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Modeling the Spatial Effects of Digital Data Economy on Regional Economic Growth: SAR, SEM and SAC Models

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Abstract: The potential for the development of digital data and their infrastructure creates new opportunities for economic growth. The purpose of this study was to develop an approach to identify a set of indicators to quantify the data economy and model its impact on economic growth. The cumulative index and Gini coefficient indicated differentiation and disparity in the digital data infrastructure of 85 regions for 2016–2021. In the presence of a positive spatial correlation, digital development does not indicate clear spatial clubs. Selected according to the calculation of Lagrange multipliers and likelihood ratios, panel econometric models with spatial lags, using SAR, SEM and SAC, showed a short-term negative effect and a long-term positive effect of the digital data economy on economic growth, confirmed by the calculation of marginal effects. During the pandemic, the data economy had a positive impact on regional economic growth. The positive spatial effect of interactions between regions detected by the models in the framework of economic growth indicates the synergistic nature of digitalization. The main conclusions of this study provide evidence-based support for the digital transformation of regions and can help create information infrastructure and accumulate human capital to eliminate disparities in the digital development of regions.

Keywords: regional economic growth; digital data economy; regional disparity; spatial model; spillover effects

MSC: 91B44; 91B62; 91B72

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1. Introduction

As a new production factor and economic resource, big data are changing business models and the boundaries of industries and market structures and increasing business activity and labor productivity [1,2], implying the achievement of social benefits [3], and the data economy as a digital ecosystem for extracting value from accumulated information [4] forms competitive advantages to support innovation, sustainable development and growth.

In the context of sanctions policy, geopolitical confrontation and restrictions, the Russian economy needs the modernization, maintenance and digitalization of production in the absence of foreign technologies, and it requires integration with economic systems in a number of countries and the creation of educational and human resource ecosystems. In this regard, the information technologies (hereafter—IT) sector has a certain potential for creating unique technological solutions, creating and exchanging data independently of foreign IT companies.

In Russia, as in the world, the pandemic has changed the structure of gross domestic spending in the digital economy. The share of organizations in terms of volume of gross domestic spending in the digital economy decreased from 59.9% in 2019 to 55.7% in 2020, whereas the share of households increased by more than 4 percentage points (from 40.1 to 44.3%). The expenses of organizations for the purchase of machinery and equipment related to digital technologies (by 1.5 times), digital content (by 3 times) and staff training (by

4 times) have grown significantly. The ratio of costs for the development of the digital economy to gross domestic product (hereafter—GDP) increased from 3.7% in 2019 to 3.8% in 2020 [5]. In 2020, 80% of households in Russia had access to the Internet (as in the United States), and almost 90% of the adult population of Russia used the Internet at least once (as in Estonia and the Czech Republic). The daily audience of the Russian Internet reached almost 77% of the adult population, an increase of more than 4 percentage points. This tendency is comparable to Italy and France [6]. The index of digitalization of sectors of the economy and the social sphere indicates the acceleration of the growth of the data economy development in domestic industries. At the end of 2021, the integral value of the index was 15.7 points, which was 0.4 points higher compared to that of 2020. The maximum value of the index was recorded in the IT industry (33.9 points), in the field of information and communication (28.6 points), in higher education (23.9 points) and in the financial sector (23.7 points) [7]. The advantages of using digital platforms and ecosystems are the optimization of business processes (78% of organizations using digital platforms) and communications (61%) and reductions in organization costs (49%); the main business purpose of their use is interaction with suppliers and partners (80%) and recruitment (92%) [8].

Nevertheless, digital platforms provide absolute dominance to their owners through the accumulation of digital capital [9] and form a gap in the data economy between platforms and emerging markets with cheap labor resources that are convenient for exporting raw data and importing finished information products. Investment in software increases the earnings of high-wage workers compared to low-wage workers, thereby increasing income inequality within and between firms [10]. The authors of studies on the impact of digitalization on achieving economic growth note the limited effectiveness of digital resources [11] and emphasize the need to develop new modeling and data aggregation tools related to the growing digital economy [12].

Another problem in the data economy's development (both for the countries of the world and for the regions) is the digital divide in the field of the access and use of the Internet for data transfer [13]. Network structures and platforms, as the basic form of interaction between participants in the digital society, generate a digital divide through differentiated access to the ecosystem of platforms through differences in the competence characteristics of human capital, and they also create new regimes of cultural values and economic policy. Therefore, the scale of the distribution of digital ecosystems and their sphere of influence are becoming global [14], and platform capitalism commercializes those areas of public life that previously could not be monetized. It is opaque, because economic and social processes are hidden in business models and data flows [15].

In general, the expansion of the scope of the application of digital technologies and the "contactless" economy during the COVID-19 pandemic [16], as well as the trend of their consolidation and development in the post-pandemic period and possible digital market distortions, motivated the study of their impact on regional economic growth.

The benefits and expansion of big data are sparking interest in the empirical study of their impact on economic growth. Therefore, the main research task is based on the analysis of inequality and the econometric assessment of the characteristics of access to the Internet and its use by companies and households as a basic condition for the distribution and accumulation of data for the purpose of economic development, as well as for the identification of Russian regions that demonstrate the most uniform development of the Internet. The purpose of this study is to expand the use of spatial econometric models to measure the impact of big data on economic growth, taking into account spatial interactions in Russian regions. The rest of this paper is organized as follows: Section 2 details the theoretical framework and literature review. Section 3 introduces the research methodology and data. Section 4 presents the results of the empirical analysis and modeling. Section 5 reports the conclusions.

2. Theoretical Framework and Literature Review

2.1. Theoretical Framework

In the middle of the 20th century, Simon Kuznets pointed out the critical importance of technology: "The present epoch is the 'scientific epoch'; and we may say that certainly since the second half of the nineteenth century, the major source of economic growth in the developed countries has been science-based technology ..." [17]. At the end of the 20th century, growth theory formulated the assumption of the endogeneity of capital and technical progress [18,19], from which the key role of information and knowledge in economic development follows. Domestic investment in the accumulation of knowledge through their dissemination indirectly contributes to the growth of world experience. Other key scientific papers explained the external effect of human capital through the creation and transfer of knowledge and patented innovations on economic growth. Later, empirical research recognized the paramount role of technology and the crucial importance of space for the dissemination of knowledge and innovations [20–22], and breakthrough "technologies of wide application" cause the development of many additional factors of production and the reorganization of workplaces. As a result, modern growth theory, as a branch of mathematical economics, acquires interdisciplinary character and proceeds to the analysis of qualitative changes in the long term [23].

Digital technologies, as an example of "technologies of wide application", prompted the academic world and businesses to form the concept of a digital society [24,25]. Digital resources and data, unlike natural ones, are produced and determined according to the presence of invented and (or) acquired technologies and human capital, and their reserves are regulated by institutions and the government. Therefore, information networks and communication technologies, as carriers of the value of digital data, become a necessary condition for the transformation of traditional sectors of the economy and industrial integration] and for the coordinated development of regional and industrial economies, which form the basis of the innovation process, leading to economic growth based on a technological perspective and interregional interactions. The impact of digital resources on growth convergence can be explained through the mechanism of technology diffusion. Countries that become technological adopters by borrowing and copying new technologies cheaply, compared to the costs of inventing new ones, are gradually catching up with technological leaders; thereby, the spread of technology contributes to the convergence of economic growth between countries. The production and ownership of digital resources and data reduces a number of specific economic costs and leads to the replacement of labor with capital. All this makes economic growth more sustainable. In this sense, digital resources are consistent with the concept of sustainable development, which provides non-diminishing utility. Table 1 briefly summarizes the theoretical framework of this study.

Table 1. Summary of theoretical framework.

Literature Statements	Digital Data (DD) Effect	Authors, (Year)
DD and traditional factors of economic growth	Capital accumulation and technological progress depend on the accumulation of knowledge. The average level of the quality of human capital depends on the "technology" of its production.	Romer (1986) [26] Lukas (1988) [27] Romer (1990) [28]
DD and technology	"Technologies of wide application" give rise to new factors of production.	Bresnahan, Trajtenberg (1995) [29]
DD as a new factor of production	Basis of the innovation process, the transformation of traditional sectors of the economy, industrial integration, interregional interaction and the conjugation of the development of regional and industrial economies.	Zhang et al. (2021) [30] Zhou (2023) [31] Sahal (1985) [32] Dosi (1988) [33] Yoffie (1996) [34] Kozonogova (2020) [35]

Table 1. *Cont.*

Literature Statements	Digital Data (DD) Effect	Authors, (Year)
DD and economic growth convergence	Borrowing and copying technologies by technology successor countries contributes to the convergence of growth.	Barro (1992) [36]
DD and sustainable development	Reduction in economic expenses, replacement of labor for capital.	Schwab K. Davis N., (2018) [37] Goldfarb, Tucker, (2019) [38] Brundtland (1987) [39]

Hence, in the economic development of countries and regions, the data-driven digital economy creates new opportunities for endogenous growth through investment in human capital, innovation and knowledge [40,41]. First, through networking, datification, algorithmization and platformization, technological change increases the transfer of knowledge and innovation as a source of productivity growth, overcomes the limiting effects of accumulation and accelerates average economic growth rates. Second, human capital, as a set of skills, receives a powerful impetus to their endless expansion and, in the long run, to economic growth at a point that exceeds the rate of technological progress.

2.2. Literature Review

The empirical analysis of economic growth is associated with three problems: variable selection, connected with different economic growth theories; parameter heterogeneity, determined according to different levels of the development of countries; and cross-sectional dependence, caused by latent general shocks, spatial features and interactions [42,43].

Two large emerging clusters stand out among the econometric studies on testing the impact of digital data on economic growth rates. The first direction includes country studies of digital resources and their infrastructure, which, in most cases, reveal more opportunities for IT technologies in less developed countries. Thus, a positive impact of broadband infrastructure providing high-speed Internet access on the annual increase in per capita income was found for the group of OECD countries in 1996–2007 [44]. The findings of this study [45] demonstrated a similar result on data from 22 OECD countries with the method of dynamic panel data. The authors of another study [46] proved a weaker impact of broadband Internet and a greater spread of mobile Internet in African countries compared to OECD countries for the period from 2006 to 2016, using the example of South African regions in 1990–2014. Another paper exposed that lower-middle-income countries are more advantageous in terms of absorbing the benefits of ICT [47]. Using the augmented mean group (AMG) method and fully modified OLS (robustness results), researchers proved a long-term stable relationship between technological innovations and the digital economy for the developed economies of the G7 countries in 1990–2017 [48]. In this study, the authors constructed an index of the digital economy using the principal component method, from the following variables: households with Internet access (%), industry Internet access and households with mobile broadband Internet access (%).

Another pool of studies explored digital resources and data and economic growth in regions, provinces and municipalities. The authors focused on the territorial heterogeneity of digitalization. Using the example of a group of 1348 regions in all member states of the European Union in 2011–2018, the authors concluded that the effect of broadband Internet access on the annual growth of real GDP per capita was weaker in agricultural regions [49]. The paper [50] implemented employment, employment growth and population growth as control variables, and the proportion of urban and rural households with broadband access that could realistically achieve download speeds of at least 30 Mbps and 100 Mbps was the variable of interest. The results of the study showed a more significant role of digital inclusive finance in the eastern provinces compared to the central and western provinces of China in 2011–2019 using the spatial economic models SAR, SEM and SDM. The authors of [51,52] obtained similar conclusions. Another study [53] investigated 275 Chinese cities in 2017 and distinguished a higher IT effect in less developed cities.

It seems necessary to emphasize the rather limited number of empirical studies of digitalization in the Russian regions. In [54], on a sample of 77 regions of Russia for the periods from 2011 to 2017 and from 2006 to 2017, based on a panel regression model with fixed effects, a significant positive impact was found for the computerization of workplaces, the use of server equipment, the use of subscriber devices for mobile communication and the connection to broadband Internet of workplaces that require a high degree of automation (percentage of organizations that used electronic data exchange between their own and external information systems, %; percentage of organizations that used electronic document management systems, %) for the growth of GRP per employee. In this study, the control variables were the number of people employed in the regional economy and the share of the depreciation of fixed assets. The authors of the study [55], using a spatial autoregressive model (SAR) and a panel vector autoregressive model (PVAR) on a sample of 83 regions of Russia for the period from 2010 to 2018, concluded that the share of organizations using Internet technologies and real wages and the share of people with higher education in the labor force lead to an increase in GRP per employee. In [56], based on the Kuznets curve and panel data from 82 Russian regions in 2010–2020, the authors found a relationship between the spread of broadband Internet access and a reduction in income inequality in Russian regions. In [57], on panel data of Russian regions in 2009–2018 using SAR and SEM models, taking into account spatial interactions, the authors did not find an effect of using the Internet in organizations on the growth rate of GRP per capita of the employed population. The control variables were the expenditures on technological innovations per capita of the working-age population, the volume of investments in fixed assets per capita of the working-age population, the number of patents for inventions and the number of university students.

In general, it can be noted that research publications are focused on the use of the Internet and are limited by the possibilities of public statistics. Most studies are consistent with the theory of endogenous growth and find a positive impact of digitalization on economic growth, focusing on its differentiation in industries and geographic areas. We also used a number of indicators that have been considered in previous studies, taking into account the specifics of Russian regions and available statistics, which affect the choice of variables for analysis.

This study tests the following hypotheses:

Hypothesis 1 (H1). *Disparities in economic growth and digital data economy development are increasing in Russian regions.*

Hypothesis 2 (H2). *A spatial interrelationship between the regions of Russia in terms of economic growth and digital data economy development is present.*

Hypothesis 3 (H3). *A positive effect of the digital economy of data on economic growth is observed in the regions of Russia.*

Hypothesis 4 (H4). *Positive spillover effects of the influence of the digital economy of the neighboring regions on the economic growth of given region are observed in Russia.*

Hypothesis 5 (H5). *The COVID-19 pandemic has reduced the indicators of the development of the digital economy and increased the concentration of the data economy in the regions of Russia. The effects of the digital data economy on regional economic growth are observed during the pandemic.*

In this regard, the following research tasks were performed:

- Formed a methodical approach to the analysis of inequality in the digital data economy and its impact on economic growth based on econometric models, taking into account spatial interactions;
- Substantiated the selection of indicators for control variables characterizing other determinants of economic growth;
- Calculated the index of digital data economy development in Russia for each region and the Gini coefficient as a whole for all regions for the period 2016–2021;
- Fitted the spatial econometric models SAR, SEM and SAC to measure the marginal effects of the digital data economy on economic growth;
- Analyzed the results of the modeling and discussion of their patterns.

The presented study continues the scientific discussion about the impact of the data economy on economic growth, considering the spatial interactions of Russian regions, contributing to the expansion of the use of spatial econometric tools. As we know, similar studies have not been conducted for the regions of Russia. The academic contribution of this research lies in the search for tools for analyzing the data economy to obtain new conclusions about the role of big data in economic growth in order to identify measures of regional information, technology and innovation policy.

3. Materials and Methods

The infrastructure of the digital data economy is a multidimensional concept. For its integral characterization at the level of Russian regions, it is necessary to build a composite quantitative assessment that allows comparing the inequality of the regions at the level of the infrastructure development of the digital economy.

At the first stage of the analysis, following the ICT Development Index developed by Zhang et al. [58], we propose evaluating the level of the development of the digital data economy using an integral index (hereinafter—DDED), which includes the indicators presented in Table 2. Sub-indices characterize the current practice of assessing digital development based on three levels. The first level is access to ICT, the second level is the use of ICT, and the third level is outcomes from the use of ICT [59–61].

Table 2. Structure of the integral index of digital data economy development (DDED).

First Level—DDED	Second Level—Sub-Indices (Sub-Indices' Weight)	Third Level—Indicators (Indicator Weight)	Units
Index of digital data economy development—DDED	Access (0.03)	Share of households with broadband Internet access in the total number of households (0.477). Share of organizations using broadband access to the Internet in the total number of organizations (0.523).	%
	Use (0.901)	Volume of information transmitted from/to subscribers of the reporting operator's fixed network when accessing the Internet (0.68). Volume of information transmitted from/to subscribers of the reporting operator's mobile network when accessing the Internet (0.32).	Petabyte
	Integration (0.069)	Share of organizations that used electronic data interchange between their own and external information systems with exchange formats, in the total number of surveyed organizations (1).	%

To calculate the weight coefficients, we used the entropy weight method (EWM) tested by Yang et al. [62] to calculate the digital index at the level of cities in China.

The EWM includes the following algorithm:

1. Standardization (normalization) of the raw data of each indicator.

Because the indicator values are positive, we can use the minimax method based on calculating the Euclidean distance [63,64]. For each variable x_q, (q = 1, . . ., k) and for each region j = 1, . . ., n at the t-th period t = 1, . . ., T, the normalized indicator is the following ratio:

$$X_{qj}^N = \frac{[x_{qj} - min\{x_{qj}\}]}{[max\{x_{qj}\} - min\{x_{qj}\}]}, \quad (1)$$

where X_{qj}^N is the standardized value of the q-th variable in the j-th region.

The following steps are related to the calculation of weighting factors.

2. The proportion of X^N by the q-th indicator in the j-th region is defined as follows:

$$\boldsymbol{p_{qj}} = \frac{\boldsymbol{x_{qj}}}{\sum_{j=1}^{n} \boldsymbol{x_{qj}}}. \quad (2)$$

3. For each q-th variable, the calculation of the entropy value is performed with the following formula:

$$E_q = -h \sum_{j=1}^{n} p_{qj} \ln(p_{qj}), \quad (3)$$

where $h = 1/\ln(n), h > 0,$ hence $E_q > 0$.

4. The weight of the parameters in the DDED Index is determined by taking into account the entropy measure, as follows:

$$\tau_q = \frac{1 - E_q}{\sum_{q=1}^{k} (1 - E_q)} \quad (4)$$

The weighting coefficients for the DEDD parameters calculated based on the EWM method for 2016–2021 are presented in Table 2. The sub-index "The use of data infrastructure" received the highest weight, with its share varied at the level of 90.1%. Access to infrastructure received a weight of 3%, and integration took a weight of 6.9%.

At the second stage of the analysis, to measure the degree of inequality in the distribution of digital infrastructure between regions, we applied the Gini coefficient, which takes values from 0 (in the case of absolute equality) to 1 (in the case of absolute inequality) [65,66]. Considering the spatial interconnection of regions, the Gini Index can be decomposed into the following form [67]:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} |x_i - x_j|}{2n^2 \overline{x}} + \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (1 - w_{ij}) |x_i - x_j|}{2n^2 \overline{x}}, \quad (5)$$

where w_{ij} is an element of a binary spatial weight matrix expressing the neighbor relationship between the i-th and j-th regions.

Let us consider the function of economic growth EG for the i-th region at time t as

$$Y_{it} = \alpha_i + \delta_t + \sum_{k=1}^{K} \beta_k X_{kit} + \varepsilon_{it}, \quad (6)$$

where Y_{it} is EG; k is the explanatory variable number; K is the number of explanatory variables; α_i is the vector of regional fixed effects, which allow for the control of unobserved spatial heterogeneity; δ_t is the time fixed effects (set by a number of dummy variables for years), which are used to control for common country factors affecting the dynamics of considering factors; β_k is the parameters to be estimated for the explanatory variables, X_k; and ε_{it} is the random error.

At the third stage of the analysis, based on research [68] and on the basis of an analysis of empirical studies on predictors of economic growth, we determined statistical indicators that characterize the factors of spatial econometric models, and they are presented in Table 3. We expect a positive coefficient for the digital data economy development, as we hypothesize that the extension of stable digital data infrastructure is a prerequisite for the further development of the rapidly changing digital economy that is central to life in the 21st century. The relationship between investment, human capital and final consumption expenditure is positive in the literature, and its corresponding sign is therefore expected to be positive as well.

Table 3. Description of the variables.

Variable	Symbol	Indicator	Effect	Data Source
		Explained variable		
Economic growth	EG	GRP at constant 2016 prices/Average annual resident population		Rosstat
		Explanatory Variables		
		Economic Growth Resources		
Physical capital	inv	Investment in fixed assets in GRP per capita	+	Rosstat
Human capital	ln_empl	Average annual number employed (logarithm)	+	Rosstat
	educ	Share of employed population aged 25–64 with higher education in the total employed population of the corresponding age group [69]	+	Rosstat
Digital Resources	l_dded	DDED Index (first lag)	+	Authors' calculations
		Additional factors		
Macroeconomic conditions	l_ln_fce	Logarithm of actual final consumption of households per capita (first lag) [70]	+	Rosstat

We use open data from the Federal State Statistics Service of the Russian Federation (Rosstat) on regional indicators [71], Monitoring the Development of the Information Society in the Russian Federation, as the results of federal surveys according to forms No. 3, inform: "Information on the use of digital technologies and the production of related goods and services", and No. 4, communication: "Information on the exchange (traffic) on telecommunication networks" [72]. The data are for 85 administrative states and regions of Russia in 2016–2021.

Following [73,74], we test hypothesis H2 about the existence of a close spatial relationship between the regions of Russia. We use the univariate Moran's index [75]. Moran's Index is similar to Pearson's linear correlation coefficient and takes values in the interval of $[-1; 1]$:

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(Y_i - \overline{Y}\right) \left(Y_j - \overline{Y}\right)}{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2} \tag{7}$$

where Y_i, Y_j are the attributes of regions i and j; $\overline{x}$ is the average value of the attribute over n regions; w_{ij} is the spatial weight for a pair of regions i and j; n is the total number of regions; and W is the sum of weights.

A positive spatial correlation coefficient means that a growing region contributes to the growth of its neighbors; a negative value means that a growing region "takes" the resources of its neighbors. The insignificance of the coefficient indicates the absence of a relationship between processes in different regions.

Let us formally define spatial relationships between regions in terms of values called spatial weights. The binary contiguity matrix of bordering objects represents spatial weights as the following: the rows of the matrix contain weights for a region in space, which is influenced by neighboring regions.

Following [76,77], we use the following specifications for the spatial econometric models:

1. SAR—model with spatial autoregressive lag:

$$\boldsymbol{Y_{it} = \alpha_i + \delta_t + \sum_{k=1}^{K} \beta_k X_{ikt} + \rho W_{ij} Y_{it} + \varepsilon_{it}} \tag{8}$$

2. SEM—model with spatial interaction in errors with fixed effects:

$$\boldsymbol{Y_{it} = \alpha_i + \delta_t + \sum_{k}^{K} \beta_k X_{ikt} + u_{it}, u_{it} = \lambda W_{ij} u_{it} + \varepsilon_{it}} \tag{9}$$

3. SAC—model with spatial autoregressive lag and spatial interaction in errors:

$$\boldsymbol{Y_{it} = \alpha_i + \delta_t + \sum_{k}^{K} \beta_k X_{ikt} + \rho W_{ij} Y_{it} + u_{it}, \quad u_{it} = \lambda W_{ij} u_{it} + \varepsilon_{it}} \tag{10}$$

where i = 1,. . .85 is the region number; Y_{it} is the GRP per capita in the i-th region; k is the explanatory variable number; K is the number of explanatory variables; α_i is the vector of regional fixed effects, which allow for the control of unobserved spatial heterogeneity; δ_t is the time fixed effects, set by a number of dummy variables for years, which are used in order to control for common country factors affecting the dynamics of considering factors; β_k is the parameters for the explanatory variables; W_{ij} is the contiguity weighting matrix (N = 85 $\times$ 85); ρ is the spatial autoregressive coefficient; ε_{it} is the random error, which is normally distributed; and λ is the spatial autocorrelation coefficient for shock [78].

The dependent variable autoregression coefficient ρ for the spatial lag allows one to identify the influence of the gross regional product per capita of the population in other regions on the studied region. A positive value indicates regional cooperation, and a negative value indicates regional competition. The spatial autocorrelation coefficient for shock λ reveals the influence of the spatial structure of errors. The statistical insignificance of λ means that the shocks of neighboring regions that affect the productivity growth rates in a given region are not related to each other.

Because the spatial lags of the dependent variable included in Equations (8)–(10) are endogenous, the corresponding models cannot be estimated using the least squares method. The main methods for estimating the parameters of these models are the maximum likelihood method, in which a fairly strong assumption is usually made about the normal distribution of errors [79], and the generalized method of moments [80].

To select spatially econometric models for cross-sections, we implement Anselin's approach [81] based on the Lagrange multiplier test. Using the Lagrange multiplier test, the hypotheses are tested, as follows:

$$\begin{gathered} H_0 : \rho = 0, \lambda = 0 (\text{corresponds to the model OLS}), \\ H_1 : \rho \neq 0, \lambda = 0 \text{ (corresponds to the model SAR)} \end{gathered} \tag{11}$$

$$\begin{gathered} H_0 : \lambda = 0, \rho = 0 (\text{corresponds to the model OLS}) \\ H_1 : \lambda \neq 0, \rho = 0 \text{ (corresponds to the model SAR)} \end{gathered} \tag{12}$$

If Hypothesis H1 is chosen in test (11) and test (12), then robust tests are performed, as follows:

$$\begin{gathered} H_0 : \rho = 0, \lambda \neq 0 \\ H_1 : \rho \neq 0, \lambda \neq 0 \end{gathered} \tag{13}$$

$$\begin{gathered} H_0 : \lambda = 0, \rho \neq 0, \\ H_1 : \rho \neq 0, \lambda \neq 0 \end{gathered} \tag{14}$$

If H1 is selected in test (13), then the SEM model is evaluated; if H1 is selected in test (14), then the SAR model is evaluated.

To select panel spatial econometric models and determine marginal effects, we follow Demidova's approach [82]. Let us represent the generalized model with spatial lags for the dependent variable, error and independent variables in matrix form in the following form:

$$Y = (I - \rho W)^{-1}(\alpha i_n + X\beta + WX\Theta + u),\ \ u_{it} = \lambda W u + \varepsilon \tag{15}$$

The marginal effects are defined as follows:

$$\begin{aligned} \frac{\partial E(Y)}{\partial X_m} &= \begin{pmatrix} \frac{\partial E(Y_1)}{\partial X_{m1}} & \cdots & \frac{\partial E(Y_1)}{\partial X_{mn}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(Y_n)}{\partial X_{m1}} & \cdots & \frac{\partial E(Y_n)}{\partial X_{mn}} \end{pmatrix} = (I - \rho W)^{-1}(\beta_m I + W\Theta_m) = \\ &= (I - \rho W)^{-1} = \begin{pmatrix} \beta_m & w_{12}\Theta_m & \cdots & w_{1n}\Theta_m \\ w_{21}\Theta_m & \beta_m & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\Theta_m & \cdots & \cdots & \beta_m \end{pmatrix} = S \end{aligned} \tag{16}$$

As a result of Equation (16), we obtain n direct effects and $(n^2 - n)$ indirect (spillover) effects. Therefore, the average direct effect (ADE) and average indirect effect (AIE) are the marginal effects, as follows [83]:

$$ADE = \frac{tr(S)}{n} \tag{17}$$

$$AIE = \frac{\sum_{i,j=1}^{n} s_{ij} - tr(S)}{n} \tag{18}$$

Summing up (19) and (20), we obtain the average total effect (ATE):

$$ATE = \sum_{i,j=1}^{n} s_{ij} \tag{19}$$

In the presence of spatial correlation and according to the results of model selection, we estimate spatial models for cross-sections (short-term effects) and for panel data (long-term effects).

4. Results

4.1. Rating of Russian Regions According to the DDED Index

The Digital Data Economy Development Index was calculated in accordance with the methodology described above, and the results are presented in Table 4. The undisputed leaders in this indicator are Moscow and St. Petersburg. The value of the Moscow DDED index is an order of magnitude higher than the values in other regions of Russia. The top 10 regions also include Samara Oblast, Moscow Oblast, Sverdlovsk Oblast, Krasnodar Krai, Chelyabinsk Oblast, Tatarstan, Rostov Oblast and Nizhny Novgorod Oblast. Among the regions with low indicators of digital development, one can see both the northern regions of Chukotka Autonomous Okrug, Nenets Autonomous Okrug and the regions of the North Caucasus—Adygea, Khakassia, Dagestan and Ingushetia.

Table 4. Ranking of Russian regions according to the DDED index in 2016–2021.

Rank	Regions	2016	Regions	2017	Regions	2018	Regions	2019	Regions	2020	Regions	2021
1.	Moscow	0.991	Moscow	0.987	Moscow	0.985	Moscow	0.989	Moscow	0.973	Moscow	0.952
2.	Saint Petersburg	0.359	Saint Petersburg	0.432	Saint Petersburg	0.512	Saint Petersburg	0.566	Saint Petersburg	0.676	Saint Petersburg	0.660
3.	Krasnodar Krai	0.202	Krasnodar Krai	0.215	Moscow Oblast	0.288	Moscow Oblast	0.291	Samara Oblast	0.367	Samara Oblast	0.367
4.	Sverdlovsk Oblast	0.170	Moscow Oblast	0.213	Krasnodar Krai	0.230	Samara Oblast	0.252	Moscow Oblast	0.340	Moscow Oblast	0.279
5.	Rostov Oblast	0.170	Tatarstan	0.189	Tatarstan	0.220	Sverdlovsk Oblast	0.242	Sverdlovsk Oblast	0.278	Sverdlovsk Oblast	0.269
6.	Tatarstan	0.168	Sverdlovsk Oblast	0.175	Sverdlovsk Oblast	0.209	Krasnodar Krai	0.237	Krasnodar Krai	0.259	Krasnodar Krai	0.251
7.	Nizhny Novgorod Oblast	0.148	Rostov Oblast	0.166	Chelyabinsk Oblast	0.196	Tatarstan	0.231	Tatarstan	0.242	Chelyabinsk Oblast	0.221
8.	Perm Krai	0.136	Chelyabinsk Oblast	0.158	Rostov Oblast	0.191	Rostov Oblast	0.200	Chelyabinsk Oblast	0.233	Tatarstan	0.218
9.	Chelyabinsk Oblast	0.133	Nizhny Novgorod Oblast	0.150	Novosibirsk Oblast	0.174	Chelyabinsk Oblast	0.200	Rostov Oblast	0.226	Rostov Oblast	0.199
10.	Samara Oblast	0.132	Perm Krai	0.142	Nizhny Novgorod Oblast	0.174	Nizhny Novgorod Oblast	0.184	Perm Krai	0.225	Nizhny Novgorod Oblast	0.186
	...		....		...		...		...		...	
75.	Zabaykalsky Krai	0.059	Khakassia	0.054	Adygea	0.058	Kostroma Oblast	0.068	Kostroma Oblast	0.068	Kalmykia	0.056
76.	Kostroma Oblast	0.055	Mordovia	0.053	Khakassia	0.055	Kurgan Oblast	0.067	Adygea	0.066	Khakassia	0.056

Table 4. *Cont.*

Rank	Regions	2016	Regions	2017	Regions	2018	Regions	2019	Regions	2020	Regions	2021
77.	Nenets Autonomous Okrug	0.054	Sevastopol	0.051	Jewish Autonomous Oblast	0.055	Tuva Republic	0.065	Kalmykia	0.064	Dagestan	0.054
78.	Kalmykia	0.053	Nenets Autonomous Okrug	0.051	Magadan Oblast	0.053	Khakassia	0.064	Karachay-Cherkess Republic	0.060	Mordovia	0.052
79.	Mordovia	0.049	Kalmykia	0.050	Kurgan Oblast	0.051	Adygea	0.063	Jewish Autonomous Oblast	0.059	Adygea	0.047
80.	Kurgan Oblast	0.047	Dagestan	0.048	Kabardino-Balkar Republic	0.048	Kalmykia	0.063	Ingushetia	0.058	Sevastopol	0.046
81.	Jewish Autonomous Oblast	0.045	Chechen Republic	0.046	Nenets Autonomous Okrug	0.046	Jewish Autonomous Oblast	0.060	Tuva Republic	0.058	Tuva Republic	0.044
82.	Chechen Republic	0.044	Magadan Oblast	0.045	Kalmykia	0.044	Nenets Autonomous Okrug	0.047	Dagestan	0.055	Ingushetia	0.044
83.	Magadan Oblast	0.043	Jewish Autonomous Oblast	0.045	Chechen Republic	0.042	North Ossetia-Alania	0.044	Chukotka Autonomous Okrug	0.051	Chukotka Autonomous Okrug	0.038
84.	Sevastopol	0.029	Kurgan Oblast	0.044	Dagestan	0.037	Chukotka Autonomous Okrug	0.044	Sevastopol	0.049	Nenets Autonomous Okrug	0.035
85.	Chukotka Autonomous Okrug	0.024	Chukotka Autonomous Okrug	0.023	Chukotka Autonomous Okrug	0.035	Dagestan	0.041	Nenets Autonomous Okrug	0.047	Jewish Autonomous Oblast	0.033

Using EWM, the results presented in Table 5 were obtained. It can be noted that the average value of the DEDD index remained approximately at a stable level throughout 2017–2020. The COVID-19 pandemic has made significant adjustments in 2021, and the indicator fell by 8.633%.It is important to note that the sub-indices demonstrate a decrease in 2021. The largest drop −19.084%—was associated with access to broadband Internet.

Table 5. Average values of sub-indices and DEDD by regions of the Russian Federation in 2016–2021.

	Values						Rate of Increase, %				
	2016	**2017**	**2018**	**2019**	**2020**	**2021**	**2017**	**2018**	**2019**	**2020**	**2021**
DDED	0.102	0.106	0.115	0.128	0.139	0.127	3.922	8.491	11.304	8.594	−8.633
I1	0.642	0.628	0.569	0.624	0.655	0.530	−2.181	−9.395	9.666	4.968	−19.084
I2	0.052	0.056	0.067	0.072	0.084	0.081	7.692	19.643	7.463	16.667	−3.571
I3	0.528	0.521	0.533	0.634	0.641	0.559	−1.326	2.303	18.949	1.104	−12.793

The effects of the pandemic have manifested themselves in the field of digitalization in different ways. Table 5 presents a decrease in the level of the development of digital data infrastructure for the Russian economy; the integral index decreased compared to the previous year.

4.2. *Assessing Inequality in Economic and Digital Development*

Figure 1 clearly shows inequality in economic development. The average and median value of the logarithm of GRP growth per capita during 2016–2021 remained at approximately the same level. Nevertheless, among the regions of Russia, one can single out regions with abnormally high values of the indicator: the Nenets and Yamalo-Nenets Autonomous Okrug. These regions are characterized by a low population density and, at the same time, high rates of industrial production.

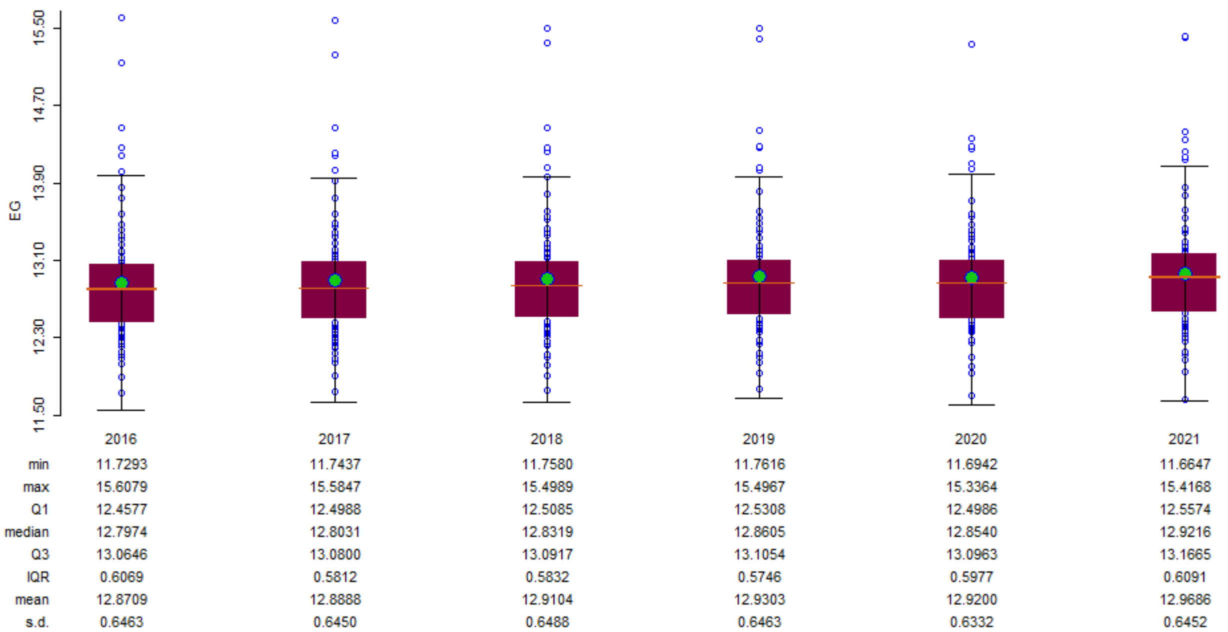

Figure 1. Boxplots for GRP per capita growth in 2016–2021.

The level of digital data economy development is also characterized by unevenness among the regions of Russia, which is shown in Table 6. However, the leaders of economic development, the Nenets Autonomous Okrug and Yamalo-Nenets Autonomous Okrug, are not at the top of the list in terms of digital development. Therefore, using the example of the leading regions, we cannot talk about the direct dependence of economic growth on the level of digital development.

Table 6. Gini Index and its decomposition in 2017–2021.

Indicator	2017	2018	2019	2020	2021
Gini coefficient for					
DEDD index	0.306	0.328	0.305	0.321	0.347
Share of households with broadband Internet access in the total number of households	0.065	0.063	0.064	0.055	0.044
Share of organizations using broadband access to the Internet in the total number of organizations	0.047	0.036	0.035	0.061	0.036
Volume of information transmitted from/to subscribers of the reporting operator's fixed network when accessing the Internet	0.625	0.592	0.585	0.581	0.588
Volume of information transmitted from/to subscribers of the reporting operator's mobile network when accessing the Internet	0.529	0.531	0.526	0.520	0.515
Share of organizations that used electronic data interchange between their own and external information systems with exchange formats, in the total number of surveyed organizations	0.074	0.058	0.051	0.060	0.049
Decomposition of the Gini coefficient for the DEDD Index					
Neighbor composition	0.297	0.314	0.293	0.307	0.333
Non-neighbor composition	0.013	0.013	0.013	0.013	0.014
Spatial Gini	0.960	0.959	0.959	0.959	0.960

Grouping according to the method of natural intervals determines the differentiation of regions according to the DDED index (Figures 2 and 3). The first group—with low values—included 16 regions: Sevastopol, North Caucasus regions (North Ossetia, Kabardino-Balkaria, Chechen, Dagestan and Khakassia), Mordovia, Kostroma, Kalmykia, Siberia and the Far East regions (Nenets Autonomous Okrug, Buryatia, Tomsk, Kurgan, Magadan, Chukotka and the Jewish Autonomous Area). The top two groups, the sixth and seventh groups, comprise the leading regions in terms of DDED: St. Petersburg and Moscow. Moreover, the indicator of the leading region is 15.7 times higher than the indicator of regions from the bottom group.

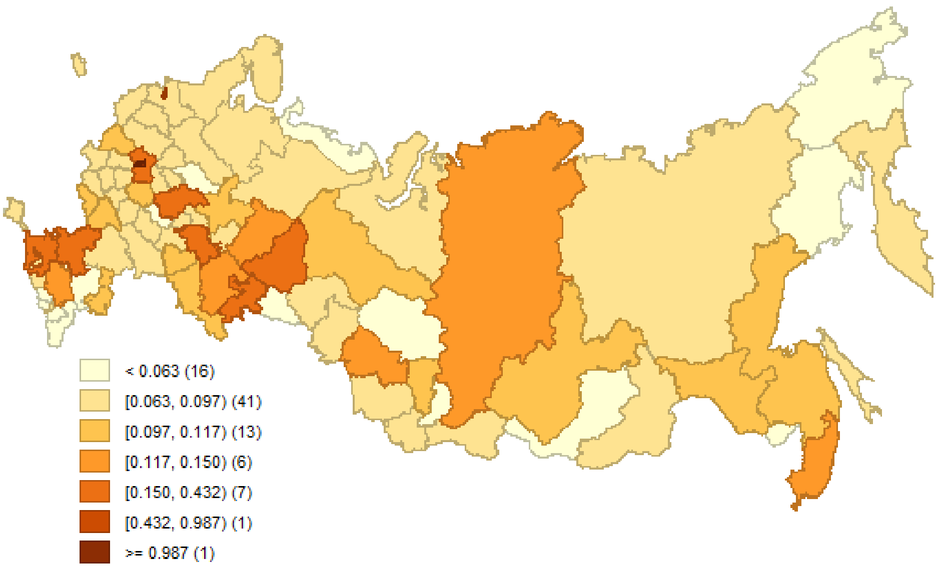

Figure 2. Grouping of regions according to DDED Index in 2017 using natural breaks.

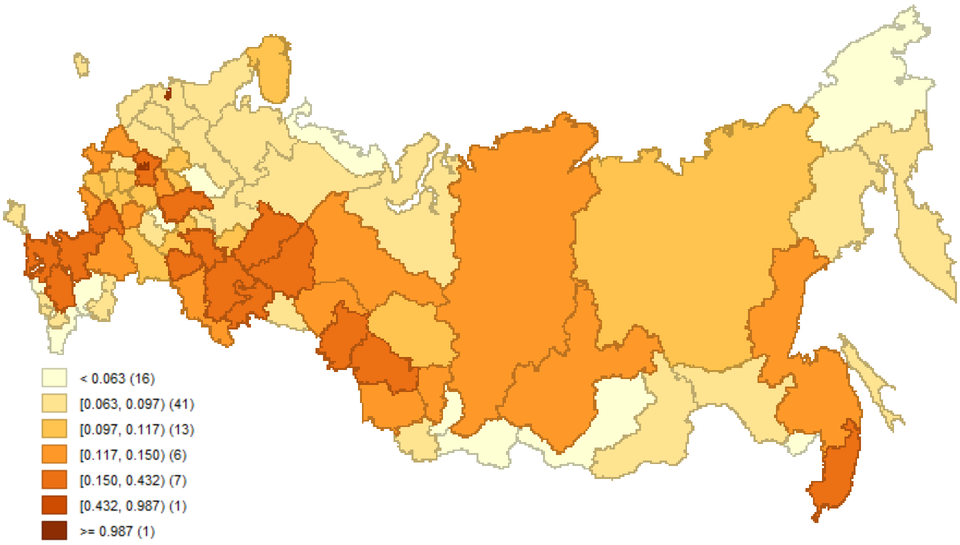

Figure 3. Grouping of regions according to DDED Index in 2021 using natural breaks.

In 2021, the differentiation of regions in terms of DDED changed compared to 2017. The index value for Moscow decreased slightly, and it formed a common sixth group with St. Petersburg. The number of regions in the first group decreased to 14 regions. The number of regions of the second group was significantly redistributed. If, in 2017, this group included the largest number of regions of 41, then, in 2021, 26 regions were included, which indicates an increase in the overall level of development of the digital data economy. However, the value of the indicator in the leading region exceeds the value in the lower group of regions also by 15.1 times. Thus, the digital divide between regions remains at a high level.

Moreover, we observe processes of increasing inequality in the distribution of digital infrastructure between regions; the Gini coefficient shows multidirectional dynamics throughout the study period. In the dynamics of the Gini coefficient, two segments can be distinguished: the periods of 2017–2018 and 2019–2021, which are characterized by an increase in the indicator (see Table 6). In 2020, there was an increase in the concentration of the share of organizations using broadband access to the Internet in the total number of organizations and the share of organizations that used electronic data interchange between their own and external information systems with exchange formats, in the total number of surveyed organizations.

The decomposition of the spatial Gini Index shows that the unevenness in the digital economy is stronger among neighbors than that among non-neighbors. The fraction of the Gini coefficient among neighbors is almost 96%.

4.3. Spatial Correlation

The descriptive statistics of main variables are presented in Table 7.

We tested the proposed hypothesis of the spatial correlation on the basis of calculations of the univariate Moran's Index for the dependent and independent variables (Table 8).

Figures 4 and 5 indicate three relatively stable spatial clubs among the regions:

1. High–high: Nenets Autonomous Okrug, Khabarovsk Krai, Krasnoyarsk Krai, Arkhangelsk Oblast, Khanty-Mansi Autonomous Okrug, Komi Republic, Kamchatka Krai, Magadan Oblast, Republic of Sakha, Yamalo-Nenets Autonomous Okrug and Chukotka Autonomous Okrug. This club unites the northern regions with high EG values, surrounded by neighboring regions with the same high economic growth values.
2. Low–Low: Ingushetia, North Ossetia-Alania, Kabardino-Balkaria, Stavropol Krai, Chechen and Dagestan. The southern regions of Russia are characterized by low values of economic growth and are surrounded by neighboring regions with low values.

3. High–Low: Krasnodar Krai and Nizhny Novgorod Oblast. Perhaps, these regions are points of growth that can "pull up" the development of neighboring regions.

Table 7. Descriptive statistics of variables.

Variable		Mean	Std. Dev.	Min	Max	Observations
EG	overall	12.924	0.641	11.664	15.585	N = 425
	between		0.643	11.724	15.463	n = 85
	within		0.039	12.790	13.067	T = 5
l_dded	overall	0.118	0.115	0.023	0.991	N = 425
	between		0.113	0.035	0.985	n =85
	within		0.023	−0.032	0.285	T = 5
inv	overall	0.266	0.112	0.113	1.089	N = 425
	between		0.102	0.159	0.938	n = 85
	within		0.048	−0.005	0.556	T = 5
ln_empl_r	overall	4.600	0.025	4.512	4.706	N = 425
	between		0.011	4.577	4.641	n = 85
	within		0.023	4.520	4.699	T = 5
l_ln_fce	overall	12.657	0.307	11.548	13.569	N = 425
	between		0.298	11.675	13.510	n = 85
	within		0.077	12.430	12.818	T = 5
educ	overall	33.528	5.526	23.648	52.500	N = 425
	between		5.256	25.120	51.152	n = 85
	within		1.782	21.391	41.267	T = 5

Table 8. Global Moran's Index of spatial correlation for regions of Russia in 2017–2021.

Variables	2017	2018	2019	2020	2021
Logarithm of GRP per capita (EG)	0.492 ***	0.498 ***	0.501 ***	0.502 ***	0.499 ***
DEDD	0.06 *	0.09 *	0.07 *	0.08 *	0.06 *
educ	0.168 **	0.138 **	0.197 ***	0.196 ***	0.26 ***
inv	0.267 ***	0.223 ***	0.140 **	0.120 **	0.206 ***
l_empl_r	0.289 ***	0.166 **	-0.01	0.074	0.008
l_ln_fce	0.332 ***	0.347 ***	0.368 ***	0.388 ***	0.401 ***

Note: * pseudo p-value < 0.1; ** pseudo p-value < 0.05; *** pseudo p-value < 0.01.

The change in the composition of the clubs affected Arkhangelsk Oblast, which ceased to belong to the High–high regions.

As illustrated in Figures 6 and 7, we can also highlight spatial patterns in digital development. A comparison of the regions included in the patterns in 2017 and 2021 suggests that Moscow Oblast, geographically adjacent to Moscow, the leader in digital development, formed a pattern of high–high values (see Table 9). There are no clearly defined patterns in digital development from a geographical point of view (as happened in the case of economic growth).

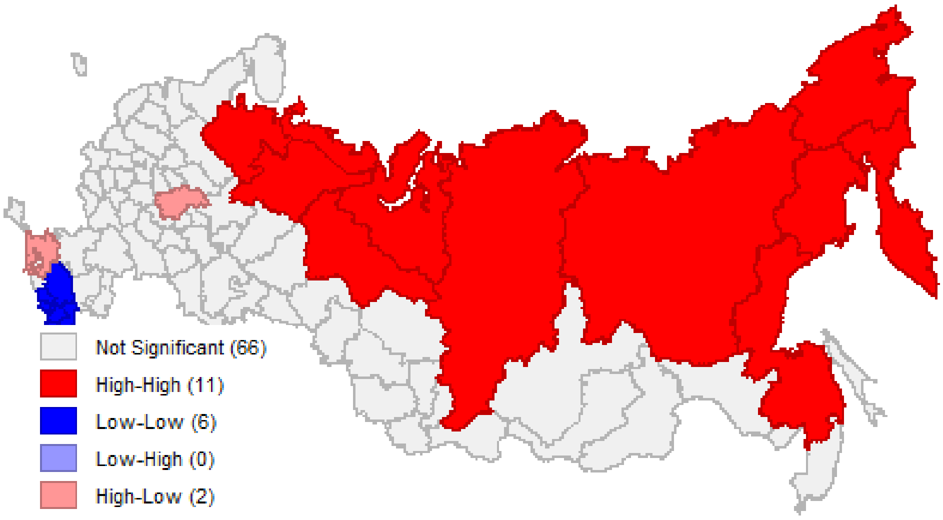

Figure 4. Spatial patterns of regional economic growth in 2017.

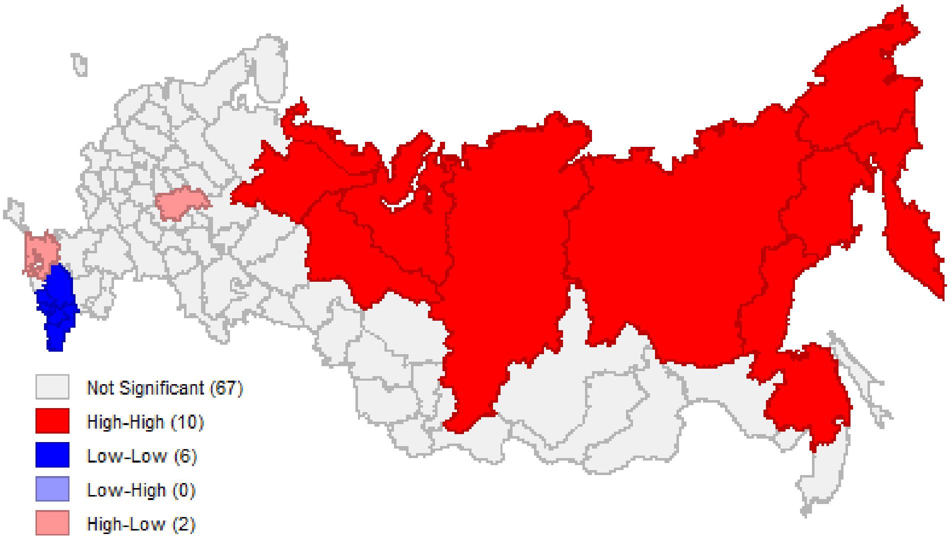

Figure 5. Spatial patterns of regional economic growth in 2021.

Figure 6. Spatial patterns of DDED in Russian regions in 2017.

Figure 7. Spatial patterns of DDED in Russian regions in 2021.

Table 9. Lists of regions with spatial patterns of DDED in 2017 and 2021.

2017	2021
HH: Moscow Oblast	HH: Moscow Oblast
LL: Ingushetia, Kamchatka Krai, Chukotka Autonomous Okrug	LL: Kamchatka Krai
LH: Adygea, Kaluga Oblast, Kaliningrad Oblast	LH: Kaluga Oblast, Kaliningrad Oblast

4.4. Analysis of Spatial Econometric Models

4.4.1. Effects in the Short Run

This paper used Stata 14.0 and GeoDa 1.18.0 software to analyze the impact of digital data economy development on regional economic growth. Two spatial economic models, SAR and SEM, were used to improve the authenticity of the empirical results. First, the Hausman test indicated that a fixed effects model should be used in this study. In order to study the short-run effects, we used cross-sectional data from 2017–2021. The results are shown in Table 10.

Regarding the control variables, we obtained a negative effect of the logarithm of the growth rate of the employed population in 2018 and 2021 (in the OLS and SAR models) on cross-sections and a positive effect in the SEM model in 2019. We observe a positive effect of investment on the regional economic growth in 2017 (SAR, SEM), 2018 (SEM) and 2020 (SEM). The positive impact of the share of people with higher education, which characterizes the quality of human capital, is statistically significant in 2018 (OLS and SAR models), 2019 (SAR and SEM) and 2021 (OLS, SAR and SEM). The growth rate of actual household final expenditures, taken with the first lag, has a positive effect on economic growth in the short run; this pattern can be traced across all types of constructed models.

The likelihood-ratio test, Lagrange multiplier, robust Lagrange multiplier for the spatial lag and Moran's I for spatial error support the adoption of the spatial lag hypotheses for regional economic growth and the spatial lag in error. The coefficients of the spatial lag ("rho") and spatial error ("lambda") are positive, which means that there is a direct spatial relationship between economic growth values in a given region and neighboring regions, as well as a direct relationship between economic growth values in a given region and shocks in neighboring regions. The statistical significance of spatial effects argues in favor of the choice of spatial models over OLS models.

Table 10. Results of model estimations for cross-sectional data in 2017–2021 (explained variable—logarithm of GRP per capita).

Variables	2017			2018			2019			2020			2021		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
L_dded	−0.643	−0.086	0.009	−0.890 *	−0.378	−0.211	−1.115 ***	−0.603 *	−0.540	−0.849 **	−0.410	−0.489	−0.915 *	−0.500 *	−0.671 **
inv	0.550	0.667 *	0.835 **	0.310	0.349	0.559 *	−0.120	−0.006	0.259	0.275	0.302	0.490 *	−0.178	−0.071	0.159
Ln_empl_r	0.787	1.631	1.385	−5.610 *	−3.384 *	−3.581 *	1.760	1.907	3.049 **	1.211	−0.594	2.486	−4.018 **	−2.111	−3.948 **
educ	−0.004	−0.002	−0.000	0.015 *	0.013*	0.009	0.011	0.015 **	0.013 *	0.005	0.006	0.004	0.011 *	0.014 **	0.0130 **
l_ln_fce	1.846 ***	1.289 ***	1.292 ***	1.794 ***	1.318 ***	1.423 ***	1.892 ***	1.348 ***	1.417 ***	1.856 ***	1.396 ***	1.538 ***	1.959 ***	1.475 ***	1.670 ***
const_	−13.840	−17.830 ***	−9.849	15.591	5.071	11.072	−19.379 **	−19.868 ***	−19.438 ***	−16.387 *	−8.411	−18.230 ***	6.393	−2.038	9.575
rho		0.540 ***			0.489 ***			0.507 ***			0.468 ***			0.433 ***	
lambda			0.644 ***			0.604 ***			0.667 ***			0.590 ***			0.542 ***
Likelihood-ratio test		27.677 ***	14.048 ***		22.821 ***	13.689 ***		26.210 ***	18.014 ***		20.129 ***	15.232 ***		17.456 ***	12.076 ***
Spatial error:															
Moran's I (error)	3.202 ***			3.543 ***			3.783 ***			3.805 ***			3.552 ***		
Lagrange multiplier	7.513 ***			9.336 ***			10.885 ***			11.102 ***			9.274 ***		
Robust Lagrange multiplier	0.022			0.250			0.568			0.994			0.931		
Spatial lag:															
Lagrange multiplier	18.726 ***			16.497 ***			18.210 ***			14.943 ***			12.696 ***		
Robust Lagrange multiplier	11.236 ***			7.411 ***			7.892 ***			4.835 **			4.353 **		
R-squared	0.662	0.7877	0.761	0.706	0.789	0.774	0.725	0.811	0.804	0.718	0.790	0.786	0.750	0.807	0.801
Log likelihood	−34.179	−20.340	−27.155	−31.340	−19.930	−24.496	−28.183	−15.078	−19.176	−27.451	−17.387	−19.836	−23.796	−15.0675	−17.757
Akaike info criterion	80.358	54.682	66.310	74.681	53.859	60.992	68.367	44.156	50.352	66.903	48.774	51.671	59.591	44.135	47.515
Schwarz criterion	95.014	71.780	80.966	89.337	70.958	75.6479	83.023	61.255	65.008	81.559	65.873	66.327	74.247	61.233	62.171

Note: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

4.4.2. Effects in the Long Run

The long-term period is estimated using panel data for 85 regions of Russia in 2017–2021. Table 11 presents the results of modeling the impact of digital data economy development on regional economic growth in the long run. The statistical significance of spatial effects made it possible to make a choice in favor of spatial models. A panel fixed effects model and three spatial models—SAR, SEM and SAC—were fitted for the period 2017–2021.

Table 11. Results of models' estimations for panel data in 2017–2021 (explained variable—logarithm of GRP per capita).

Variables	FE	SAR				SEM	SAC			
		Main Effects	Direct Effects	Indirect Effects	Total Effects		Main Effects	Direct Effects	Indirect Effects	Total Effects
l_dded	0.140 *	0.145 **	0.149 **	0.028	0.177 **	0.145 **	0.138 **	0.162 **	0.226 *	0.388 **
inv	0.063 *	0.059 **	0.059 **	0.011	0.070 **	0.060 **	0.041 *	0.047 *	0.064	0.111
ln_empl_r	−0.001	0.005	0.001	0.001	0.002	0.014	−0.027	−0.035	−0.048	−0.083
educ	−0.001	−0.001	−0.001	−0.000	−0.001	−0.001	−0.001	−0.001	−0.001	−0.002
l_ln_fce	0.249 ***	0.230 ***	0.230 ***	0.042 **	0.272 ***	0.215 ***	0.222 ***	0.252 ***	0.343 ***	0.595 ***
const	9.820 ***									
rho		0.164 ***					0.630 ***			
lambda						0.134 **	−0.654 ***			
Time variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq within	0.494	0.498				0.493	0.507			
Hausman	2114.630 ***	0.494								

Note: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

The effect of digital data economy development on regional economic growth is positive and significant for all types of fitted models. The direct effect is positive and significant in both the SAR and SAC models. This means that the growth of the level of digital data economy development leads to an increase in economic growth in the region. In addition to the direct effect, spillover (indirect) effects were calculated and found to be significant in the SAC model. Therefore, the level of the development of the data economy in neighboring regions has a positive effect on economic growth in this region.

4.4.3. Effects in the Pandemic Period

The pre-pandemic and pandemic periods differ in the degree of dissemination of digital technologies and their use by organizations and households. During the pandemic, organizations and households were forced to switch to a remote format for working, studying and communicating with other agents; therefore, the impact of the data economy on economic growth at the regional level may have its own characteristics. Tables 12 and 13 point out the differences in the effect of data economy development on economic growth. If, in the pre-pandemic period of 2017–2019, we do not observe a statistically significant impact of the digital data economy on regional economic growth, then, during the pandemic period of 2020–2021, this effect is positive and statistically significant. We observe this pattern both in the panel with fixed effects and in the SAR and SAC models. Moreover, direct and indirect effects are also significant. Thus, economic growth in this region was influenced by the level of data economy development both in this region and neighboring regions.

Table 12. Results of models' estimations for panel data in the pre-pandemic period of 2017–2019 (explained variable—logarithm of GRP per capita).

Variables	FE	SAR				SEM	SAC			
		Main	Direct	Indirect	Total		Main	Direct	Indirect	Total
L_dded	−0.068	−0.067	−0.065	0.009	−0.056	−0.065	−0.034	−0.035	−0.035	−0.070
inv	0.028	0.026	0.026	−0.004	0.022	0.015	−0.007	−0.007	−0.007	−0.014
ln_empl_r	0.036	0.046	0.049	−0.007	0.042	0.072	0.075 *	0.084	0.078	0.162 *
educ	−0.000	−0.001	−0.000	0.000	−0.000	−0.001	−0.000	−0.000	−0.000	−0.000
l_ln_fce	0.350 ***	0.365 ***	0.364 ***	−0.053 *	0.311 ***	0.425 ***	0.362 ***	0.397 **	0.369 ***	0.766 ***
const	8.341 ***									
rho		−0.167 **					0.520 ***			
lambda						−0.304 ***	−0.877 ***			
Time variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq within	0.601	0.595				0.598	0.619			

Note: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 13. Results of models' estimations for panel data in the pandemic period of 2020–2021 (explained variable—logarithm of GRP per capita).

Variables	FE	SAR				SEM	SAC			
		Main	Direct	Indirect	Total		Main	Direct	Indirect	Total
l_dded	0.633 **	0.650 ***	0.664 ***	0.193 *	0.857 ***	0.659	0.577 ***	0.638 ***	0.637 *	1.275 ***
inv	0.100	0.071	0.071	0.018	0.089	0.038	0.110 ***	0.121 ***	0.119 *	0.240 **
ln_empl_r	−0.167	−0.117	−0.120	−0.032	−0.152	−0.089	−0.140 *	−0.157 **	−0.155	−0.312 **
educ	0.000	0.001	0.001	0.000	0.001	0.001	0.001	0.002	0.001	0.003
l_ln_fce	−0.039	−0.048	−0.045	−0.014	−0.059	−0.066	−0.034	−0.035	−0.040	−0.075
const	14.081 ***									
rho		0.230 **					0.530 ***			
lambda						0.243 *	−0.472 ***			
Time variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq within	0.716	0.719				0.711	0.725			

Note: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

4.5. Robustness Tests

4.5.1. DDED Using PCA

In this study, we used the entropy weight method to calculate digital data economy development. To test the robustness of the estimates obtained, we implemented the principal component method (see Table 14) and the robust principal component method based on the Minimum Covariance Determinant [84] (see Table 15).

The results of both tests indicate that the proposed five indicators are combined into three components, which are implemented in the DDED Index as three sub-indices.

Table 14. Principal component analysis for DDED Index.

				Variable Loadings		
Components	**Eigenvalues**	**Cumulative Proportion**	**Variables**	**PC1**	**PC2**	**PC3**
PC1	2.47805	0.495611	X1.1	0.3550	0.1444	0.9206
PC2	1.33286	0.762182	X1.2	0.4158	0.5167	−0.2802
PC3	0.777297	0.917642	X2.1	0.5127	−0.4596	−0.1650
PC4	0.321871	0.982016	X2.2	0.5001	−0.4975	−0.0760
PC5	0.0899191	1.000000	X3.1	0.4337	0.5034	−0.2023
95% threshold criterion	3					

Table 15. Robust principal component analysis for DDED Index.

				Variable Loadings		
Components	**Eigenvalues**	**Cumulative Proportion**	**Variables**	**PC1**	**PC2**	**PC3**
PC1	2.01215	0.4024	X1.1	0.1410	0.0658	0.9766
PC2	1.52589	0.7076	X1.2	−0.4544	0.5265	0.1116
PC3	0.99331	0.9063	X2.1	0.5285	0.4808	−0.0407
PC4	0.302565	0.9668	X2.2	0.5944	0.3433	−0.1604
PC5	0.166097	1.0000	X3.1	−0.3755	0.6078	−0.0796

4.5.2. Spatial Models Using Inverse Distance Matrix

The choice of the weight matrix can affect the results of the regressions; therefore, to test the stability, we calculated the spatial models using the inverse distance matrix. The evaluation results for short-term periods are presented in Table 16, and those for long-term periods are presented in Table 17.

The results of the fitted models confirm a negative effect of the digital data economy on regional economic growth in 2019, 2020 and 2021, which is consistent with the results obtained using the contiguity matrix. In the long term, the use of spatial models with an inverse weight matrix has not been confirmed, and the spatial coefficients are not statistically significant.

The use of the contiguity matrix in assessing the effect of the digital data economy on regional economic growth may be more justified due to the presence of regions that differ greatly from each other in geographical distances. In the eastern part of Russia, the regions represent large territories; however, close interaction occurs between regions regardless of distance, and to a greater extent due to the system of regional government cooperation.

Table 16. Results of models' estimations for cross-sectional data in 2017–2021 (explained variable—logarithm of GRP per capita) using the inverse distance weight matrix.

Variables	2017			2018			2019			2020			2021		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
L_dded	−0.643	−0.072	−0.315	−0.890 *	−0.375	−0.592	−1.115 ***	−0.608	−0.982 **	−0.849 **	−0.430	−0.843 **	−0.915 *	−0.551	−0.885 ***
inv	0.550	0.692 *	0.875 **	0.310	0.322	0.530 *	−0.120	−0.018	0.149	0.275	0.319	0.440	−0.178	−0.172	0.110
Ln_empl_r	0.787	0.312	0.621	−5.610 *	−4.724 **	−5.554 ***	1.760	1.000	1.540	1.211	0.442	1.747	−4.018 **	−3.572 **	−4.439 ***
educ	−0.004	−0.002	0.000	0.015 *	0.014 *	0.018 **	0.011	0.011 **	0.017 **	0.005	0.003	0.009	0.011 *	0.011 **	0.016 ***
l_ln_fce	1.846 ***	1.471 ***	1.591 ***	1.794 ***	1.471 ***	1.613 ***	1.892 ***	1.585 ***	1.727 ***	1.856 ***	1.593 ***	1.757 ***	1.959 ***	1.687 ***	1.851 ***
const_	−13.840	−13.552 *	−10.111	15.591	9.770	17.508 **	−19.379 **	−17.223 **	−16.514 **	−16.387 *	−13.953	−17.776 **	6.393	3.558	9.465
rho		0.501 ***			0.452 ***			0.401 ***			0.343 ***			0.324 ***	
lambda			0.683 ***			0.691 ***			0.698 ***			0.640 ***			0.682 ***
Likelihood-ratio test		13.450 ***	11.567 ***		11.489 ***	13.887 ***		9.243 ***	12.808 ***		6.454 **	10.542 ***		6.371 **	13.502 ***
Spatial error:															
Moran's I (error)	4.543 ***			5.011 ***			5.177 ***			4.902 ***			5.646 ***		
Lagrange multiplier	10.392 ***			12.806 ***			12.531 ***			11.154 ***			14.189 ***		
Robust Lagrange multiplier	1.227			4.141 **			4.092**			3.948 **			7.331 ***		
Spatial lag:															
Lagrange multiplier	16.032 ***			11.929 ***			11.850 ***			9.336 ***			7.937 ***		
Robust Lagrange multiplier	6.867 ***			3.264 ***			3.412*			2.130			1.079		
R-squared	0.662	0.735	0.737	0.706	0.748	0.764	0.725	0.757	0.776	0.718	0.741	0.762	0.750	0.771	0.799
Log likelihood	−34.179	−27.454	−28.396	−31.340	−25.596	−24.397	−28.183	−23.562	−21.780	−27.451	−24.225	−22.181	−23.796	−20.610	−17.044
Akaike info criterion	80.358	68.908	68.791	74.681	65.191	60.794	68.367	61.124	55.560	66.903	62.449	56.361	59.591	55.220	46.088
Schwarz criterion	95.014	86.007	83.447	89.337	82.290	75.450	83.023	78.222	70.215	81.559	79.548	71.017	74.247	72.318	60.744

Note: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 17. Results of models' estimations for panel data in 2017–2021 (explained variable—logarithm of GRP per capita) using the inverse distance weight matrix.

Variables	FE	SAR				SEM	SAC			
		Main Effects	Direct Effects	Indirect Effects	Total Effects		Main Effects	Direct Effects	Indirect Effects	Total Effects
l_dded	0.140 *	0.141 *	0.144 **	0.039	0.183	0.141 *	0.141 *	0.145 *	0.034	0.178
inv	0.063 *	0.063 **	0.062 **	0.015	0.077 *	0.062 **	0.062 **	0.061 **	0.012	0.073
ln_empl_r	−0.001	−0.001	0.007	0.004	0.011	−0.002	−0.002	0.007	0.005	0.012
educ	−0.001	−0.001	−0.001	−0.000	−0.001	−0.001	−0.001	−0.001	−0.000	−0.001
l_ln_fce	0.249 ***	0.249 ***	0.250 ***	0.063	0.313 ***	0.252 ***	0.252 ***	0.254 ***	0.049	0.303 ***
const	9.820 ***									
rho		0.124					0.015			
lambda						0.169	0.160			
Time variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq within	0.494	0.493				0.494	0.494			
Hausman	2114.630 ***									

Note: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

5. Discussion

The conducted study exposes that the features of the available national statistics limit the assessment of the degree of development and territorial uniformity of the data economy and the comparison of its scale between different locations. The authors of regional studies who used methods for the integral assessment of the level of digitalization and digital inequality came to the same conclusion [85,86]. The calculation of the DDED Index for Russian regions presents that the maximum value of the index (Moscow) in 2021 is 29 times higher than the minimum value (Jewish Autonomous Oblast). This result is consistent with [87]. Differences in the level of the digital economy of regions can be associated with population density, the level of industrial development and geographical distances. The observed decrease in the DDED Index is consistent with [88], in which the authors pointed to the growth of digital inequality, asymmetry and competition between the regions of Russia, which requires special forms of consolidated and effective government regulation and appropriate resources. The "Use" sub-index received the highest weight among the components of digital infrastructure, which is consistent with work on the digital divide, indicating that there is a shift in emphasis from access to ICT to their use [89].

The growing inequality in the distribution of digital infrastructure between regions, found in the study using the Gini coefficient, can signal to public administration institutions about the need to stimulate investment in less "digitized" sectors of the economy and regions in order to increase their business activity. The Gini coefficient indicates that the highest concentration is observed for the volume of information transmitted from/to subscribers of the reporting operator's fixed network when accessing the Internet and the volume of information transmitted from/to subscribers of the reporting operator's mobile network when accessing the Internet. Along with the expansion of the Internet, this result confirms the existence of a gap in the flow of digital data in different territories. In the absence of the use of the Internet and the exchange of electronic data, their interregional distribution is even indicative of the ubiquitous penetration of the Internet that is already familiar to businesses and households and the potential opportunity to practice the potential of the data economy for interregional integration and strengthening growth rates in regions and the country as a whole. The value of the spatial Gini Index, close to one, as a measure of the concentration of values on the map, also indicates the digital inequality of regions and predicts the presence of geographical digitalization clubs.

The hypothesis about the spatial interconnection of Russian regions in terms of digital development is confirmed; the global Moran's Index is positive and statistically significant during 2017–2021. We can conclude that the regions of Russia are interconnected in terms of digital data economy development. The novelty of this study lies in the construction of an index for digital data economy development and its assessment according to regions of Russia. Consequently, the conclusion about the spatial relationship of Russian regions in terms of the level of digital data economy development was made for the first time.

The main conclusion is that the logarithm of GRP per capita shows a strong positive spatial correlation. The unidirectional relationship between the change in GRP per capita in a given region and neighboring regions confirms the cooperation of regions. These results present the potential of government institutions to influence the development of weak regions through stimulation of the leading regions. This conclusion partially agrees with the conclusions of [90]; the Moran index showed a positive spatial correlation in 2008–2014 and was not statistically confirmed in 2006–2007 and 2015–2017 (calculated for 80 regions of Russia using the contiguity matrix for the logarithm of the growth rate of GRP per capita). In [91], the authors obtained positive indices of the global Moran correlation for the GRP growth of 75 regions of Russia for the period from 2008 to 2011.

The presence of stable spatial clubs of regions on the cartograms of the local Moran's Index suggests a stronger growth reserve in the northern resource-producing regions with a developed sector of raw material processing and industrial production. In this regard, the territorial concentration of production activities and digital resources makes it possible for its qualitative development through the network interaction of technologically complementary companies, interregional cooperation and the creation of macroregions. The concentration of digital infrastructure and technologies in a relatively small number of regions indicates their increasing role in the distribution of factors and outputs of production.

The results of the assessment of the impact of digital data economy development on regional economic growth in the short run distinguish that the first lag of DDED negatively affects the logarithm of GRP growth, which is statistically confirmed in the OLS models in 2018, 2019, 2020 and 2021, in the spatial models of SAR in 2019 and 2021 and of SEM in 2021. The negative effects of the digital data economy are consistent with the concept of the diminishing returns of the factor of production, with an increase in labor not accompanied by an increase in capital. The resulting negative effect can be explained by significant costs in the development of DDED, which leads to a decrease in economic growth in the short run. Moreover, in this case, we assume a deferred time effect; infrastructure facilities that provide data transmission require significant investments, the return on which is manifested only in the long run. This result is consistent with previous studies. Thus, the author of [92] used a set of panel data for 30 regions of China for 2010–2015 and explored how investments in "new type" infrastructure have a time delay but a greater effect on economic growth, in contrast to "old type" infrastructure, such as roads, ports and airports. In [93] on a set of panel data on sectors of the Tunisian economy for 1997–2015, the authors also found a negative short-term effect from the spread of IT infrastructure, due to the time lag of investment. These patterns can help investors and government institutions make short-term economic policy decisions. The delayed impact of IT infrastructure on economic growth may be due to the complementary nature of its effect and the need for related investments on organizational and structural changes in the economy.

The simulation results demonstrate that the level of data economy development has a positive effect on economic growth in the long run. In the presented work, the period of 2017–2021 was taken to control for time effects. Similar results were obtained on regional panel data for China; the authors showed a positive impact of the digital economy on green economic growth using data for 30 provinces in 2006–2018 [94] and came up with recommendations for state support for the modernization and development of digital networks, for the creation of software and hardware for the digital economy and for the acceleration of the integration of the digital industry with other sectors of the economy in order to improve the use of resources and the structure of the industry. In addition, the results of [95] pointed out similar trends for a panel of 30 countries in 1995–2018; the demographic dividend and digitalization are driving strong economic growth across all quintiles and formulate a conclusion about the role of digital innovation in achieving sustainable development. It should be noted that the Russian economy is no exception, in which digital data and technologies change the culture of production, the nature of work and the qualitative characteristics of products and services and transform their consumption patterns. Such changes contribute to an increase in labor productivity, an increase in the welfare of the population, the rapid development of IT technologies and, as a result, economic prosperity.

In the short and long run, the constructed models indicate the positive impact of investments in fixed assets on regional economic growth. This pattern is similar to the results of [96], which show that the use of the Internet and late-stage venture capital influence economic growth in the short and long run. We agree with the authors that policy makers should emphasize an integrated policy approach to the co-development of ICT infrastructure, venture capital and economic growth. In addition, in the short run, we observed the positive impact of the quality of human capital—the share of employees with higher education—on regional economic growth. Similar results on the positive impact of education were obtained in a study on China [97]. Moreover, [98] explored how human capital plays the role of a moderator in the mechanism of the influence of the digital economy on the servitization of industrial structures. In the short and long run, we see positive effects of final consumer spending on regional economic growth. These results are consistent with the findings of [99], which found that the new driver of future economic growth lies mainly in technological innovation and demand stimulation. In another study [100], a panel regression analysis was performed with a GDP per capita growth dependent variable and physical capital, human capital and ICT explanatory variables based on data for eight ASEAN countries from 1999 to 2014. As a result, ICT performance has a significant positive impact on economic growth, along with physical and human capital.

In addition to the direct effect, the spatial models revealed spillover (indirect) effects in the impact of the digital data economy on GRP growth. The development of the digital data economy in neighboring regions has a positive effect on economic growth in this region in the long run. Similar results were obtained in [101] using panel data for the Chinese economy in 2013–2019, with a positive spillover effect of digitalization on green economic growth.

The hypothesis about the positive impact of digitalization on economic growth during the pandemic is confirmed. We note that, in the pre-pandemic period, the statistical significance of the impact of the digital data economy on economic growth is not proven. Moreover, during the pandemic, this relationship can be traced both in terms of direct and spillover effects. The findings about the positive impact of the digital economy on economic growth are in line with the study by Ganichev and Koshovets [102] on the Russian economy, which concludes that the new model of digital economy growth is forming, and the pandemic acted as a catalyst for the development of digital infrastructure, for higher consumption in the field of ICT services and for the redistribution of a significant part of resources from other sectors. However, despite the global digital transformation based on big data, Russia needs to focus on the primary digital infrastructure.

In general, the results of this study confirm the insufficiency of the market mechanisms of the data economy for sustainable economic growth and can be used to justify government policies on the digitalization of the economy and the development of technological territorial production complexes based on cooperation.

6. Conclusions

6.1. Conclusions and Policy Recommendations

In the context of the formation of the digital economy as a strategic goal of Russia's development until 2030, this study explores the issue of regional inequality in digital development and the impact of the digital economy on economic growth. The fundamental differences between this paper and previous studies are the following: (1) The focus of this study is on the digital data economy, which corresponds to global trends in presenting data as a key factor in the digital economy. (2) For the first time, based on data from Russian regions, the impact of the digital data economy on regional economic growth was determined, which is of scientific interest in terms of assessing the impact within the domestic economy on a particular country, taking into account specific features of the regions.

Based on the construction of an integral index of digital data economy development and modeling using panel and spatial models, this study draws the following conclusions:

1. Using the construction of an integral index of the digital data economy development, it was concluded that, in 2017–2019, there is an upward trend both in the average value of the index as a whole and in its sub-indices. However, in 2021, there was a decrease of 8.6%, which was a delayed effect of the COVID-19 pandemic.
2. The Gini Index exposes that two segments can be distinguished: the periods of 2016–2018 and 2019–2021, which are characterized by an increase in the data economy development index. The highest concentration is observed for the volume of information transmitted from/to subscribers of the reporting operator's fixed network when accessing the Internet and the volume of information transmitted from/to subscribers of the reporting operator's mobile network when accessing the Internet. The spatial Gini Index confirms the geographic concentration of digital resources.
3. The division of regions based on the method of natural intervals according to the index of the digital data economy development indicates a significant differentiation of regions, when the leading regions outnumber the regions of the first group with low values of the indicator by 15 times.
4. The global Moran's Index verifies a positive spatial correlation of Russian regions both in terms of growth in GRP per capita and in terms of the index of digital data economy development. Stable spatial clubs for economic growth were identified: northern regions with high values of the indicator, surrounded by neighboring regions with high rates, and southern regions with low values of the indicator, surrounded by neighboring regions with low rates. We do not observe clearly expressed spatial patterns from a geographical point of view in digital development, as is the case with economic growth.
5. Based on the tests of Lagrange multipliers and the likelihood-ratio test, a choice was made in favor of the spatial models of SAR, SEM and SAC. Modeling showed that, in the short term, we observe a negative impact of digital data economy development on regional economic growth, whereas in the long term, it is positive.
6. The calculation of marginal effects in the SAR and SAC models indicates the presence of spillover effects of the impact of digital data economy development on regional economic growth. The positive impact of the data economy can be traced to the pandemic period of 2020–2021, which suggests that the pandemic amplified this effect.

The public policy recommendations based on the findings are as follows. First, when pursuing a national policy for the development of the digital economy, it is necessary to consider the differentiation of regions and the growing inequality in the digital data economy. Policy makers should take measures to smooth the situation and provide infrastructural support to remote regions. Second, the empirical substantiated spatial relationship between regions and the allocation of spatial clusters makes it possible to focus state policy measures on groups of regions that are closely interconnected to support growth points. Third, the specifics of economic growth and the digital data economy in regions can be taken into account in subnational development programs and in forms of interregional cooperation to create infrastructure facilities. Fourth, government support is needed in the development of data infrastructure for both households and businesses, which is a driver of regional economic growth. The obtained results indicate that the positive impact of the digital data economy is manifested in the long run, which is associated with the presence of a time lag in the return on investment in ICT infrastructure.

6.2. Limitations and Future Research

The study of digital data economy development and its impact on economic growth at the subnational level requires further research on other countries and regions and is the object of close attention from the scientific community. Here, some limitations and future directions of the research are proposed. First, when constructing the index of digital data economy development, we proceeded from the currently available open data. However, the emergence of regional data on fiber optic networks and 5G and 6G Internet will deepen this indicator. More detailed statistics on the quality of human capital will make it possible to include a number of indicators and build an integral index. Second, the time period was limited to 2021; accordingly, the release of statistics for longer time series will allow us to conduct a study on the post-pandemic period.

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