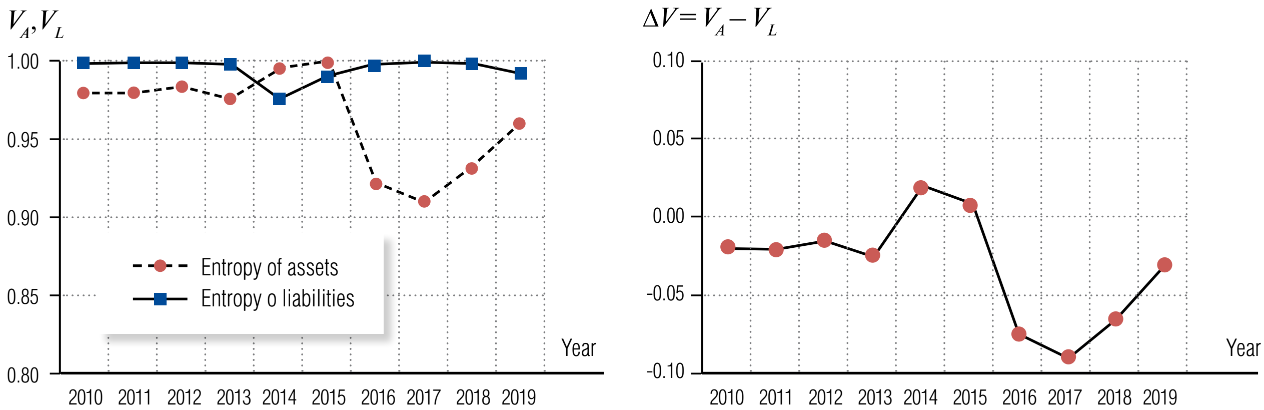

Fig. 9. Entropy of assets (V_A) and entropy of liabilities (V_L) of Uralsib Bank.

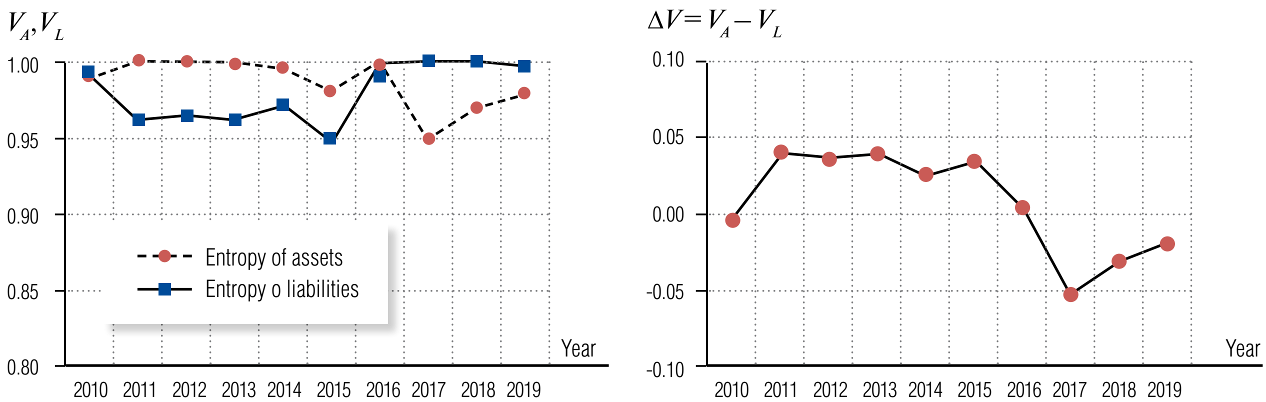

Fig. 10. Entropy of assets (V_A) and entropy of liabilities (V_L) of TEMBR-BANK.

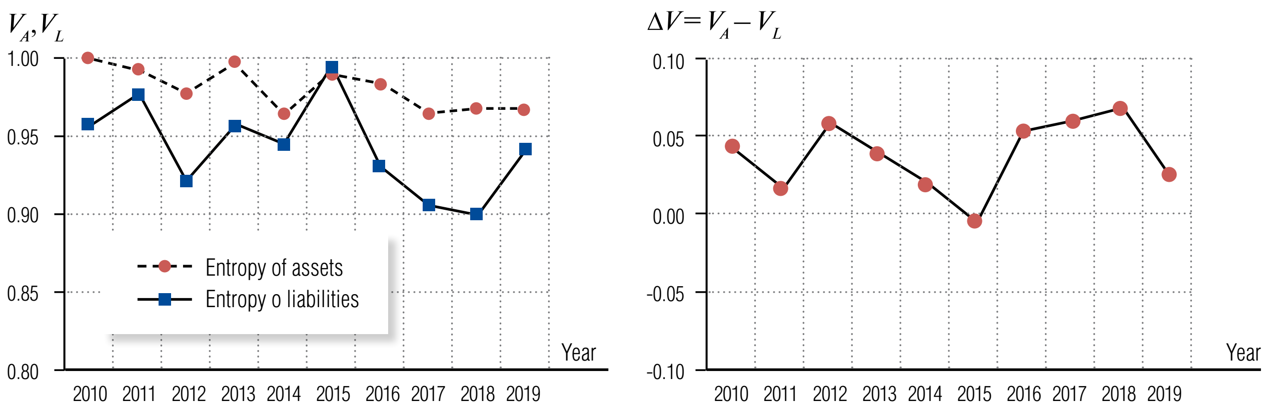

Fig. 11. Entropy of assets (V_A) and entropy of liabilities (V_L) of NVKbank.

Figures 6–11 show characteristic graphs of the time dependencies of the entropy of assets (V_A) and the entropy of liabilities (V_L), calculated by the authors on the basis of data on the balance sheets of [1]:

- licensed banks (*Figs. 6, 7*);
- sanitized banks (*Figs. 8, 9*);
- banks whose license has been revoked (*Figs. 10, 11*).

5. Variances of time dependencies of entropies

An important conclusion of the visual comparison of the time graphs of the entropy of assets and the entropy of liabilities of balance sheets is the obvious presence (*Figs. 6, 7*) or violation (*Figs. 8–11*) of the synchronous behavior of the time dependencies of the entropy of assets (V_A) and the entropy of liabilities (V_L). This fact indicates the expediency of using an estimate of the variance (volatility) of time series of values of the difference in the entropy of assets and liabilities ($\Delta V = V_A - V_L$) as a measure of the spread of the real values of the relative average:

$$\sigma = \sqrt{\frac{\sum_{t=1}^{T}\left(\Delta V_t - \overline{\Delta V}\right)}{T}},$$

where $T = 10$ is the number of observations.

The results of calculating the variances of the time dependencies of the entropy of assets (σ_A), liabilities (σ_L) and the entropy difference ($\sigma_{\Delta V}$) for the period 2010–2019 are shown in *Table 3* for three conditional groups of banks: large, medium and relatively small.

A line-by-line comparison of the variances of the entropy difference ($\sigma_{\Delta V}$) and the status of the banking license gives grounds to assert that existing banks, as a rule, have lower values of the parameter ($\sigma_{\Delta V}$) than those whose license has been revoked.

This statement is not strict in a quantitative sense. That is, the parameter $\sigma_{\Delta V}$ is not a clear criterion that allows you to unambiguously attribute any bank to a particular group. For example, the variance of the entropy difference between assets and liabilities of the rehabilitated bank Uralsib Bank ($\sigma_{\Delta V} = 4.55$) is higher than that of TEMBR-BANK ($\sigma_{\Delta V} = 3.18$). However, the license of Uralsib Bank has not been revoked. It is possible that a permit for the right to operate a credit institution is issued taking into account many factors, including, for example, the size of the bank. Nevertheless, the variance of the entropy difference ($\sigma_{\Delta V}$)) can be used as an integral indicator of problems in the activities of specific banks. Probably, at the next stage of research, it would be advisable to study more broadly and in detail the statistics of the limits of the values of $\sigma_{\Delta V}$ for various groups of banks. It can be assumed that a corresponding study of a larger number of banks (for example, all banks that had a license in 2010) will allow us to estimate the values of constants σ and $\overline{\sigma}$ such that if the inequality $\sigma_{\Delta V} < \underline{\sigma}$ is fair, it can be argued that in the medium term the license of the corresponding bank will not be revoked, and if the inequality $\sigma_{\Delta V} > \overline{\sigma}$ is fair, it can be argued that in the medium term, the license of the relevant bank will be revoked.

In addition, in order to more accurately and objectively determine the time, size and source of the imbalance in the bank's activities, it is necessary to separately analyze the time dependencies of the entropies of the item-by-item distributions of assets and liabilities. It is the method of calculating the entropy of line-by-line distributions proposed in this paper that can give an answer to this question. Moreover, it becomes possible to manage the entropy of banks by purposefully adjusting the item-by-item distributions of assets and liabilities.

Conclusion

The application of the entropy approach to the assessment of the equilibrium of the item-by-item distributions of assets and liabilities of the balance sheet significantly expands the boundaries of the practical use of

[1] See: Banking Analyst portal "Analysis of Banks" (https://analizbankov.ru).

Table 3

Variances of time dependencies of entropies and entropy differences of assets and liabilities

Bank	Currency balance on 01.01.2019 (RUB, thou.)	Entropy variance		Variance of the entropy difference $\sigma_{\Delta V}$ (%)	License
		Assets σ_A (%)	Liabilities σ_L (%)		
VTB Bank	14 331 232 043	1.43	1.47	0.47	Have
SberBank	28 361 319 019	3.23	3.11	0.72	Have
Promsvyazbank	1 667 080 707	3.53	2.17	2.88	Rehabilitation
Uralsib Bank	582 185 086	4.64	0.86	4.55	Rehabilitation
TEMBR-BANK	11 636 190	2.21	2.91	3.18	Withdrawn
NVKbank	12 319 149	2.39	6.42	4.34	Withdrawn

Note: In order to correctly perceive the data, we note that the variance of the entropy difference is not an algebraic sum or the average value of the variances of assets and liabilities.

system methods of analysis and management of the state of credit and financial organizations, since a formalized relationship of entropy with the distribution of financial resources by assets and liabilities has been established.

In particular, within the framework of the study, a methodology for calculating entropy as an integral parameter of arbitrary numerical series is proposed and pilot results of its use in analyzing the dynamics of the state of the management system of specific banks are presented. It is shown that a violation of the synchronicity of changes in the entropy of assets and the entropy of liabilities indicates the occurrence of an imbalance in the state of the bank.

Taking into account the unimodal nature of the dependence of entropy on the parameter of uneven distribution, it becomes possible to localize the cause of the imbalance and make targeted adjustments to the distribution of assets and liabilities. ■

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About the authors

Valentin V. Matokhin

Advisor to the General Director, Joint Stock Company "TEKORA", of. 19-23, fl. 15, 56, Profsoyuznaya Str., Moscow 117393, Russia;

E-mail: vmatokhin@tekora.ru

ORCID: 0000-0003-4447-8922

Anatoliy V. Sigal

Dr. Sci. (Econ.), Professor;

Professor, Department of Business Informatics and Mathematical Modeling, V.I. Vernadsky Crimean Federal University, 4, Vernadskogo Prospekt, Simferopol 295007, Russia;

E-mail: ksavo3@cfuv.ru

ORCID: 0000-0003-2090-4464

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The impact of ICT on inter-organizational knowledge sharing for SMEs growth

Naief Azyabi

E-mail: nazyabi@jazanu.edu.sa

Jazan University

Address: Prince Mohamed Street, Jazan 45142, Saudi Arabia

Abstract

It is common knowledge that information and communication technologies (ICTs) have made continuous inroads in the knowledge management field; thus, this study is modeled to examine the impact of ICTs on inter-organizational knowledge sharing (IOKS) and its subsequent effect on the growth of small and medium-sized enterprises (SMEs). The study adopts a descriptive survey design, using the quantitative research approach. Using the simple random sampling technique, a web-based questionnaire was used to collect data from 187 respondents. Results showed that IOKS among SMEs is not carried out to a great extent, which means that it is not a common practice among SMEs. Findings showed that less than half of the SMEs used training programs, internship programs, research collaboration and workshops for IOKS. It further showed that IOKS enhances sales, productivity, profit, organizational assets and equity. This study provides evidence of how ICT systems/tools have been used in IOKS and their impact on the growth of SMEs.

Keywords: inter-organizational knowledge sharing, small and medium-sized enterprises, information and communication technologies

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Introduction

Generally, the emergence of information and communication technologies (ICTs) has changed practices and procedures in numerous domains. This is evident in knowledge management practices, which include knowledge sharing. IOKS is typically mutually beneficial to all sides involved [1], with the most significant benefit being the integration of ideas [2], which promotes the interchange of concepts on shared goals among collaborating organizations [3]. The relevance and strategic importance of inter-organizational knowledge systems for healthcare providers, government, and other citizens have been demonstrated in several research studies [4, 5]. However, there is no evidence that ICTs have an impact on IOKS in small and medium-sized businesses (SMEs) in terms of SMEs' growth or lack thereof. More importantly, ICTs have permeated all walks of life and it has also been shown that SMEs play a significant role in the driving knowledge-based economy [6, 7]. Moreover, SMEs' growth will positively improve the economic growth of a country [8]. Therefore, it becomes pertinent to understand how SMEs have fared in their use of ICT for inter-organizational knowledge sharing (IOKS) in Saudi Arabia since there is no current empirical evidence in respect of that.

Generally, knowledge has been described by different authors in different contexts. The perspective of this study, however, is viewed from the information science/information systems context, which is the foundation of management information systems. Knowledge is an idea that emanates from human minds and spreads widely when people are interested in its acquisition. It was stated further that efficient knowledge requires awareness, identification and application of it for the advancement of humanity [9]. Huda et al. [10] described knowledge as a tool that is used in enabling the development of an individual and/or society. This suggests that knowledge is dynamic: it evolves by developing from one shape or form to another in the enhancement of a person, group of people, or societal advancement. Nonaka [11] proposed a four-stage model to explain the process of switching from one type of knowledge to another, which includes socialization-externalization-combination-internalization (SECI).

Socialization is concerned with social interaction among individuals to share and exchange tacit knowledge which can be through training programs, while externalization is the conversion of tacit knowledge into knowledge-bearing resources or tangible innovations [12]. Meanwhile, the combination in the SECI model postulates that inter- and intra-organization knowledge coalesce by collecting, merging, editing, and processing, through the use of computers and other information technologies [13]. Internationalization is the assimilation of explicit knowledge pooled together, for example, an online database, which would enhance the tacit knowledge base of the employees in the union organization [14]. Consequently, the newly acquired knowledge would serve as the basis for employees' new routines at work whereby they will put into practice what they have learned or know. Going by Nonaka's model [11], it is evident that there is a clear distinction between tacit and explicit knowledge. Meanwhile, both tacit and explicit knowledge are considered for this study.

IOKS can be described as a process that concerns the distribution and redistribution of employees' inputs among different organizations, where knowledge can be regarded as the input while sharing is the process [15]. Since there is a dearth of literature on inter-organizational knowledge sharing, some scholars' definitions of knowledge sharing are considered to underpin the explanation of the concept. Teixeira et al. [16] viewed knowledge sharing as the generation and donation of knowledge to enhance innovation or creativity. Loebbecke et al. [17] argued that IOKS concerns interpersonal interactions, team-based systems, network ties and business intelligence. This provides that knowledge sharing is the exchange of business and logistics ideas using techniques such as collaboration, combination, compromise, accommodation, avoidance and competition [18]. Yang [19] showed that the use of internal marketing in knowledge sharing enhances organizational effectiveness. It is important to note that organizational effectiveness does not translate into growth [20, 21].

Hinder et al. [2] found that shared technology is one of the facilitators of IOKS. ICTs play a considerable role in IOKS [22], although the overall influence on SMEs' growth is unknown. Audretsch and Belitski [23] recommended that future studies should provide insights into how resources acquired through inter-organizational knowledge exchange might help SMEs' growth. Meanwhile, Oyebiyi [24] asserted that ICTs are critical for SMEs to improve customer service delivery and remain competitive in their respective industries. Based on this, the goal of this research study is to ascertain how ICT can help facilitate IOKS. Inter-organizational knowledge exchange is critical to SMEs [25, 26]. However, there is no specific evidence of the influence of knowledge sharing on SMEs growth in Saudi Arabia. Thus, this study seeks to fill the identified gap.

Moreover, previous studies [27–29] have been conducted on SMEs' adoption of ICTs for knowledge management, which is regarded as knowledge management systems or knowledge management networks. Also, some studies have investigated the impact of IOKS on regional sustainable development [30], cultural differences among different organizations [31] and innovative ideas [32]. While these studies showed how the infusion of ICT in IOKS influences sustainable development, cultural differences and innovations, there is no evidence as to how IOKS influences SMEs' growth. Thus, this study seeks to provide empirical evidence that would plug this obvious gap. The study is significant, because it establishes the influence of applying ICT to IOKS, and how that would impact the expansion and growth of SMEs. The article begins with an introduction that presents essential background information which rationalizes the importance of the research study. The first section establishes the gaps that are present in the literature and, based on these, sets out the research questions that the study findings seek to answer. The second section presents a review of literature related to the themes of the study and illustrates the conceptual model that guides the research. The third section is the methodology section, followed by the results, discussion of findings, conclusion, and practical/theoretical implications set out in a sequential manner.

1. Research questions

Drawing on the background introduction and rationale for carrying out this study, the following research questions guide the study's overall aim:

1. To what extent are SMEs in Saudi Arabia practicing IOKS?
2. What are the ICT systems/tools used by SMEs in inter-organizational knowledge sharing?
3. To what extent is SMEs growth influenced by inter-organizational knowledge sharing?

2. Review of related literature and hypotheses

This section analyses literature related to the use of ICT for facilitating IOKS in SMEs, and the influence of IOKS on SMEs growth.

2.1. IOKS in SMEs

IOKS is a relatively recent topic, but it is expanding [33]. Tesavrita et al. [34] used constructs of collaborative engagement activities that include the timeframe (short or long-term collaboration), technological factor, learning mechanism (discussion, training, internship, research collaboration, and workshops) and entity (stakeholders) to propose a conceptual model for IOKS in SMEs (among stakeholders). The framework was tested using data from two Indonesian SMEs, and the results revealed that IOKS occurred through training, research, internships and discussions. IOKS is essential for social and economic development, most especially in service-based and knowledge-based sectors [5]. Ibidunni et al. [35] considered SMEs as being part of the knowledge-based sector, implying that cross-organizational knowledge sharing is possible.

Chong et al. [26] found that SMEs owners in Malaysia consider how to best design an appropriate strategy to collect relevant information from stakeholders, use this information to enhance business growth, learn from relevant stakeholders and sponsor employees to attend conferences or pursue further studies, as is important in IOKS. It was, however, shown that most of the actions required in inter-organizational knowledge exchange are difficult to implement for SMEs, except for the customer-supplier relationship and license ownership. A qualitative study by Al-Jabri and Al-Busaidi [25] revealed that the influencing elements of IOKS among Omani SMEs include donor firm features, recipient firm features, nature of the knowledge, and inter-organizational dynamics. However, risk and trust were found to be the core factors in the IOKS. It was revealed that knowledge exchange among SMEs is accompanied by a degree of trust. Knowledge intensity has a beneficial effect on inter-organizational trust [36]. Furthermore, the result showed a positive significant relationship between inter-organizational trust and SMEs performance.

Li et al. [37] analyzed the influence of IOKS on enterprise resource planning (ERP) deployment. Organizational preparedness, positive benefits and costs, and external influences were found to be factors that could improve inter-organizational information sharing. Guedda [38] showed that social proximity, leadership style and organizational orientation enhance IOKS. Similarly, Cheng and Fu [39] revealed that both relationship and organizational orientations are essential in promoting cross-organizational knowledge exchange, since they reduce risk in the process of sharing knowledge and improve collaborative behavior. Cheng [40] discovered that in the Taiwanese manufacturing business relational risk is adversely associated with IOKS. Meanwhile, Oliveira et al. [41] showed that trust is essential in inter-organizational relations. This indicates that trust is critical in relational risk and that it is interconnected to the exchange of knowledge among organizations.

2.2. Impact of ICT use in facilitating IOKS in SMEs

Nowadays, ICT is crucial to SMEs, and its impact on social, economic and personal development is well-established in the literature [42, 43]. Technologies and tools have been adopted in inter-organizational collaboration [1, 44, 45] and more technologies are emerging for knowledge sharing with the aim of organizational development [46]. Tesavrita et al. [34] revealed that IOKS was practiced by two SMEs in Indonesia both online and offline; hence, there were no technological issues. This indicates that ICT's influence on facilitating knowledge sharing in SMEs may be limited. Scuotto et al. [28] showed that ICT-driven intra-organizational knowledge sharing would improve innovation processes and enhance new product development for SMEs. Chong et al. [26] showed that the technologies used in IOKS among SMEs include social media, extranet, e-mail, customer management systems, desktop computer conferencing, knowledge repository/company database and teleconferencing.

Organizations in the business and health sectors employ repository information sharing and networking tools for IOKS [5]. The study established that ICT influences the knowledge-sharing patterns of different media, such as text, images, audio and video. However, there is no evidence of the effect of using ICT to facilitate IOKS in SMEs. Al-Busaidi [47] revealed medical doctors' perceptions of the impact of using technologies in IOKS; namely that it resulted in improved staff collaboration, information availability, knowledge-sharing processes, individual learning, and decision-making processes, increased information flow and customer service, saved the organization time and enhanced innovation. Premised on this gap in the literature, this study seeks to provide new insight into SMEs' perspectives.

Altarkait [48] showed that social media have a good social and transactional impact on the inter-organizational interactions of SMEs in Kuwait. Results further showed that the use of social media influences the use of traditional technologies for the inter-organizational exchange of ideas among SMEs. Pérez-González et al. [49] found that adopting social media platforms by SMEs for knowledge sharing has a favorable effect on organizations. Soto-Acosta et al. [50] revealed that technological expertise and competencies have a substantial impact on SMEs' web knowledge sharing. It was shown in another study that technical assistance has a considerable favorable impact on explicit knowledge exchange [51]. This indicates that the significance of technology is unknown in tacit knowledge sharing among SMEs. However, Castaneda and Toulson [52] demonstrated that ICT tools like text messaging and video conferencing enable tacit knowledge exchange, whereas e-mail does not. Burnett [53] established that explicit knowledge sharing plays an important role in technological innovation compared to tacit knowledge sharing. Based on the foregoing, it is hypothesized that:

H1: ICT use has a statistically significant positive effect on IOKS in SMEs.

2.3. Influence of IOKS on SMEs growth

Ahokangas et al. [54] showed that IOKS is a daunting task, especially when it is technology-driven and executed by SMEs without a knowledge management structure. The results further showed that SMEs engage in IOKS when their workload is explosive and there is no alternative to enhance the deliveries. Also, IOKS was found to have a substantial impact on SMEs growth. Chong et al. [26] revealed that the influence of ICT on IOKS is unclear, since the majority of the respondents were neutral regarding the effectiveness of IOKS on corporate performance. Mohsam and Van Brakel [55] found that the strategy taken in sharing both tacit and explicit knowledge determines the success of SMEs in the Western Cape, South Africa and that the IOKS mechanism is a factor of SMEs' competitive advantage.

Cresswell et al. [56] revealed that formal knowledge sharing prompts learning and enhances the growth of an organization. However, it was shown that the formal network in knowledge sharing is more effective when supported by informal networks. Hinder et al. [2] also showed that a hybrid of informal and formal networks in IOKS enhances learning and growth. Al-Jabri and Al-Busaidi [57] revealed that SMEs garnered learning benefits from informal IOKS, and it was discovered that IOKS has no substantial impact on SMEs' innovation performance. Rivera et al. [58] suggested that there is a need for SMEs to consider networks of trust, deference to other SMEs, patience and an enabling work environment. This indicates that there is a need for credibility and belief among SMEs that are participating in IOKS, whether in an informal or formal domain.

Alashwal et al. [59] showed that there is a statistically significant, positive association between IOKS and SMEs performance in the construction industry in Kuala Lumpur, Malaysia. The results showed that inter-organization learning, externalization (tacit knowledge to explicit knowledge), and internalization (explicit knowledge to tacit knowledge) improve SMEs' performance. Hsieh [60] revealed that a successful SMEs adopts a knowledge-sharing mechanism that includes a feedback apparatus, language diversity, personal focus and the availability of multiple cues. Chong et al. [26] found that it is better to share external (explicit) knowledge than internal (implicit) knowledge in inter-organizational knowledge exchange. It was shown that IOKS strategies have been found to have a substantial impact on SMEs success. SMEs growth was not explored by all of the studies in the extant literature, which studied inter-organizational knowledge sharing. Shepherd and Wiklund [61] pointed out that the elements used for measuring SMEs growth include sales, employees, profit, assets and equity. Meanwhile, the impact of IOKS among different organizations was studied in relation to SMEs success. As a result, the goal of the research is to determine how IOKS affects SMEs growth. The following hypothesis will be tested based on the foregoing:

H2: IOKS has a statistically significant, positive effect on SMEs growth.

Moreover, understanding the influence of ICT-enabled IOKS on SMEs' growth may be over simplistic without having evidence on how each ICT tool determines SMEs' growth. Thus, this study attempts to establish how each ICT system/tool predicts SMEs' growth. This will enable SMEs owners to be informed about the most relevant and effective ICT tool to adopt in IOKS. Gaviria-Marin et al. [62] found that ICT has an enabling effect on more complex competencies like knowledge management capability and product innovation flexibility, which serve as mediating variables to add value and boost performance through innovation in business. Ceci et al. [63] established that ICT tools promote creative, strategic and practical tasks when using knowledge sharing in the innovation process. Ammirato et al. [64] concluded in their study that there is low awareness of using social media for knowledge transfer among B2B companies in the Finnish technology industry. This indicates that social media may not significantly predict SMEs' growth. Byosiere et al. [65] showed that social networks do not enhance explicit knowledge, but they enhance tacit knowledge. This was established in an attempt to establish the interrelationships among social networks, knowledge types and knowledge sources. Therefore, this study will test the alternate hypothesis which states that:

H3: ICTs are statistically significant predictors of SMEs' growth.

3. Theoretical framework

This study is underpinned by the open innovation theory. The relationships of the theory with the major themes of the study were established.

Remneland-Wikhamn and Knights [66] chronicled that the open innovation model was proposed by Chesbrough [67]. They noted that the proponent argues that companies tend to protect their innovation by barring any form of knowledge exchange with the external environment, which is regarded as "closed innovation." However, it was shown that a seamless exchange of relevant and appropriate knowledge would expand market opportunities and growth. External knowledge that would enhance organizational performance should be integrated to enhance business performance [68]. This indicates that IOKS is hinged on a business model. Internal knowledge that does not support the business model will be shared. The shift in the practice of open innovation management in organizations gave rise to the idea of open innovation theory [68]. Santoro et al. [69] showed that SMEs in the United States rely on their customers for external knowledge when developing a new product or service.

The move from closed to open innovation theory emphasized the importance of external sources of knowledge and ideas in the innovation process [69, 70]. The open innovation paradigm encourages a systematic approach to rely on both internal and external resources, as well as maximizing both internal and external channels to boost market presence and buoyancy [67]. Gassman and Enkel [71] stated that openness takes place when there is a search for a new source of knowledge from external partners to enhance the internal process; generating and bringing new ideas to market and passing on technology and knowledge to others, and relying on the shared knowledge or ideas to create a synergy that would enhance collaboration. Meanwhile, Eseryel [72] showed that ICTs enhance knowledge creation for open innovation through effective knowledge inflow and outflow. It was established that SMEs size and technology intensity are considered factors of the extent of open innovation in an organization [73, 74].

Open innovation has been studied from the perspectives of open innovation mode, organizational cooperation, and open innovation performance [75]. The authors stated further that open innovation theory is difficult to understand, owing to the lack of clarity on its fundamental concept and measures. Research and technical systems are critical elements in open innovation theory, which guides the perspectives of innovation in SMEs through IOKS [67]. Van de Vrande et al. [74] found that, in comparison with small organizations, medium-sized enterprises are heavily involved in open innovation. The results, however, revealed that SMEs use open innovation to improve their performance in terms of meeting customer needs and gaining a competitive edge. Howells et al. [76] adopted the theory to explore the impact of interactions and collaborations among universities and other higher institutions of learning. Subrahmanya et al. [77] concluded that innovation in sales is a significant contributor to SMEs growth in terms of gross value added. Hence, the result of open innovation, which stems from the integration of external knowledge, contributes to SMEs growth. Studies [78, 79] have shown that technological innovation enhances SMEs growth. Contextually, this implies that ICT-supported, IOKS among SMEs can facilitate their growth. The contemporary technological innovation among SMEs includes the adoption of social media, computerized record management and digital marketing [80]. Love and Roper [81] concluded that, aside from productivity, growth (sales) is another important measure for innovation in SMEs.

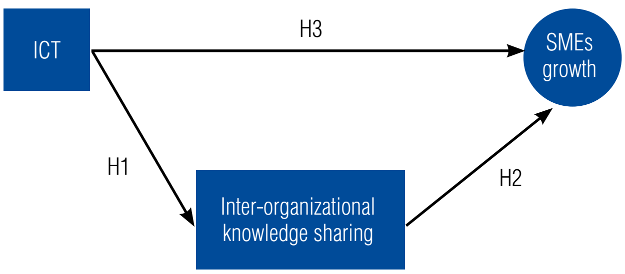

Fig. 1. Conceptual model.

The conceptual model is the framework that guides the interconnected relationships that exist among the variables in this study. The conceptual model is presented in *Fig. 1*. It is proposed that ICT tools (such as social media, extranet, e-mail, customer management systems, desktop computer conferencing, knowledge repository/company database and teleconferencing) have a statistically positive effect on IOKS among SMEs. Moreover, the model illustrates that ICT-enabled IOKS has a statistically significant, positive effect on firm growth. It is also proposed in the model that IOKS (such as discussions, training, internship, research collaboration, and workshops) has a positive effect on SMEs growth (sales, profit, employee productivity, assets and equity).

4. Methodology

A descriptive survey research design was adopted in this study as it seeks to describe a particular phenomenon [82].The quantitative research approach was chosen, because it allows the collection of numerical data from a wide range of individuals or entities [83]. The data were collected using a five-point Likert scale questionnaire with the following scale: Strongly Agree – 5 to Strongly Disagree – 1; Great Extent – 5 to No Extent – 1. Two scholars in the area of knowledge management were given the questionnaire to ensure that the items on the questionnaire were understandable and could elicit the necessary information from the respondents. The questionnaire was revised based on the comments and observations of the scholars, and it was then designed to be a web-based questionnaire. Mubasher [84] reported that the total number of SMEs in the Kingdom of Saudi Arabia (KSA) is 614 000, which represents the population of the study. The simple random sampling technique was adopted for the study. This kind of technique gives equal opportunity to all SMEs owners in KSA [85]. Furthermore, the Raosoft sample size calculator was used to determine the 384-sample size. The link to the web-based questionnaire was shared with the potential respondents and only 187 of them responded to the questionnaire, which amounts to a 48.7% response rate. It has been argued that a 30–40% response rate is appropriate for the web-based questionnaire [86, 87].

Collected data were analyzed with the use of IBM SPSS (version 23). Moreover, the research questions were analyzed using the descriptive statistics of frequency count and simple percentage, while the hypotheses were tested with the inferential statistics of ANOVA and multiple regression. The H1 and H2 are tested with ANOVA, while H3 is tested using multiple regression. Meanwhile, the items that answered questions on IOKS in SMEs were adapted from Tesavrita et al. [34]. The items adapted included discussion, training, internship, research collaboration and workshops. All of these items are designed to elicit the perception of SMEs owners about IOKS. All of these items pose questions about the opinion of SMEs owners in the KSA about discussing knowledge with other SMEs owners. Moreover, the study adopted Chong et al.'s [26] measure to ascertain the impact of ICT use in facilitating IOKS among SMEs. These items are to show how SMEs owners in the KSA have been using ICT to enhance inter-organizational sharing of knowledge. The items adapted included social media, extranet, e-mail and customer management systems. To ascertain the influence of ICT-enhanced IOKS on SMEs growth, items were adapted from Shepherd and Wiklund [61]. The items include sales, employees, profit, assets and equity.

5. Results

This section presents the results from the collection and analysis of the data. The data were analyzed using descriptive statistics (frequency count and simple percentage) and inferential statistics, as described in the methods section (ANOVA and multiple regression). *Tables 1–9* are used to display the results.

Table 1 shows the demographic information from the responses of the respondents. This table shows that the construction industry has the highest representation of respondents (3.58%), while the least representation comes from IT services (11.2%). Meanwhile, manufacturing industry has 21.4%, the restaurant and food industry has 19.3% and retail service has 12.3%. This implies that the participants have more representation from organizations in the construction industry. *Table 1* shows that more than half (54.5%) of the respondents' organizations were between 5–10 years old, while a meager 10.7% were less than two years. It can be seen from table 1 that more than half of the respondents' organizations had less than 50 employees, as 30.5% of them had between 1–5 employees and 47.6% had between 6–49 employees. Meanwhile, only 21.9% had between 50–249 employees. Moreover, a significant number of the respondents' organizations (65.8%) earned less than 3M, while 34.2% earned between 3–40M. Furthermore, it can be observed in *Table 1* that more than half of the respondents (63.1%) were chief executive officers in their organizations. This figure outweighed total representation with roles of director of human resources (9.6%), director of information technology (10.2%), director of accounting and finance (10.7%) and others (6.4%).

Table 2 shows that only 6.4% used discussion as a technique to a very great extent, while 27.3% used it to a great extent, which amounted to 33.7% of the respondents using a discussion with other SMEs as a technique to enhance IOKS. This indicates that discussion with other SMEs was not used to a great extent or a very great extent. Moreover, 7.5% used training programs to enhance IOKS to a very great extent, 25.1% used it to a great extent, 24.6% used it to some extent, 29.9% used it to a little extent, and 12.8% used it to no extent. This implies that only 32.6% used training programs as a means of IOKS to a great and very great extent.

It can be seen in *Table 2* that 8.9% used the internship program to a very great extent, 27.3% used it to a great extent, 27.8% used it to some extent, 28.3% used it to a little extent, and 8.0% used it to no extent. This implies that more than half (54.1%) of the respondents did not use the internship program as a mechanism to partake in IOKS to a great or very great extent. *Table 2* further shows that parsimonious (3.7%) of the respondents used research collaboration with other SMEs to improve IOKS to a very great extent, 24.6% used it to a great extent, 25.1% used it to some extent, 31.0% used it

Table 1.

Demographic information of respondents

Items	Frequency	Percentage (%)
Sector		
IT services	21	11.2
Retail	23	12.3
Manufacturing	40	21.4
Restaurants and food	36	19.3
Construction	67	35.8
Organization's age		
Less than 2 years	20	10.7
2–5 years	65	34.8
5–10 years	102	54.5
Number of employees		
1–5	57	30.5
6–49	89	47.6
50–249	41	21.9
Annual income of organization		
Less than 3M	123	65.8
3–40M	64	34.2
Respondents' role		
Chief Executive Officer	118	63.1
Director of Human Resources	18	9.6
Director of Information Technology	19	10.2
Director of Accounting and Finance	20	10.7
Other	12	6.4

to a low extent, and 15.5% used it to no extent. This suggests that most of the respondents (71.6%) did not use research collaboration with other SMEs to enhance IOKS to either a great or very great extent. Similarly, over two-thirds (67.4%) of the respondents did not organize workshops to enhance IOKS to either a great or very great extent.

Table 3 shows that two-thirds (65.2%) of the respondents either disagreed or strongly disagreed that they adopt social media to share knowledge with other SMEs. Meanwhile, more (20.9%) respondents were neutral compared to those that either agreed or strongly agreed (13.9%) that they adopt social media to share knowledge with other SMEs. *Table 3* shows that more

Table 2.

IOKS practices among SMEs

Items	VGE		GE		SE		LE		NE	
	F	%	F	%	F	%	F	%	F	%
Discussions with other SMEs	12	6.4	51	27.3	55	29.4	43	23.0	26	13.9
Training programs	14	7.5	47	25.1	46	24.6	56	29.9	24	12.8
Internship programs	16	8.6	51	27.3	52	27.8	53	28.3	15	8.0
Research collaboration	7	3.7	46	24.6	47	25.1	58	31.0	29	15.5
Workshops	9	4.8	52	27.8	59	31.6	40	21.4	27	14.4

Table 3.

ICT systems/tools used by SMEs in IOKS

Items	SA		A		N		D		SD	
	F	%	F	%	F	%	F	%	F	%
Social media	9	4.8	17	9.1	39	20.9	78	41.7	44	23.5
Extranet	12	6.4	61	32.6	49	26.2	32	17.1	33	17.6
E-mail	5	2.7	27	14.4	46	24.6	65	34.8	44	23.5
Customer management systems	4	2.1	20	10.7	58	31.0	69	36.9	36	19.3
Computer conferencing	68	36.4	88	47.1	8	4.3	21	11.2	2	1.1

than a quarter (39.0%) of the respondents agreed or strongly agreed that they use extranet in IOKS with other SMEs, while a quarter was neutral on whether they used extranet in IOKS with other SMEs. The *Table 3* also shows that more than half (58.3%) of the respondents disagreed or strongly disagreed that they used e-mail in IOKS with SMEs. It is noteworthy that about a quarter (24.6%) of the respondents were neutral and only about 17.1% either agreed or strongly agreed.

In *Table 3*, greater than half (56.2%) of the respondents disagreed or strongly disagreed that they used customer management systems to share knowledge with other SMEs. Also, it is significant to note in the table that 31.0% were neutral, while 12.8% either agreed or strongly agreed. This suggests that the customer management system is not a popular system/tool used in IOKS among SMEs. Moreover, *Table 3* demonstrates that the majority (83.5%) of the respondents agreed that computer conferencing is used as a tool for inter-organizational conferencing in IOKS with SMEs. This suggests that most organizations used computer conferencing as an IOKS system/tool. As seen in the *Table 3*, only a scanty 4.3% were neutral and 12.3% either disagreed or strongly disagreed.

Table 4 shows that the majority (79.7%) of the respondents believed that IOKS improved sales to a great or very great extent. It also demonstrates that 3.7% viewed IOKS as improving sales only to some extent, 16.0% believed it is improved to a little extent, while a meager 0.5% believed it is improved to no extent. Also,

Table 4 shows that most (75.9%) of the respondents agreed that IOKS enhanced employee productivity. Meanwhile, some 13.9% were of the position that IOKS improved employee productivity to some extent, 9.6% believed it is to a low extent and 0.5% agreed that it was to no extent. Similarly, it was observed that 77.5% responded that IOKS increased profit, 11.2% believed it is to some extent, 9.6% believed it is to a low extent, and 1.6% believed it is to no extent.

Furthermore, *Table 4* indicates that most (69.5%) of the respondents answered that IOKS increased the asset value of an organization; 23.5% believed that it is to some extent, 5.3% answered that it is to a low extent, while 1.6% agreed that it is to no extent. *Table 4* shows that a significant majority (84.0%) of the respondents believe that inter-organizational knowledge improves an organization's equity. It can also be seen in the *Table 4* that 15.5% answered that IOKS improved equity to some extent, while only 0.5% agreed that it is to no extent. It is noteworthy that none of the respondents answered that IOKS improved equity to a low extent.

Table 5 shows that the degree of freedom is 186. The R-value is 0.598, which indicates that there is a positive but linear relationship between the extent of ICT use and IOKS. This means that the sample lies on a positive slope. Also, the *r*-square is 0.357, showing that there is a 35.7% variation in the response variables and explaining the relationship between the extent of ICT use and IOKS. The *f*-statistic is 102.98 for the testing of the hypothesis. Meanwhile, the *p*-value is 0.000, which is less than the 0.05 level of significance. Thus, the alternate hypothesis will be accepted. This means that the extent of ICT use has a statistically significant, positive effect on IOKS.

Table 4.

SMEs growth indicators

Items	VGE		GE		SE		LE		NE	
	F	%	F	%	F	%	F	%	F	%
Improvement of sales	66	35.3	83	44.4	7	3.7	30	16.0	1	0.5
Employee productivity	90	48.1	52	27.8	26	13.9	18	9.6	1	0.5
Profit increase	70	37.4	75	40.1	21	11.2	18	9.6	3	1.6
Asset increase	66	35.3	64	34.2	44	23.5	10	5.3	3	1.6
Improved equity	123	65.8	34	18.2	29	15.5	0	0.0	1	0.5

Table 5.

The relationship between ICT use and IOKS

	Sum of Squares	Mean Square	Std. Error	Df	R	R^2	Adj. R^2	F-stat	Sig.
IOKS	1175.319	1175.319	1.117	186	0.598	0.357	0.354	102.918	0.000
ICT use	2112.692	11.420	0.077						
Total	**3288.011**								

Predictors: (Constant), ICT Use
Dependent Variable: IOKS

Table 6.

The relationship between IOKS and SMEs growth

	Sum of Squares	Mean Square	Std. Error	Df	r	R^2	Adj. R^2	F-stat	Sig.
IOKS	0.145	1175.319	1.117	186	–0.009	0.000	–0.005	0.014	0.906
SMEs growth	1899.321	11.420	0.077						
Total	**1899.465**								

Predictors: (Constant), IOKS
Dependent Variable: SMEs Growth

The hypothesis on IOKS has a statistically significant, positive effect on SMEs growth, as shown in *Table 6*, indicating that the degree of freedom is 186. The R-value is −0.009 can also be seen in the *Table 6*, indicating that there is a negative linear association between IOKS and SMEs growth. This indicates that the sample lies on a negative slope. The *r*-square is 0.000, which shows that there is a 0.00% variation in the response variables, elucidating the association between the two variables. It is also shown that the *f*-statistic is 0.014. The *p*-value is 0.906, which is higher than the significance level of 0.05. Therefore, the alternate hypothesis will be dismissed. Thus, IOKS has a statistically significant, negative effect on SMEs growth.

Table 7 shows that there is a correlation of 0.386 between SMEs' growth (dependent variable) and the model. This shows a positive but weak relationship between the dependent and independent variables (social media, extranet, e-mail, customer management systems, and computer conferencing). Meanwhile, SMEs' growth accounts for 0.149 of the total variation. This indicates that the independent variables only account for 14.9% of SMEs' growth. Also, the goodness-of-fit for the model is 0.125, which implies that the model is not good.

Table 8 shows that the Regression Sum of Squares is 282.8 while the Total Sum of Squares is 1899.4, which indicates that the regression model explains only 282/1899 (about 15%) of the variability in the dataset. The *f*-statistic is 6.332 and the *p*-value is 0.000, which indicates that the model fits the data better than a model without predictor variables. This suggests that the independent variables in the model improve the fit of the model. Since the *p*-value (0.000) is lower than the significance level of 0.05, the alternate hypothesis is hereby accepted. This means that ICT tools/systems are statistically significant predictors of SMEs' growth.

Table 7.

The relationship between ICT tools and SMEs' growth – Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	0.386	0.149	0.125	2.989	0.149	6.332	5	181	0.000

Predictors: (Constant), social media, extranet, e-mail, CMS, conferencing

Table 8.

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	282.803	5	56.561	6.332	0.000
	Residual	1616.662	181	8.932		
	Total	1899.465	186			

Predictors: (Constant), social media, extranet, e-mail, CMS, conferencing
Dependent Variable: SMEs' Growth

Table 9.

Coefficients

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	15.593	1.165		13.385	0.000
	Social media	0.150	0.222	0.050	0.674	0.501
	Extranet	–0.348	0.208	–0.132	–1.673	0.096
	E-mail	–0.041	0.235	–0.014	–0.173	0.862
	CMS	0.419	0.260	0.129	1.611	0.109
	Conferencing	1.171	0.225	0.358	5.205	0.000

Dependent Variable: SMEs' Growth

This, however, may be low as explained by the variability of the dataset.

Table 9 shows that an increase in the use of computer conferencing ($t = 1.171$) for IOKS would increase SMEs' growth. Also, an increase in the use of customer management systems ($t = 0.419$) for IOKS would increase SMEs' growth. Similarly, an increase in the use of social media ($t = 0.150$) for IOKS would increase SMEs' growth. Unlike computer conferencing, social media, and customer management systems, both extranet and e-mail show negative coefficients. This means that an increase in the use of extranet ($t = –0.438$) for IOKS would lead to a decrease in SMEs' growth. Lastly, an increase in the use of e-mail ($t = –0.041$) for IOKS would lead to a decrease in SMEs' growth. In conclusion, the use of computer conferencing in IOKS is the highest predictor of SMEs' growth while the use of an extranet in IOKS would lead to the highest decrease in SMEs' growth.

6. Discussion

The study focuses on the impact of ICT on IOKS for SMEs growth. The conceptual model of the study shows the inter-relationships among ICT use, IOKS and SMEs growth. Findings showed that IOKS among SMEs is carried out only to some extent. It is largely unpopular among the different SMEs that were sampled in this study. It was revealed that not even half of the organizations used discussions with other SMEs, training programs, internship programs, research

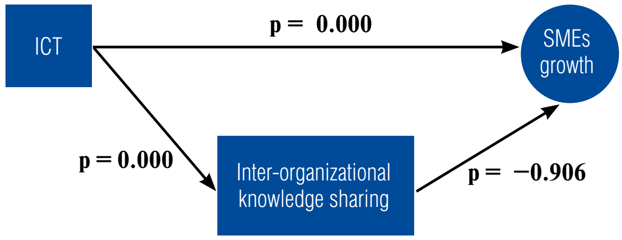

Fig. 2. Research framework showing the results of tested hypotheses.

collaboration and workshops. The finding of this study is different from that of Tesavrita et al. [34], which showed that training, research, internship and discussion are all avenues for IOKS. While it is accepted that IOKS is relatively recent [33], evidence provided in this study shows that it has not been adopted to a great extent among SMEs. The result of the study reinforces the findings of Chong et al. [26] that IOKS among SMEs in Malaysia is unpopular and difficult to implement. Al-Jabri and Al-Busaidi [25], however, showed that some factors that determine this challenge include the nature of knowledge, senders' and recipients' characteristics, and inter-organizational dynamics.

The findings of this study showed that social media are not popular as a medium for IOKS among SMEs. Results showed that more of the respondents were neutral compared to those that agreed they used social media for IOKS. Tesavrita et al. [34] revealed that IOKS could be offline and online. This suggests why social media may not be popular and why there may be more offline mediums of IOKS. This is supported by findings from the literature that social media are an avenue for IOKS [26, 48, 49]. Also, the results of the study showed that extranet, e-mail, customer management systems and computer conferencing were among the least used for IOKS among SMEs. This differs from the findings of Al-Busaidi and Olfman [5] that the business sector used ICT tools for IOKS organizations. Castaneda and Toulson [52] revealed that video conferencing can facilitate IOKS, while e-mail does not enhance IOKS.

Results of this study showed that ICT-enabled IOKS improves sales and enhances employee productivity to a great extent. Shepherd and Wiklund [61] had this same finding. The findings also showed that IOKS increased profit to a great extent. The study results showed that IOKS increases organizational asset value to a great extent. It was also shown by Mohsam and Van Brakel [55] that IOKS among SMEs will enhance competitive advantage. The study findings revealed that the IOKS improves organizational equity to a great extent. Chong et al. [26] revealed that the influence of ICT on IOKS among business owners is unclear.

Furthermore, Cresswell et al. [56] showed that IOKS enhances organizational growth, which supports the findings of this study. Similarly, other studies [2, 57] found that IOKS not only improves learning among employees but enhances the growth of SMEs. It was found that the extent of ICT use has a statistically positive significant effect on IOKS. Also, IOKS has a statistically significant, negative effect on SMEs growth. This is dissimilar to the findings of Alashwal et al. [59] that there is a statistically significant, positive relationship between inter-organizational sharing and SMEs performance in the construction industry in Malaysia. Meanwhile, the greatest representation (35.8%) of the sampled respondents was from the construction industry.

The findings of this study showed that ICT tools are statistically significant predictors of SMEs' growth. However, the findings showed that the correlation between the model and SMEs' growth is positive but weak ($r = 0.386$). Results indicate that the independent variables improve the fit of the model, but the model explains only 15% of the variability in the dataset. The test of the hypothesis further shows that the model is not of good fit, suggesting that the model is not good. However, it was established that the model is better than a model without predictors of SMEs' growth. This suggests that the predictors improve the fit of the model, albeit minimally. Results illustrate that out of the five predictors, only computer conferencing, customer management systems and social media positively predict SMEs' growth. This buttresses previous studies' [26, 48, 49] findings that social media, customer management systems and computer conferencing have a significant effect on the performance of SMEs. Meanwhile, both extranet and e-mail are negative predictors of SMEs' growth. This has mixed findings with Castaneda and Toulson [52] that showed that video conferencing has a significant impact on the adoption of ICT among SMEs, but e-mail does not have a significant impact.

7. Conclusion and implications

This study examined the impact of ICT on IOKS for SMEs growth. It was established in the study that IOKS among SMEs takes place to some extent and that SMEs do not use avenues such as training programs, internship programs, research collaboration and workshops to share knowledge. The study also concluded that the use of ICT tools such as social media, extranet, e-mail, customer management systems and computer conferencing was not common for IOKS among SMEs. The study established that ICT-enabled, IOKS enhances sales, productivity, profit, organizational asset value and equity to a great extent. The first alternate hypothesis tested was accepted, as it was concluded that ICT use has a statistically significant, positive impact on IOKS. The second alternate hypothesis was rejected, and it was thus established that IOKS has a statistically significant, negative effect on SMEs growth. The third alternate hypothesis is accepted, which shows that ICT tools-enabled IOKS are statistically significant predictors of SMEs' growth. Moreover, it was shown that using social media, computer conferencing and customer management systems for IOKS would improve SMEs' growth. However, the use of e-mail and extranet in IOKS would lead to a decrease in SMEs' growth. Based on the study's conclusions, the following recommendations were proffered:

1. SMEs should ensure they use the avenue of training programs, internship programs, research collaboration and workshops to share knowledge among themselves.
2. There should be an increase in the use of ICT tools/systems to enhance IOKS among SMEs.
3. Future studies may consider examining the same research area using a qualitative research approach to have a detailed understanding of how IOKS enhances SMEs' growth.

The theoretical implication of the findings is that ICT can be used to facilitate IOKS among SMEs. Moreover, ICT tools enhanced IOKS and SMEs' growth. It has been further established that IOKS among SMEs has a statistically negative effect on SMEs growth. This means that theoretical models should consider that ICT has a significant effect on IOKS among SMEs. In practice, the study showed that SMEs owners and employees should endeavor to leverage the opportunity of sharing knowledge with other SMEs using avenues such as training programs, internship programs, research collaboration and workshops. Based on the findings, it is suggested that SMEs owners should consider using social media, computer conferencing and customer management systems in order to enhance their business expansion and growth. The findings of the study also added to the theory that the use of ICT tools/systems enhances IOKS among SMEs. Moreover, the Ministry of Commerce (KSA) should endeavor to provide enabling policies to enhance ICT-enabled IOKS among SMEs. ■

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About the author

Naief G. Azyabi

Ph.D.;

Associate Professor, Department of Management Information Systems, College of Business Administration, Jazan University, Jazan 45142, Saudi Arabia;

E-mail: nazyabi@jazanu.edu.sa

ORCID: 0000-0003-0798-8114

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Driving factors of changes in energy intensity: A comparison between energy exporting and importing countries

Mehdi Fallah Jelodar [a]
E-mail: Mehdi.fallah_jelodar@yahoo.com

Somaye Sadeghi [b*]
E-mail: Somysadeghi@yahoo.com

[a] Department of Mathematics, Ayatollah Amoli Branch, Islamic Azad University
Address: 5 Km of the old road from Amol to Babol, Amol 678, Iran

[b] Department of Financial Management, Ayatollah Amoli Branch, Islamic Azad University
Address: 5 Km of the old road from Amol to Babol, Amol 678, Iran

Abstract

This paper compares the driving factors of changes in energy intensity in both net energy exporting and importing countries using a DEA-Malmquist (Data Envelopment Analysis) and panel GMM (Generalized Method of Moments) methods over the period of 2000–2021. The findings show that

* Corresponding Author

technological progress has played a significant role in reducing of energy intensity in both groups. Moreover, we use the DEA method to decompose the Malmquist total factor productivity (*TFP*) into its components including technical change (*TC*), efficiency change (*EC*), pure efficiency change (*PEC*) and scale efficiency change (*SEC*). The results show that in energy exporting countries, the effects of each of these *TFP* components on energy intensity are negative but relatively weak, while the effects of these components on reducing energy intensity in importing countries is considerable. Specifically, the estimated coefficient of the pure efficiency component in reducing energy intensity in very remarkable, which shows the high importance of the efficiency components of *TFP* in energy management. Next, we investigate what is the main driver of technological progress in both the energy exporting and importing countries. The findings imply that in net energy exporting countries trade openness is a dominant factor to improve productivity, while in net energy importing countries, internal R&D is the dominant factor for improving technological efficiency.

Keywords: energy intensity, DEA-Malmquist, trade liberalization, foreign direct investments, internal R&D, energy dependence countries

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Introduction

The sustainability of energy and hence economic development depends crucially on the efficient use of energy [1]. Therefore, the energy intensity of a country is regarded as an important indicator of economic development. Due to the extreme importance of energy intensity reduction, numerous researchers have focused on identifying the key determinants of energy intensity and providing an improved understanding of this trend. Economic growth, technology, structural effects and international trade are widely accepted as the factors that have contributed most to the decline in energy intensity [2–5]. Many authors have agreed that technological change has a stronger impact on the energy intensity than other factors [6, 7]. Overall, the empirical results are mixed and the literature has not provided any information about whether the energy endowment could influence the driving factors of the energy intensity changes of a country. However, there is a large imbalance between not only regions but also countries with respect to the use of energy resources around the world. The evidence shows that the energy intensities of most energy exporting countries have historically been very high compared with energy importing and industrialized economies. Also, the International Energy Agency (IEA) [8, 9] has emphasized that higher endowment of energy has led to a rapid rise of energy intensity. On the other hand, the scarcity of energy resources around the world begets the emergence of a great competition for increasing energy efficiency among countries, especially energy importing countries. However, understanding the determinants (or drivers) of energy intensity in countries with energy dependence (exporting or importing) is important for economic researchers and policymakers; despite this, the studies are scarce. Therefore, this paper has compared the main driving factors of energy intensity changes between net energy exporting and importing countries using dynamic panel data during 2000–2021. In order to have a better understanding of technological progress, we employed DEA-Malmquist approach for each country to decompose *TFP* into technical change and efficiency change. Next, we would determine the sources of technical efficiency in the selected energy exporting and importing countries; such a comparison enables us to identify the main factors that most effectively influence technical efficiency and result in declining energy intensity.

The rest of the paper is organized as follows. The first section is an overview the literature. Section two presents the research methodology and data description. In section three, we analyze the empirical results related to DEA-Malmquist and GMM regressions for both net energy importing and exporting countries. The last section includes the conclusion and recommendations.

1. Literature review

Energy intensity is an important index that plays a significant role in sustainable development. The experience of economies shows that advanced industrial economies consume less energy per unit of production than traditional economies. This is highly dependent on the economic infrastructure factors in any country. One of the main factors is economic development and technological advancement. The process of economic growth and development is accompanied by widespread structural changes in the economy, technology and lifestyle of society. These all influence the consumption behavior and productive structure of the country, resulting in changes in energy intensity [10, 11]. Some researchers confirm that the relationship between economic growth and energy intensity is an inverse *U*, so that energy consumption will increase at the beginning of the process of economic development and industrialization due to the expansion of the mother industries, infrastructures and other energy-intensive economic activities. Then, in the post-industrial phase, energy intensity decreases due to technological progress and its spillovers [12, 13]. Sun [14] confirms that the main reason of declining energy intensity in OECD countries during 1971–1998 was technological advancements. Lin and Du [15] reveal that technological change has had a stronger impact on the energy intensity than other factors, so that contributes to declining energy intensity in China by 22.4% during 2003–2010. Huang et al [7] decomposed technical progress using DEA and found that technical change and its components (technical efficiency and pure efficiency) have significant influences on the regional energy intensity in China. By contrast, Gillingham et al. [4] claim that the reduced cost of use brought about by technological improvements may increase energy use, which can lead to higher energy intensity.

At the same time as globalization in economic issues, the degree of economic openness (trade and financial) has been another factor affecting energy intensity. Major studies have demonstrated that technical spillovers to industrializing countries from advanced economies are given a fillip by trade openness [16–19]. According to the literature, the impact of economic openness on energy intensity varies, and the final effect depends on the resultant force of scale, composition and technical effects. The scale effect suggests that along with economic opening and expanding trade, economic activities increase and thus lead to changes in energy consumption. The composition effect shows up in a change in the composition of the manufactured goods. Thus, how energy intensity is affected depends on the pattern of specialization of the economies and in other words on the type of comparative advantage. According to the composition effect, energy consumption is reduced when the economy is specialized in less energy-intensive sectors. The technique effect refers to utilizing energy-saving technologies and their spillover effects in the domestic economy [6]. The technique effect indicates that economic opening and foreign direct investment enhance the chances of imitating and learning from foreign firms and hence would encourage domestic firms to adopt technologies with higher energy efficiency. Ultimately, the competition created by economic opening reduces energy intensity in the host country [20, 21]. Adom [18, 22] indicates that energy intensity in Nigeria is significantly reduced by trade openness, and the author reports similar results for South Africa. He argues that shifts in trade patterns in favor of imports tend to decrease energy intensity, implying that the reduction in energy intensity in South Africa is the result of an increase in imports relative to exports. Rafiq, Salim, and Nielsen [23] investigate 22 developing economies' energy intensity, including Angola, Gambia, Namibia, Sudan, and Zambia, demonstrating reduced energy intensity from trade openness. Cole [24] found that trade openness and energy use can have either a positive or a negative relationship, depending on the structure of trade; in particular, this is affected by countries being net exporters or importers of energy-intensive products. This intersection leads each country to shift resources into sectors that make the most efficient use of lucrative resources in order to decrease energy intensity.

Resource endowment is associated with the reserves of coal, oil and natural gas, exerting great influence on the selection and development of industry (or technology) and indirectly determining energy consumption. IEA [8, 9] has reported that higher endowment of energy has led to a rapid rise of energy intensity. Jiang et al [25] analyzed the China provinces' energy consumption taking into account energy-resource endowment. They indicate that provinces endowed with rich energy reserves were inclined to consume much more energy than those otherwise. Evidence also shows that in countries with greater domestic resource availability, their energy intensity is relatively high because of lower prices, fewer incentives to maximize energy efficiency and less fear of import dependency [26, 27]. Likewise, government subsidies and naturally low energy prices (due to proximity to source) in these countries impede factor productivity and reduce the incentive for investment in energy efficiency. Wing [28] indicates that eliminating energy subsidies can optimize energy consumption and thereby reduce energy intensity, especially if it follows investments in the appropriate infrastructures that increase productivity and modernize technology and equipment. Also, Samarghandi [29] explains that all OPEC countries have begun to tentatively eliminate or reduce their subsidized energy sectors, though much more must be done as these countries have to adopt energy efficient production technologies.

However, this question of what drives a decline in energy intensity in countries with energy dependence (exporting or importing) is important for economic researchers and policymakers; despite that, the studies are scarce. Samarghandi [29] investigates the roles of trade openness, technological innovation, and energy price in energy intensity in OPEC countries using panel ARDL approaches during the period 1990–2016. The findings show that trade openness plays a key role in diminishing energy intensity and demonstrates that innovation is insignificantly associated with energy intensity. Huang et al [7] investigate the driving forces of China's provincial energy intensity by using DEA-Malmquist approaches during 2000–2014. The results indicate that technological progress plays a dominant role in decreasing China's overall energy intensity. Moreover, rapid industrialization should be responsible for China's currently high energy intensity, while energy price hikes are conducive to reducing energy intensity. Atalla and Bean [30] investigated the drivers of energy productivity changes occurring in 39 countries during 1995–2009. They found that higher levels of income per capita and higher energy prices are associated with greater energy productivity, while a greater share of output from industry is associated with lower energy productivity levels. In particular, higher energy prices and income levels are associated with improvements in sectoral energy productivity. Rühl et al. [31] draw on evidence from the last two centuries of industrialization and analyze energy intensity over the long- and short-run. They argue that the increased specialization of the fuel mix, coupled with accelerating convergence of both the sectoral and technological composition of economies, has improved energy intensity of economic output. Fankhauser and Cornillie [32] investigate energy intensity in transition countries. Their findings show that energy prices and progress in enterprise restructuring are the two most important drivers for more efficient energy use.

2. Methodology and data description
2.1. Model specification

We use a Cobb–Douglas production function as follows:

$$Q = A\,K^{\alpha}\,L^{\beta}\,E^{\gamma}\,, \qquad (1)$$

where Q is the output;

A is the total factor productivity (TFP);

K is the capital stock;

L is the employment;

E is the energy consumption.

Assuming constant returns to scale, production cost can be expressed as follows:

$$C(P_K;P_L;P_E;P_M;A) = A^{-1} P_K^{\beta_K} P_L^{\beta_L} P_E^{\beta_E} P_M^{\beta_M} Q, \qquad (2)$$

where P_L, P_K, P_E and P_M are defined as the prices of labor, capital, energy and raw materials;

β_L, β_K, β_E and β_M represent the related price elasticity, respectively.

According to Shepard's lemma, after making P_E-derivation, *Eq. 2* can be changed to the following as:

$$E = \frac{\beta_E A^{-1} P_K^{\beta_K} P_L^{\beta_L} P_E^{\beta_E} P_M^{\beta_M} Q}{P_E}. \qquad (3)$$

By setting $P_Q = P_K^{\beta_K} P_L^{\beta_L} P_E^{\beta_E} P_M^{\beta_M}$ and dividing both sides on Q, the energy intensity (EI) equation is extracted as follows:

$$EI = \frac{E}{Q} = \frac{\beta_E A^{-1} P_Q}{P_E}. \qquad (4)$$

Now, by taking a logarithm on both sides, we get the energy intensity equation for country i as follows:

$$\ln\left(EI\right)_{it} = \beta_0 + \beta_1 \ln\left(\frac{P_E}{P_Q}\right)_{it} + \beta_2 \ln\left(TFP\right)_{it} + \beta_3 \ln\left(Induva\right)_{it} + \varepsilon_{it}. \qquad (5)$$

According to Huang et al. [7], the Malmquist total factor productivity (*TFP*), which is expressed as a Data Envelopment Analysis (DEA), measures the *TFP* change over time and has been proven well-suited for measuring technological progress. Hence, to capture the influence of technological progress on energy intensity exactly, we use the DEA approach and make the *TFP* decompose into technical progress change (*TC*) and comprehensive technical efficiency (*EC*). Therefore, we get:

$$\ln\left(EI\right)_{it} = \beta_0 + \beta_1 \ln\left(\frac{P_E}{P_Q}\right)_{it} + \beta_2 \ln\left(TC\right)_{it} + \beta_3 \ln\left(EC\right)_{it} + \beta_4 \ln\left(Induva\right)_{it} + \varepsilon_{it}. \qquad (6)$$

Moreover, the comprehensive technical efficiency change (*EC*) can be further decomposed into pure technical efficiency change (*PEC*) and scale efficiency change (*SEC*) by introducing variable returns to scale distance functions. The model reads as follows:

$$\ln\left(EI\right)_{it} = \beta_0 + \beta_1 \ln\left(\frac{P_E}{P_Q}\right)_{it} + \beta_2 \ln\left(TC\right)_{it} + \beta_3 \ln\left(PEC\right)_{it} + \beta_4 \ln\left(SEC\right)_{it} + \beta_5 \ln\left(Induva\right)_{it} + \varepsilon_{it}. \qquad (7)$$

According to the production process, accessing energy resources, technical standards and the extent of opening up are different in countries, hence the energy intensity of each country is quite different. Thus, such an analysis is likely most useful at the comparison level between energy exporting and importing countries. Therefore, we classify the countries into two groups including net energy exporting and importing countries. Then, we estimate *Eq. 7* for each group. In addition, following previous studies, the countries may seek to increase efficiency, encourage the firms to conduct internal R&D [33] or adopt foreign technology [34, 35] or trade openness [36]. Hence, for determining the sources of technical efficiency in energy exporting and importing countries, such a comparison enables us to identify the main factors that most effectively influence technical efficiency and result in declining energy intensity.

2.2. Data description

As implied before, we attempt to evaluate the driving factors of energy intensity changes by comparing between energy exporting[1] and importing[2] countries. The final regression model for each group follows from *Eq. 7*. Data are annual and per constant price GDP 2015 year and extracted from the World Bank and IEA. The studied period is selected during 2000–2021, considering availability of data.

The data description is as follows: EI_{it} denotes energy intensity of country i at time t. Energy intensity is calculated as the ratio of energy consumption (barrels of oil) to GDP at constant purchasing power parities of the year 2015; α_i are country-fixed effects; P_E/P_Q is the energy relative price that is calculated as the ratio of the fuel and power price index to producer price index. *Induva* is the share of the industrial sector in economic, and ε_{it} is disturbance terms assumed to be white-noise and uncorrelated.

TC, *PEC*, *SEC* are the technological progress and its components. In order to measure these dynamic efficiencies, we employed the DEA-Malmquist approach to gain *TFP* changes for all countries. We use the productivity with distance function. There is a production possibility set S. S represents the ability to achieve the transformation of x to y, and the point (x, y) in the S at which it can achieve the largest output y in every given input x is in the production frontier. With production possibility set S, the distance function in time t (1, 2, ..., T) is shown in *Eq. 8*.

$$D(x;y) = \inf\left\{\theta : \left(x; y\middle|\theta\right) \in S\right\} = \left(\theta : (x;\theta y) \in S\right)^{-1}, \quad (8)$$

where $D(x, y) \leqslant 1$, if and only if point $(x, y) \in S$; and $D(x, y) = 1$, if and only if point (x, y) is in the production frontiers.

The Malmquist index is defined as:

$$M(x^{(t+1)}; y^{(t+1)}; x^t; y^t) = \left[\left(\frac{D^t(x^{t+1}; y^{t+1}}{D^t(x^t; y^t)}\right) \cdot \left(\frac{D^{t+1}(x^{t+1}; y^{t+1}}{D^{t+1}(x^t; y^t)}\right)\right]^{1/2}. \quad (9)$$

We have divided it into two functions, D^t and D^{t+1}, in time t and $t+1$. Thereby, *Eq. 9* has two parts: the first one is the percentage in the distance function D^t, between the possible output in time $t+1$ and its real time t. The second part is the distance function D^{t+1}, between the real output in $t+1$ and the possible output in time t. Fare and Grosskopf [37] constructs the technical Malmquist index from t to $t+1$ and decompose it into two parts: comprehensive technical efficiency (*EC*) and technical progress change (*TC*) that are called "frontier" technological progress and "following" technological progress, respectively:

$$EC = \frac{D^{t+1}(x^{t+1}; y^{t+1})}{D^t(x^t; y^t)}. \quad (10)$$

$$TC = \left(\frac{D^t(x^{t+1}; y^{t+1})}{D^{t+1}(x^{t+1}; y^{t+1})} \cdot \frac{D^t(x^t; y^t)}{D^{t+1}(x^t; y^t)}\right)^{1/2}. \quad (11)$$

In the formulas above: the Malmquist index M is defined as productivity changes, $M > 1$ means productivity level increase, $M < 1$ indicates productivity level decrease and $M = 1$ means productivity level remains unchanged. Also, *EC* is defined as the comprehensive technical efficiency and indicates the advantages and disadvantages of management decisions and resource allocation, $EC > 1$ means improvement in *EC* , management methods and resource allocation. $EC < 1$ indicates decline of technical efficiency, inappropriate management decisions and insufficient

[1] Net energy exporting countries include Norway, Kazakhstan, Russia, Uzbekistan, Canada, Colombia, Mexico, Venezuela, Indonesia, Malaysia, Australia, Algeria, Egypt, Nigeria, South Africa, Iran, Kuwait, Saudi Arabia and United Arab Emirates.

[2] Net energy importing countries include Ukraine, South Korea, China, Thailand, United States, The Czech Republic, New Zealand, Belgium, Sweden, Argentina, Poland, India, Brazil, Chile, France, The Netherlands, Japan, Germany, Spain, Portugal, Romania, Italy, Turkey and the United Kingdom.

utilization of resource, and $EC = 1$ means the EC remains unchanged. Moreover, TC indicates changes in technological progress, that is, changes in technological innovation and industrial production technology. $TC > 1$ indicates progress in production technology. $TC < 1$ indicates a decline in production technology, and $TC = 1$ means the technological progress remains unchanged.

According to the DEA model, the technical efficiency change (EC) can be further decomposed into pure technical efficiency change (PEC) and scale efficiency change (SEC), by introducing variable returns to the scale distance function. Thereby, the Malmquist index is expressed as *Eq. 12*:

$$M(x^{t+1}; y^{t+1}; x^t; y^t) = EC \cdot TC = (PEC \cdot SEC) \cdot TC. \quad (12)$$

By supposing the subscripts v and c refer to variable returns to scale technology and constant return to scale technology, respectively, thereby, the PEC and SEC can be expressed as:

$$PEC = \frac{D_v^{t+1}(x^{t+1}; y^{t+1})}{D_v^t(x^t; y^t)}. \quad (13)$$

$$SEC = \frac{D_c^{t+1}(x^{t+1}; y^{t+1})}{D_c^t(x^t; y^t)} \cdot \frac{D_v^t(x^t; y^t)}{D_v^{t+1}(x^{t+1}; y^{t+1})}. \quad (14)$$

Finally, we employ the dynamic panel data method to run the regression model. A reliable solution for the efficient estimation of dynamic panels was set by Arellano and Bond [38] by using the Generalized Method of Moments (GMM). This estimator has become extremely popular, especially in the context of empirical dynamic research, because it allows one to relax some of the OLS assumptions. The Arellano and Bond estimator corrects for the endogeneity in the lagged dependent variable and provides consistent parameter estimates even in the presence of endogenous right-hand-side variable. It also allows for individual fixed effects, heteroscedasticity and autocorrelation within individuals [39]. Consistency of the GMM estimator depends on the validity of the instruments. As suggested by Arellano and Bond [38], Arellano and Bover [40], and Blundell and Bond [41], two specification tests are used. Firstly, the Sargan/Hansen test of over-identifying restrictions which tests for overall validity of the instruments and the null hypothesis is that all instruments as a group are exogenous. The second test examines the null hypothesis that error term ε_{it} of the differenced equation is not serially correlated particularly at the second order (AR(2)), and one should not reject the null hypothesis of both tests.

Table 1.

IPS unit root test at level

Variables	Energy exporting countries	Energy importing countries
ln(*EI*)	–7.44 (0.000) *	–3.14 (0.0008)
ln(*TFP*)	–6.88 (0.000)	–3.67 (0.0001)
ln(*TC*)	–8.64 (0.000)	–3.180 (0.0007)
ln(*EC*)	–11.96 (0.000)	–14.08 (0.000)
ln(*PEC*)	–8.41 (0.000)	–10.26 (0.000)
ln(*SEC*)	–12.47 (0.000)	–12.61 (0.000)
ln(*PE/PQ*)	–4.56 (0.000)	–2.93 (0.0017)
ln(*Induva*)	–5.09 (0.000)	–7.01 (0.000)
ln(*trade*)	–2.05 (0.020)	–2.32 (0.010)
ln(*FDI*)	–2.85 (0.002)	–3.46 (0.0003)
ln(*internal RD*)	–5.78 (0.000)	–2.79 (0.0026)

* Figures in parentheses are significant prob. value

3. Results

Before estimating the regression models for each group of countries, an important step was to test for unit roots with stationary covariates. Hence, we used the Im, Pesaran, and Shin [42] unit root test assuming that the series are non-stationary. *Table 1* presents the results of the IPS unit root test. The findings demonstrate that all variables in both groups are stationary at the level. In other words, all variables are integrated with order (0).

Tables 2, *3* report the results of dynamic panel estimations in net energy exporting and importing countries. The findings imply that in net energy exporting countries, technological progress and its components enhance productivity; thereby they have significant effects to reduce energy intensity. However, the effects are relatively weak. According to the results, a percent increase of total factor productivity (*TFP*) in the energy exporting countries causes a decrease in energy intensity of 0.047 percent. Also, after *TFP* decomposing into the technical change (*TC*) and the efficiency change (*EC*), in energy exporting countries *TC* has a negative and significant effect on energy intensity, interestingly, so that a percent increase in *TC* causes a decrease in energy intensity by 0.051 percentage. The effect of *EC* on declining energy intensity is not significant, as expected. When *TFP* is further decomposed into the technical change (*TC*), the pure efficiency (*PEC*) and the scale efficiency change (*SEC*), the results show that the coefficients of the components related to *TC* and *SEC* are significantly negative in energy exporting countries, although, the estimated coefficients are weak. Some causes are the imperfect infrastructures and relatively lower level of technology and economic development in most energy exporting countries, so the positive effects of technology progress on energy intensity are not be maximized. Another main note is that the negative effect of *PEC* on energy intensity is not significant in these countries. In other words, due to the cheapness of energy resources in exporting countries, the role of net efficiency in reducing energy intensity has not been paid enough attention.

The findings in net energy importing countries indicate that technological progress and its components have significant and negative effects on energy intensity, so that these effects are at least very much greater than those in energy exporting countries. The results show that a percent increase of total factor productivity (*TFP*) in the importing countries causes a decrease in energy intensity of 0.120 percent. Also, after *TFP* decomposing into the technical change (*TC*) and the efficiency change (*EC*), both coefficients are significant and negative, so that a percent of increases in *TC* and *EC* causes a decrease in energy intensity by 0.078 and 0.245 percentages, respectively. This means that in energy importing countries, the coefficient of efficiency change is very much larger than that of technical change. It implies that the effects of technical progress on energy intensity can occur through both technical and efficiency changes. When *TFP* is further decomposed into the technical change (*TC*), the pure efficiency (*PEC*) and the scale efficiency change (*SEC*), the coefficients of these components are negative and highly significant in energy importing countries. Specifically, the estimated coefficient of the pure efficiency component in reducing energy intensity in very remarkable and shows the high importance of the efficiency components of *TFP* in energy management.

Overall, we can say that technological progress and its components are a main driver of energy intensity changes in both energy exporting and importing countries. However, the elasticity in energy importing countries is much greater than in energy exporting countries. A large portion of the stronger effects of *TFP* on the energy intensity in energy importing countries is through the pure efficiency change and its spillovers.

Next, we investigated what is the main driver of technological progress in the energy exporting and importing countries. However, there are differences in the development level, R&D inputs, energy resources and education between energy exporting and importing countries. We examine whether innovation activities

Table 2.

The GMM results for energy intensity changes in energy exporting countries

Variables	Model 1 (TFP)	Model 2 $(TFP = TC \cdot EC)$	Model 3 $(TFP = TC \cdot PEC \cdot SEC)$
$\ln(EI)$	0.9011 (0.0000) *	0.9127 (0.0000)	0.8973 (0.0000)
$\ln(TFP)$	–0.0475 (0.0003)		
$\ln(TC)$		–0.0513 (0.0024)	–0.0392 (0.0064)
$\ln(EC)$		–0.0428 (0.136)	
$\ln(PEC)$			–0.0189 (0.1144)
$\ln(SEC)$			–0.0300 (0.0020)
$\ln(PE/PQ)$	–0.0178 (0.337)	–0.0167 (0.486)	–0.0379 (0.6062)
$\ln(Induva)$	0.1215 (0.0000)	0.1198 (0.0000)	0.0502 (0.0058)
Sargan – p-value	0.358	0.325	0.337

* Figures in parentheses are significant prob. values

Table 3.

The GMM results for energy intensity changes in energy importing countries

Variables	Model 1 (TFP)	Model 2 $(TFP = TC \cdot EC)$	Model 3 $(TFP = TC \cdot PEC \cdot SEC)$
$\ln(EI)$	0.9760 (0.0000) *	0.9643 (0.0000)	0.9662 (0.0000)
$\ln(TFP)$	–0.1202 (0.0000)		
$\ln(TC)$		–0.0782 (0.0000)	–0.0590 (0.0000)
$\ln(EC)$		–0.2454 (0.0000)	
$\ln(PEC)$			–0.2584 (0.0000)
$\ln(SEC)$			–0.1613 (0.0000)
$\ln(PE/PQ)$	–0.1035 (0.0000)	–0.0998 (0.0000)	–0.1016 (0.0007)
$\ln(Induva)$	0.12173 (0.0000)	0.1262 (0.0000)	0.1526 (0.0003)
Sargan – p-value	0.397	0.364	0.327

* Figures in parentheses are significant prob. values

including internal R&D and adoption of foreign technology (*FDI*) have differential effects on their technological efficiency. Likewise, we examined the role of trade liberalization on technological efficiency by considering the argument that trade liberalization enables firms to achieve high levels of efficiency through "learning-by-exporting-effects". *Table 4* reports the results of GMM estimations for *TFP* in both groups of selected energy exporting and importing countries. The findings imply that in net energy exporting countries, *FDI* inflows and trade openness causes improved productivity. The estimated coefficient for trade openness is larger than *FDI* inflows, so that a percent of increase in *FDI* inflows and trade openness causes enhancement of *TFP* by 0.014 and 0.058 percentages, respectively. Also, the effect of internal R&D is not significant. This result is reasonable because internal R&D is a risky and costly path-dependent process in comparison with the adoption of foreign technology by *FDI* inflows and trade openness, especially for firms in energy exporting countries. Hence the firms in these countries spend low levels of investment in internal R&D and thereby, there is a lack of organized R&D activity in most energy exporting countries.

As expected, the findings in net energy importing countries indicate that the internal R&D, trade openness and *FDI* inflows have positive and significant effects on technological efficiency. The role of internal R&D is dominant, so that a percent of increase in the internal R&D, trade openness and *FDI* inflows causes enhancement of *TFP* by 0.0269, 0.0045 and 0.0007 percentages, respectively.

However, it is important to note that the result confirms that in energy exporting countries trade openness is a dominant factor for improving technological efficiency. This result is reasonable, because trade liberalization policies can increase competition between domestic and foreign firms that may allow domestic firms access to cheaper and better technology and better quality inputs and managerial skills from abroad, thereby increasing productivity. Additionally, we found that in energy importing countries, R&D activities were important contributors to the decline in energy intensity. This finding can be attributed to the greater share of foreign R&D expenditures in this group. Put differently, energy exporting countries lack incentives to incur domestic expenditures on technology development and technological innovation because, presumably, this costs a lot and is time-consuming. Thus, exporting countries opt to purchase international technology that is from R&D activities in importing countries.

Table 4.

The GMM results for TFP change model

Variables	Energy exporting countries	Energy importing countries
ln(*TFP*)	0.1593 (0.0006) *	0.1405 (0.0000)
ln(*TRADE*)	0.0584 (0.0256)	0.0045 (0.0134)
ln(*FDI*)	0.0149 (0.0253)	0.0007 (0.0090)
ln(internal R&D)	0.0387 (0.2965)	0.0269 (0.0000)
Sargan – *p*-value	0.330	0.559

* Figures in parentheses are significant prob. values.

Finally, we performed the Sargan test for over-identification, and tests for serial correlation of the differenced error term. As can be seen from the corresponding *p*-values of these tests, reported at the bottom of all *Tables 2–4*, the null hypothesis of the validity of instruments cannot be rejected. Also, the first- and second-order serial correlation tests show that there exist negative first-order serial correlations and there is no evidence of second-order serial correlation in the differenced error terms.

Conclusion

The energy intensities of most energy exporting countries have historically been very high compared with energy importing and industrialized economies. Although energy efficiency improved over the period 2000–2021, the production process, access to energy resources, technical standards and the extent of opening up are different in energy exporting and importing countries, and hence their energy intensity changes are quite different. Therefore, this question is still an important argument for the factors that are driving the decline in energy intensity in each group of countries. Hence, this paper has compared the main driving factors of energy intensity changes in net energy exporting and importing countries using dynamic panel data during 2000–2021. The findings show that technological progress has played a negative role in energy intensity in both groups; of course, this effect is greater in importing countries, as expected. Furthermore, in order to have a better understanding of technological progress, we employed the DEA-Malmquist approach for each country to decompose *TFP* into the technical change (*TC*) and the efficiency change (*EC*), the pure efficiency (*PEC*) and the scale efficiency change (*SEC*).

The findings for energy exporting countries indicate that *TC* has a negative and significant effect on energy intensity, although, the estimated coefficient is relatively weak. Meanwhile, the effect of *EC* on declining energy intensity is not significant, as expected. Also, the coefficient of the component related to *SEC* is significantly negative in energy exporting countries. Because of imperfect infrastructures and relatively lower level of technology and economic development in most energy exporting countries, this finding is reasonable. Finally, the negative effect of the *PEC* on energy intensity is not significant in exporting countries. Hence, these findings confirm that due to the cheapness of energy resources in exporting countries, they have not paid enough attention to the role of net efficiency in reducing energy intensity.

The results for net energy importing countries indicate that the negative effects of efficiency change (*PE*) on energy intensity are slightly larger than that of *TC*, implying that the effects of technical progress on the energy intensity can occur through both technical and efficiency changes. Also, the coefficient of the component related to *SEC* is significantly negative in energy importing countries, as expected. Finally, the estimated coefficient of *PEC* in reducing energy intensity is very remarkable, which shows the high importance of the efficiency components of *TFP* in energy management. However, the results confirm that a large portion of the stronger effects of *TFP* on declining energy intensity in energy importing countries has occurred through the pure efficiency change and its spillovers.

Next, we investigated what is the main driver of technological progress in the energy exporting and importing countries. However, there is a difference in the development level, research and development (R&D) inputs, energy resources and education between energy exporting and importing countries. We examined whether innovation activities including internal R&D and adoption of foreign technology (*FDI*) have differential effects on their technological efficiency. Likewise, we examined the role of trade liberalization on technological efficiency by considering the argument that trade liberalization enables firms to achieve high levels of efficiency through "learning-by-exporting-effects." The findings imply that in net energy exporting countries, trade openness is a dominant factor for improving technological efficiency. Because trade liberalization policies can increase competition between domestic and foreign firms they may allow domestic firms access to cheaper and better technology and better quality inputs and managerial skills from abroad and finally increase the productivity. Also, the effect of internal R&D is not significant. This result is reasonable because internal R&D is a risky and costly path-dependent process in comparison with the adoption of foreign technology by trade openness, especially for firms in energy exporting countries. Hence the firms in these countries spend low levels of investment in internal R&D and exporting countries opt to purchase international technology that is from R&D activities in importing countries. Meanwhile, the findings in net energy importing countries indicate that R&D activities were important contributors to the decline in energy intensity. This finding can be attributed to the greater share of internal R&D expenditures in this group.

Overall, the results of this study might have important policy implications. Most significantly, it shows that the energy intensity fluctuation is simultaneously forced by both technical change and efficiency change, although these effects are stronger in net energy importing countries compared with net energy exporting countries, as expected. Specifically, the role of pure efficiency change in reducing energy intensity is very considerable. However, policy makers in both energy exporting and importing countries need to be aware of the fact that technological progress and innovation are powerful tools in reducing energy intensity. Hence, this study suggests that the governments should encourage use of advanced technologies and management experience, especially in energy exporting countries. Also, policy makers in exporting countries should focus on trade liberalization, especially on information exchange via learning-by-exporting effects. As well, we found that innovation investments (internal R&D) play a substantial role to improve energy efficiency in importing countries. Therefore, this study suggests that governmental intervention especially in exporting countries should strengthen innovation capacity and also promote energy saving technology. ■

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About the authors

Mehdi Fallah Jelodar

Ph.D.

Associate Professor of Mathematics, Department of Mathematics, Ayatollah Amoli Branch, Islamic Azad University, 5 Km of the old road from Amol to Babol, Amol 678, Iran;

E-mail: Mehdi.fallah_jelodar@yahoo.com

ORCID: 0000-0002-8473-564X

Somaye Sadeghi

Ph.D.

Assistant Professor of Economics, Department of Financial Management, Ayatollah Amoli Branch, Islamic Azad University, 5 Km of the old road from Amol to Babol, Amol 678, Iran;

E-mail: Somysadeghi@yahoo.com

ORCID: 0000-0002-9464-0011