

## Article

# Impacts of Energy Efficiency and Economic Growth on Air Pollutant Emissions: Evidence from Angara–Yenisey Siberia

Yulia I. Pyzheva <sup>1,\*</sup>, Evgeniya V. Zander <sup>1</sup> and Anton I. Pyzhev <sup>1,2</sup> 

<sup>1</sup> School of Economics, Siberian Federal University, Svobodny Prospect 79, 660041 Krasnoyarsk, Russia; ezander@sfu-kras.ru (E.V.Z.); apyzhev@sfu-kras.ru (A.I.P.)

<sup>2</sup> Institute of Economics and Industrial Engineering, Siberian Branch, Russian Academy of Sciences, Academician Lavrentyev Av. 17, 630090 Novosibirsk, Russia

\* Correspondence: ystartseva@sfu-kras.ru

**Abstract:** Environmental problems of urban and rural areas are now high on the agenda of industrialized countries, becoming a key challenge for regional-level policymaking. The mutual influence of population growth, economic and technological development, and the anthropogenic pressure on the environment is still insufficiently studied in many countries, including Russia. In this paper, this relationship is studied for the municipalities of Angara–Yenisey Siberia using an ensemble of the STIRPAT-like regression models, adapted according to the available data. We found that population size and gross municipal product were positively associated with pollutant emissions ( $p < 0.01$ ), while energy efficiency had no significant impact on air pollution. In addition to the poor national data quality and completeness issues, which can distort statistical conclusions, the cause of the observed lack of spatial correlation between energy efficiency and air pollutant emissions may be path dependence and an insufficient pace of transition to a greener economy. This leaves room for institutional transformations aimed at intensifying energy efficiency to reduce the environmental burden.

**Keywords:** air pollution; emissions; economic growth; energy intensity; industrial pollution; STIRPAT model; municipality; Angara–Yenisey Siberia; Russia



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## 1. Introduction

Today's global society places a high demand on minimizing air pollution, placing the reduction of industrial emissions at the top of the planet's sustainable development agenda. As the economic growth of resource-rich countries is usually associated with intensive air pollution caused by different types of energy consumption, reducing the environmental impact of production should become one of the main tasks of national policymaking.

However, even in countries with pronounced environmental agendas and massive ecologically driven investments, such as China, there are many unsolved issues which hinder the mitigation of habitat degradation [1–3]. Other developing countries face the same problems while being less capable of solving them [4–9]. As a result, emissions are still growing in most countries, both in absolute and per capita terms, resulting in various adverse effects.

In recent years, the literature on establishing diverse interlinkages between air pollution, economic growth, and social development of territories became more focused on regional- and local-scale studies rather than cross-country comparisons. The growing interest in ecological topics drives the development of data collection and methods for testing various hypotheses, such as the negative impact of air pollution on housing prices [10,11], effects of urban planning quality on the local environmental conditions [12–14], the presence of decoupling between energy consumption and economic growth [15–17], and so forth.

There are several methodological frameworks to detect patterns of mutual impacts between economic development and environmental quality, such as the environmental

Kuznets curve (EKC) and the IPAT model. The idea of EKC, first introduced by Grossman and Krueger [18,19], is that the relation between per capita income and pollution emissions can be described with an inverse U-shaped curve: increase of income drives new emissions before reaching a point where the trend inverts to a decline in pollution. An important practical implication of this idea is that a period of rapid economic growth and intensive environmental pollution in developing countries will be succeeded by a relief of environmental pressure, as national income reaches a threshold level. Few empirical studies of cross-country and cross-regional comparisons support EKC-like hypotheses [20–24]. The IPAT approach, developed from a discussion between Commoner, Ehrlich, and Holdren in the early 1970s [25,26], studies the human impact on the environment (I) as a mathematical function of population (P), affluence (A), and technology (T). Dietz and Rosa suggested a stochastic version of IPAT, then called STIRPAT (Stochastic Impacts by Regression on Population, Influence and Technology) [27]. STIRPAT allows the empirical application of the IPAT concept to test hypotheses about the contribution of different structures of growth factors to environmental pressures [15,28–32]. In past years, evidence also emerged that merging both IPAT and EKC concepts is beneficial to better understand the genuine effects of economic and social development for the state of the environment [33,34].

Russia is a promising case study of economic drivers of environmental pollution, as it is a resource-abundant country with huge territory and notable environmental pressure in most industrial centers. According to the State report on the state and protection of the environment by the Ministry of Natural Resources and Ecology, in 2019 air pollution was “high” and “very high” in 40 out of 250 Russian cities, where the regular environmental monitoring system was in operation. Most cities were affected by the emissions of specific pollutants: particulate matter (209), nitrogen dioxide (231), nitrogen oxide (136), sulfur dioxide (225), carbon monoxide (208), benzopyrene (174), and formaldehyde (150). The highest level of air pollution was reported for 18 Russian cities geographically located in industrially developed areas in Siberia and the Russian Far East, specifically in the Angara–Yenisey rivers basin (15).

It is worth mentioning that the quality of official data on air pollution is usually controversial [35–38], so we assume that all the figures from state sources are the lower estimates of the factual levels of corresponding indicators. Meanwhile, the data from non-governmental sources such as IQ Air (<https://www.iqair.com/> (accessed on 15 July 2021)) and similar independent air quality monitoring projects should also be used with care in respect to the unknown accuracy and credibility of primary measurements and probable overestimation of the results [39].

Recently, some studies of interactions between carbon emissions and energy use, real income, and education in Russia using the EKC approach have emerged [40]. Unfortunately, regional- and municipal-scale studies of ecological and economic issues are still rare [41–44], despite their obvious relevance for understanding the current state of the problem and efficient policymaking. Local-level studies are of crucial importance for large countries such as Russia, because of their pronounced spatial heterogeneity.

The lack of consistent and reliable data is a known problem when dealing with statistical studies in Russia [6,45,46]. However, the situation with environmental Russian statistical data is relatively more complicated, especially when downscaling studies to the regional or municipal level. Publicly available municipal statistical datasets are represented by a much smaller nomenclature of observed indicators, with shorter and often inconsistent time series.

Many EKC and IPAT studies primarily test greenhouse gas emissions data to identify decoupling with the level of economic development [47–50]. However, Russia still lacks public data on greenhouse gas emissions by region or municipality, so such studies are virtually impossible without relying on alternative sources such as independent satellite monitoring data. On the contrary, the monitoring of air pollutant emissions, including in a cross-section down to individual municipalities, has been carried out for two decades.

In this paper, we study the key drivers of environmental pollution in the regions of the Angara–Yenisey macroeconomic region using the common methods of basic statistical analysis and STIRPAT methodology.

## 2. Materials and Methods

### 2.1. Study Area

This study focused on the Angara–Yenisey macroeconomic region, an uncommon geographical ensemble of four Russian regions based on the river basin approach [51], including Krasnoyarsk Krai, Irkutsk Oblast, Tyva Republic, and the Republic of Khakassia.

At a sub-regional scale, Russian regions are divided into municipalities, which may be rural (*rayons*) or urban (*goroda, poselki gorodskogo tipa, gorodskiy okruga*) areas. In the Russian language there is no distinguishment between the terms “town” and “city”, so in this paper we use the term “city” in all cases when a settlement has a status of *gorod* or *gorodskoy okrug*. Historically, a city in Russia is a human settlement with more than 12,000 inhabitants, mostly employed in agriculture. During the last decades, a few cities substantially depopulated (e.g., Igarka, a small but important local transport hub in the north of Krasnoyarsk Krai, has lost 80% of its population since 1989) but kept the official status of a city.

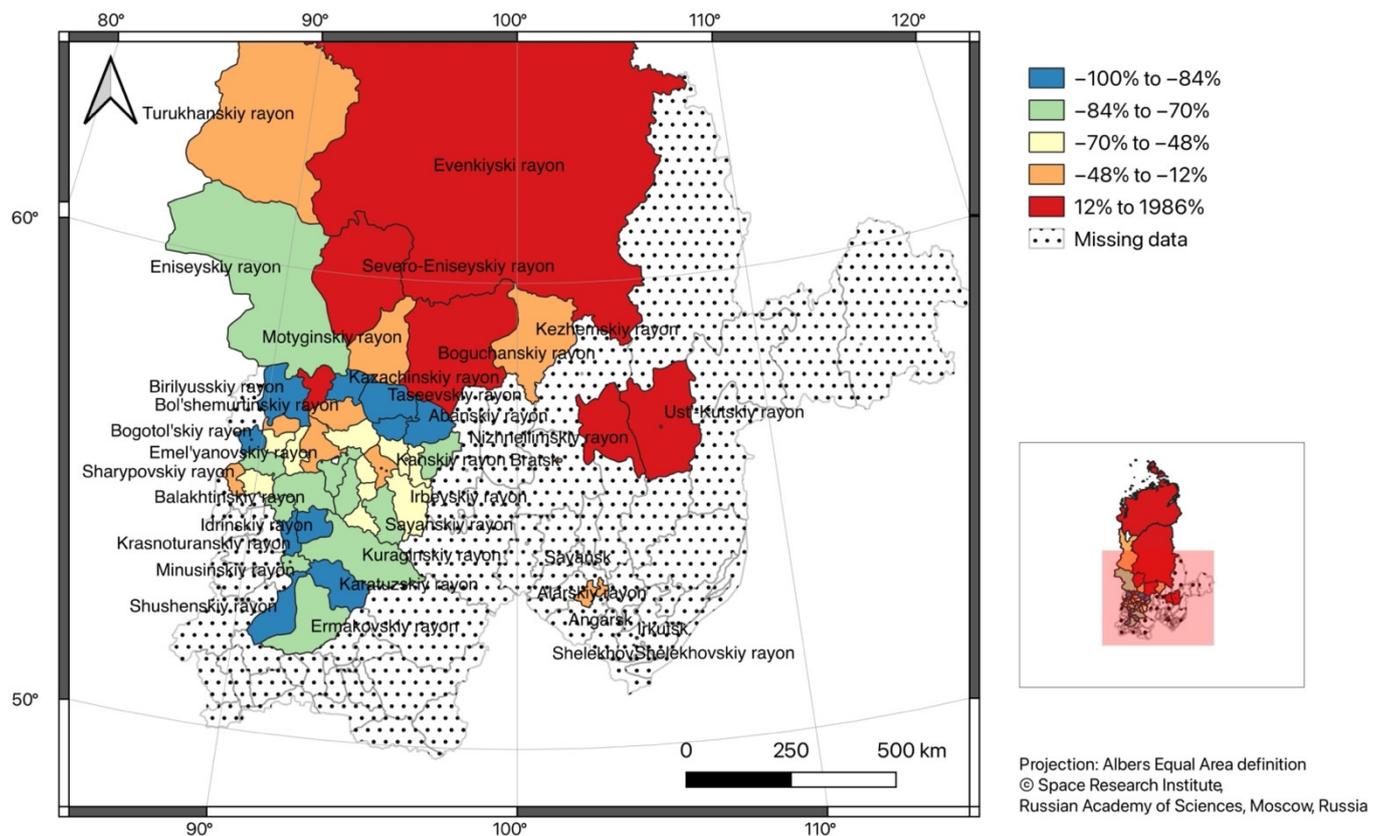
The main parameters of the studied regions are summarized in Table 1. It is evident that the most economically developed region is Krasnoyarsk Krai, which generates four times more economic activity (measured through the gross regional domestic product, GRDP) than the Tyva Republic, the poorest subject of the sample and indeed the whole country. However, the air pollutant emissions are not proportional to the economic activity across the regions. Generally, the considered regions are cases of acute heterogeneity of the main macro-level indicators.

**Table 1.** Main characteristics of the ensemble of studied regions. Source: Rosstat, Russian Federation State report on the state and protection of the environment 2019.

Region	Area, 1000 sq. km	Population, 1000 Persons	GRDP Per Capita, 1000 RUB	No. of Municipal Areas/Cities	Air Pollutant Emissions from Stationary Sources Per Capita, t
Krasnoyarsk Krai	2366.8	2875.3	793.0	44/17	806.5
Irkutsk Oblast	774.8	2401.0	580.1	32/10	267.0
Republic of Khakassia	61.6	536.8	438.3	8/5	199.3
Tyva Republic	168.6	323.1	212.9	17/2	12.4

Trends in the aggregate emissions of pollutants into the atmosphere at the municipality level in the regions under consideration are shown in Figure 1. There is a pronounced tendency of a substantial decrease in annual air emissions for most parts of the southern regions (−95% to −50% percent) while the northern regions suffer from a dramatic growth of air pollution load (up to 20 times in Taymyrskiy, Evenkiyski, and Severo-Eniseysk rayons). This is due to the intensive development of new mineral deposits, such as Vankor and Yurubchen oil and gas fields.

The significant emission reductions in the central and northwestern regions also have an explanation. After the collapse of the Soviet Union, the main driver of the spatial development of Russia was the shift from the east and the periphery to the west and towards Moscow, the biggest city in the country and its capital [52,53]. A similar trend is observed at the intra-regional level, where there is a shift of economic activity and population towards the central cities. The gradual slowdown of industrialization and technological modernization of existing production chains in peripheral areas led to a decrease in the emission of air pollutants.



**Figure 1.** Percentage change in the total emissions of air pollutants across the municipalities of the Angara–Yenisey microregion between 2010 and 2020. Source: Rosstat data. Made using QGIS version 3.16 [54]. Administrative boundaries are retrieved from GADM project (<https://gadm.org> (accessed on 25 July 2021)) and then updated by the authors to comply with the current administrative division of northern territories of Krasnoyarsk Krai.

## 2.2. Data

We used the data from Rosstat (The Federal Statistics Service of the Russian Federation), which provides the database of municipal indicators (<https://www.gks.ru/dbscripts/munst/> (accessed on 1 August 2021)). To the best of our knowledge, this is the only source of systematic data on the development of the Russian provinces and cities. For some indicators, the dataset contains observations since 2007, however because of the large number of data omissions and unexplained fluctuations of some rows, it was not possible to compile complete and consistent time series for panel data analysis.

The Russian statistical and hydrometeorological services operate the following list of main air pollutants that are reported in the public datasets: solid particulate matter, sulfur dioxide ( $\text{SO}_2$ ), nitrogen oxides ( $\text{NO}_x$ ), hydrocarbons ( $\text{C}_x\text{H}_y$ ), volatile organic compounds (VOCs), and “other” pollutants. The concentrations and emissions of particulate matter are usually given as a composite indicator without highlighting  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$ , which is a common worldwide practice.

The misreporting of environmental data is a common phenomenon and is widely studied in China [35,55]. Despite there being no statistically grounded evidence of systematic distortions of the official Russian environmental data, we assumed that the available data may also be affected by various kinds of intentional or accidental errors [46].

Outliers were manually detected and replaced with averages from the corresponding time series. Missing values were restored using simple linear trends.

### 2.3. Methods

The original IPAT model is described with a trivial equation [25,26]:

$$I_i = P_i A_i T_i. \quad (1)$$

It establishes a connection between environmental impact ( $I_i$ ); population ( $P_i$ ); per capita economic activity, or affluence ( $A_i$ ); and the impact per unit economic activity, or technology ( $T_i$ ) subject to  $i$  and is an index of observation. The first idea was to use this equation to express  $T_i$  and then calculate its value through other known terms.

Dietz and Rosa [27] extended the IPAT to allow empirical studies based on retrospective statistical data. The expression for their STIRPAT model is the following:

$$I_i = a P_i^b A_i^c T_i^d e_i, \quad (2)$$

where  $e_i$  is a residual term. This formulation allows a simple linearization, and so it can be further used as a linear regression equation:

$$\ln(I_i) = a + b \ln(P_i) + c \ln(A_i) + d \ln(T_i) + e_i. \quad (3)$$

Although most recent STIRPAT applications use the panel data to explore both the spatial and temporal heterogeneity of the pressure of social and economic development on the environment (e.g., [15,28,56–58]), the original works by York, Dietz, and Rosa [27,31] were made using static cross-sectional samples. We use this approach and Formula (3) as a general form of regression due to the lack of available data for some critical variables.

To control for heteroscedasticity, we use the standard error estimators by MacKinnon and White [59]:

$$\text{Var}(e) = \frac{n}{n-k} \text{diag}(\hat{e}_i^2), \quad (4)$$

where  $n$  stands for the number of observations,  $k$  is the number of parameters to estimate, and  $\hat{e}_i$  denotes the estimated value of residual for the  $i$ th observation.

Due to data availability, we suggest using the proxies given in Table 2 for the corresponding components of the STIRPAT equation.

**Table 2.** Definitions of variables for STIRPAT analysis. Source: compiled by the authors using the data available from Rosstat (<https://www.gks.ru/dbscripts/munst/> (accessed on 15 July 2021)).

STIRPAT Component	Designation	Variable	Unit
Human impact on the environment (I)	Emissions: Total	Pollutants emitted into the atmosphere from stationary sources—total	1000 t
	Emissions: PM	Pollutants emitted into the atmosphere from stationary sources—solid substances (particulate matter)	1000 t
	Emissions: Gas and liquid	Pollutants emitted into the atmosphere from stationary sources—gaseous and liquid substances	1000 t
	Emissions: SO <sub>2</sub>	Pollutants emitted into the atmosphere from stationary sources—sulfur dioxide	1000 t
	Emissions: CO	Pollutants emitted into the atmosphere from stationary sources—carbon monoxide	1000 t
	Emissions: NO <sub>x</sub>	Pollutants emitted into the atmosphere from stationary sources—nitrogen oxides	1000 t
	Emissions: C <sub>x</sub> H <sub>y</sub>	Pollutants emitted into the atmosphere from stationary sources—hydrocarbons	1000 t
	Emissions: VOCs	Pollutants emitted into the atmosphere from stationary sources—volatile organic compounds	1000 t

Table 2. Cont.

STIRPAT Component	Designation	Variable	Unit
Population (P)	Population	Average annual permanent population	1000 persons
Affluence (A)	Gross municipal product	Self-produced goods shipped, works performed, and services rendered using own resources	1,000,000 RUB
Technology (T)	Energy intensity of GMP	Self-produced goods shipped, works performed, and services rendered using own resources (section D: electricity, gas and steam supply; air conditioning)	1,000,000 RUB

Human impact on the environment (I) is proxied with eight available variables on air pollutant emissions from stationary sources. These figures are not measured but reported by all business entities. The quality and reliability of these data remain unclear because they are not the subject of independent or state inspection.

Population (P) is the most trustworthy indicator, stating the number of all people who are officially registered at their place of residence.

Affluence (A) and Technology (T) are measured using the same type of statistical observations: the sum of all products shipped and services rendered at the territory. Energy production formally includes air conditioning, which is not required for the sake of our study. Since we do not know the actual production of air conditioning allocated to the appropriate type of economic activity, we believe this indicator can be neglected.

### 3. Results

The main descriptive statistics are reported in Table 3.

Table 3. Summary statistics of the variables.

Variable	Mean	S.D.	Median	Min	Max	Skew	Kurtosis
Emissions: Total	11.32	27.00	1.56	0.00	193.96	3.89	17.29
Emissions: PM	1.78	3.75	0.78	0.00	22.04	3.18	0.34
Emissions: Gas and liquid	9.54	24.68	1.19	0.00	171.93	3.98	17.88
Emissions: SO <sub>2</sub>	16.32	151.84	0.13	0.00	1675.0	10.70	113.97
Emissions: CO	4.66	13.70	0.73	0.00	77.46	4.02	15.74
Emissions: NO <sub>x</sub>	1.65	5.54	0.10	0.00	53.27	6.99	59.23
Emissions: C <sub>x</sub> H <sub>y</sub>	0.57	2.46	0.02	0.00	15.63	5.63	31.22
Emissions: VOCs	384.44	1499.94	33.03	0.02	13,123.44	6.75	49.37
Population	46,122.02	114,045.18	20,061.00	3355.00	1,087,714.00	7.16	57.58
Gross municipal product	28,860.99	89,310.00	2541.0	70.33	555,920.86	4.55	21.37
Energy production	2818.57	11,458.25	133.86	0.00	101,520.32	6.33	46.53

High values of skewness and kurtosis and sufficient range between means and medians indicate that the distributions of all the variables in the study are exponential, with a shift of the top to the left relative to the median. Logarithms successfully convert distributions to a normal law. The relatively small sample size does not allow grouping and clustering of data to obtain more complex modeling results.

All the models were estimated using conventional ordinal least squares with standard errors from (3) for all available air pollutant variables. Affluence and Technology were finally recalculated per capita.

Table 4 shows the estimated results for the STIRPAT model.

**Table 4.** Estimates of STIRPAT regression models. All the dependent variables and covariates are in natural logarithms. Calculated by the authors using R with “sandwich” and “stargazer” packages [60–62].

Variable	Total	PM	Gas and Liquid	SO <sub>2</sub>	CO	NO <sub>x</sub>	C <sub>x</sub> H <sub>y</sub>	VOCs
Constant	−6.313 *** (1.264)	−10.430 *** (1.351)	−6.633 *** (1.284)	−15.937 *** (1.836)	−4.985 *** (1.710)	−9.972 *** (1.848)	−12.274 *** (4.311)	−5.137 *** (1.896)
Population (P)	0.817 *** (0.116)	1.014 *** (0.124)	0.830 *** (0.118)	1.505 *** (0.168)	0.586 *** (0.157)	0.953 *** (0.170)	0.977 ** (0.393)	1.011 *** (0.174)
Gross municipal product per capita (A)	0.678 *** (0.065)	0.476 *** (0.070)	0.703 *** (0.066)	0.559 *** (0.095)	0.706 *** (0.088)	0.917 *** (0.095)	1.038 *** (0.254)	0.869 *** (0.099)
Energy intensity of GMP (T)	−0.042 (0.044)	−0.063 (0.047)	−0.033 (0.044)	−0.067 (0.064)	−0.049 (0.059)	−0.064 (0.064)	0.191 (0.191)	0.006 (0.065)
Observations	113	113	114	113	114	114	76	107
R <sup>2</sup>	0.664	0.573	0.672	0.576	0.485	0.603	0.334	0.594
AIC	346.9	361.8	353.3	431.2	418.6	436.4	404.2	411.5

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$  Standard errors are provided in parentheses.

The estimated models are of high quality, with  $R^2$  varying between 0.485 and 0.672. The model for C<sub>x</sub>H<sub>y</sub> is an exception ( $R^2 = 0.334$ ); it is not a predominant pollutant and the data contains many missing or zero values. VIF tests showed no multicollinearity (values not reported).

Two components of the STIRPAT equation, Population (P) and Production per capita (A), are statistically significant with  $p < 0.01$  for all cases. Meanwhile, Energy production per capita is not significant for all cases.

All presented models have stable values of parameter estimates and standard errors. Population size has an elasticity of influence on emissions of corresponding pollutants in the range from 0.586 for CO to 1.505 for SO<sub>2</sub>. Here, the high value for SO<sub>2</sub> emissions is characteristic of production processes in metallurgy, for example, in the Norilsk industrial region in the northern region of Krasnoyarsk Krai. Gross municipal product (A) is also described by a rather weak scatter of estimates of elasticities of its effect on ecological load: from 0.476 for particulate matter to 1.038 for C<sub>x</sub>H<sub>y</sub>, with an average of 0.678 for all types of pollutants. Analysis of the coefficients allows us to draw conclusions about the robustness of the obtained results across all types of pollutants, as they converge to narrow bands around their means:  $0.96 \pm 0.16$  for Population,  $0.74 \pm 0.15$  for GMP, and  $-0.02 \pm 0.05$  for Energy intensity.

The signs for both Population and GMP are positive in all models, indicating an apparent direct relationship between the relevant factors and the dependent variables—that is, an increase in population and economic growth leads to an increase in emissions. It is important to note that regression model parameter estimates for aggregate emissions are approximately equal to medians among estimates for individual pollutant components.

We conclude that the estimated models are robust, considering the limitations regarding the quality and completeness of the data as well as the impossibility of using time series for the analysis.

#### 4. Discussion

Our analysis shows that a STIRPAT-like form of statistical influence of population size, gross municipal product, and energy intensity of the economy on air pollutant emissions is partially fulfilled for the municipalities of Angara–Yenisey Siberia. While the first two factors directly impact on atmospheric emissions, energy efficiency cannot be considered a significant driver for their reduction based on these results.

We identify at least two reasons for this lack of spatial correlation between energy intensity and air pollutant emissions. First, the known limitations of the analysis performed, related to the unclear quality of the data used, as well as their apparent inadequacy for panel studies. In addition to the lack of observations proper for certain indicators for some

years for some municipalities, the sets of indicators themselves are scarce and often do not allow us to select the data suitable for testing meaningful hypotheses.

Secondly, if the conclusions drawn from our models hold in future studies (including on broader data sets), it can be assumed that such decoupling takes place in practice. On the one hand, this contradicts many previous studies in other countries and regions, which have shown a full implementation of the IPAT identity or STIRPAT model. However, it is highly likely that for the regions of Siberia and other resource territories of Russia this situation is typical due to path dependence and the lack of qualitative changes in the greening of the economy and social sphere. This conclusion is in agreement, for example, with the work of Zabelina [44], which shows the decoupling between the ecological and economic development of the cross-border regions of Siberia and the Far East. It is important to note that our work cannot contribute to the broader literature on decoupling, as it only considers a static spatial context of the problem. An extension of the dataset is needed to provide a more sophisticated and robust analysis.

In any case, there remains an ample space for new institutional transformations aimed at intensifying energy efficiency to reduce the environmental burden. This is especially important for depopulating Siberian cities and rural areas, where the quality of life is already low compared to the large developed cities of the central part of the country, where a large number of capable young people move.

The results of this study provide a basis for the continuation and expansion of work on testing various EKC- and STIRPAT-like hypotheses at the regional and municipal levels in Russia.

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