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Energy and Emission Efficiency of the Slovak Regions

Vladimír Baláž [1], Eduard Nežinský [1,2], Tomáš Jeck [3,*] and Richard Filčák [1]

[1] Institute for Forecasting, Centre of Social and Psychological Sciences, Slovak Academy of Sciences, 813 64 Bratislava, Slovakia; vbalaz@yahoo.com (V.B.); eduard.nezinsky@savba.sk (E.N.); richard.filcak@savba.sk (R.F.)
[2] Department of Economic Policy, University of Economics in Bratislava, Bratislava 85106, Slovakia
[3] Institute of Economic Research, Slovak Academy of Sciences, 811 05 Bratislava, Slovakia
* Correspondence: tomas.jeck@savba.sk; Tel.: +421-2-5249-8214 (ext. 122)

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Abstract: This paper examines changing regional patterns of energy and emission efficiency in the Slovak regions in the period of 2008–18. Firstly; we review literature on key approaches to evaluating energy and emission efficiency; followed by discussing the pros and cons of specific methods. A slacks-based model of data envelopment analysis is applied in order to investigate changing patterns of energy and emission efficiency in 79 Slovak regions (LAU 1). Thereafter; changes in energy and emission efficiency are associated with policy interventions supported by the European Structural and Cohesion Funds (ESCF) in the period of 2011–15. The evaluation found no support for the hypothesis with regard to the positive impact of the ESCF on the increase in energy and emission efficiency. Combined support from three ESCF policy measures (€606.44m) was substantial; but accounted for a mere 6.3% of the total firm expenditure on product and process innovations in the period of 2007–15 (€9,573m). Productivity-boosting technological innovations and structural changes in the Slovak economy (a shift towards industries with a lower consumption of energy but a higher production of gross value added GVA) were major drivers of trends in energy and emission efficiency. If an increase in energy (emission) efficiency; rather than energy savings (a decrease in pollution), is a major objective of sustainable development policies; then innovation-oriented policies and changes in the structure of economic activities should be preferred to schemes supporting simple energy-saving (emission-cutting) projects

Keywords: energy efficiency; emission efficiency; data envelopment analysis; policy evaluation

1. Introduction

1.1. Structural Change and Energy and Emission Efficiency

The European Green Deal [1] set ambitious targets for increasing energy efficiency and transforming the economy with the aim of climate neutrality. An increase in energy efficiency is key to the mitigation of climate change, as the production and use of energy across economic sectors account for more than 75% of the EU's greenhouse gas emissions [1] (p. 6). A specific focus is upon industry. Some energy-intensive industries (steelmaking and aluminium making, the manufacture of chemicals and cement) are significant contributors to total emissions. Decoupling energy inputs from the production of emissions and economic growth is a possible task. The EU economy reduced greenhouse gas emissions by 23% while the economy grew by 60% in the period of 1990–98 [1] (p. 4).

Slovakia ranks amongst those countries with the highest rates of growth in energy productivity in the EU. Energy efficiency, in terms of one euro of GDP per kilogramme of oil equivalent (KGOE), increased by 2.083 times in the period of 2000–18. The increase was much higher than that for the

EU28 average during the same period (1.345 times). The greenhouse gas emission intensity of energy consumption decreased by 17.0% (EU28: 13.5%) in the period of 2000–17 [2].

Slovakia has a small and extremely open economy. Manufacturing is the key export sector. The total value of manufacturing exports was €79.9bn or some 88.3% of the Slovak GDP in 2018. The manufacturing industries use roughly one half of the total energy consumption in Slovakia. Furthermore, manufacturing is the main source of pollution, including CO, NO_x, SO_2, and particulate matter (PM). Steelmaking and energy production from the combustible process in manufacturing enterprises contribute to the air pollution in Slovakia significantly.

Important structural changes happened in the Slovak manufacturing sector from 2008 to 2016. Traditional heavy industries, such as mining and the production of basic metals, somewhat decreased in importance, while the manufacture of cars and car parts and the manufacture of consumer electronics became prominent export-oriented industries in Slovakia. Such changes resulted in growth in labour productivity and energy efficiency. Eurostat data on the labour productivity of manufacturing (Eurostat 2020) indicate that the average added value per one hour worked in manufacturing (at factor costs) increased from €12.54 in 2008 to €22.36 in 2018 at constant prices. There were vast differences in labour productivity and energy and emission efficiency in manufacturing amongst Slovak regions (Appendix A, Table A1). The differences in labour productivity in manufacturing essentially refer to regions' ability to attract technologically advanced industries. Branches of multinational companies (MNCs) generate the bulk of total Slovak exports, as well as the economies of their host regions. High growth in value added translates to improvements in energy productivity and emission efficiency. Economic growth based on foreign direct investment, technology transfer, and international trade, as well as equivalent improvements in energy and emission efficiency, is not unique to Slovakia. The FDI and trade-led convergence in energy efficiency explains as much as 30–40% of the unobserved variation in energy efficiency across EU countries [3].

Another factor of increasing energy and emission efficiency may relate to investments from public (mainly the European Union) sources focused on innovations and increasing energy effectiveness. An increase in value added and energy efficiency and decreasing pollution in manufacturing are two of the key components in industry policies in Slovakia. The European Structural and Cohesion Funds (ESCF) provided the bulk of public resources for manufacturing industries in Slovakia in the period of 2007–15.

This paper examines changing regional patterns of technical energy and emission efficiency in the Slovak regions in the period of 2008–18. We opted for a regional approach, rather than international comparisons. Definitions of energy consumption and efficiency, as well as coverage and methodology in respect of data collection, may differ across countries. We first review literature on key approaches to evaluating energy and emission efficiency, and then discuss the pros and cons of specific methods. Data envelopment analysis is applied in order to analyse energy and emission efficiency in 79 Slovak regions.

Thereafter, changes in energy and emission efficiency are associated with policy interventions supported by the ESCF in the period of 2011–15. Firstly, we present policies supporting technological innovation, energy efficiency, and emission efficiency in manufacturing. Afterwards, standard evaluation procedures are applied in order to examine potential effects of the EU-assisted policies on a regional level. The concluding part of the paper discusses the limitations of the analysis and suggests directions for further research.

1.2. Literature Review

The literature was identified primarily on the basis of searches on Scopus and Google Scholar pages for various keywords (e.g., "energy productivity / energy efficiency" AND "regions"). Energy types, desirable and undesirable outputs, research methods, timespan, and sample size were of prime interest.

Some studies provide details on specific energy types [4], while others refer to total or aggregate energy consumption [5,6]. Several papers provide details on the computation of energy equivalents by specific energy types, including machine and human power [7] or biomass [8]. Meanwhile, other studies simply refer to total energy consumption reported in statistical yearbooks [5,9]. Using total or aggregate energy consumption may result in double counting and biased estimates of energy efficiency. Crude oil, for example, firstly is counted as an input to the refining sector, and the subsequent refined products as inputs to all other sectors [6] (p. 220). Moreover, it is not always clear as to how 'total energy consumption' is computed, as well as how far the data on energy consumption are comparable across studies. We opted for a clear identification of energy types (electricity, gas and diesel) in our own study. Two key approaches were applied in studies on energy and emission efficiency. The first approach computes the total-factor energy efficiency change index (TFEPI). The TEEPI integrates the concept of the total-factor energy efficiency index into the Malmquist productivity index (MPI) [4]. The TFEPI combines production factors (labour and capital) with inputs from various types of energy (electricity, oil, gas, gasoline, biomass, human and machine power, etc.). Regional GDP is the usual output variable. The second approach computes the index of total-factor energy efficiency (TFEE) [8]. The TFEE is a ratio of the target energy input to the actual energy input. If the target energy input is equal to the actual one, the TFEE index equates to 1. The consumption of energy is at the optimal level with regard to the maximised output of the region. The TFEE index close to 0 indicates very low levels of efficiency. The majority of studies consider a desirable output only, i.e., an increase in energy efficiency. Some studies [9] consider both desirable and undesirable outputs. The latter outputs include emissions of air pollutants. We consider undesirable outputs to be an important factor of sustainable growth and include 'emission efficiency' in our own study.

Data envelopment analysis (DEA) was the preferred method for establishing efficiency levels. Earlier studies used the Charnes, Cooper and Rhodes (CCR) model with constant returns to scale [4,8] or the Banker–Charnes–Cooper (BCC) model with variable returns to scale [7]. Newer studies apply non-radial, slacks-based [10,11], and meta-undesirable EBM DEA models [9,12]. We computed all DEA models and compared their results. We opted for the SBM measure (see Section 2).

The timespan varied from two to 12 years in the studies reviewed. A short time span does not allow for reasonable conclusions on trends in energy efficiency. Annual changes, for example, may be impacted upon by business cycle and/or random fluctuations. Observations made over longer time periods enable detecting some structural changes in a national or regional economy. The data in our study span 10 years. Structural changes in energy and emission efficiency are clearly visible.

Sample sizes varied from 23 counties/cities in Taiwan [13] to 282 Chinese cities [12]. Some studies on energy efficiency aimed at quite small territories (see the study on Iranian farms by [7]), but the majority of studies concerned Chinese or Japanese provinces. Many Chinese provinces match large European countries in respect of the size of the population and economy. The size of the region impacts upon the availability of data and the choice of research methods. Studies on large territorial units rely on extensive statistical coverage of energy consumption and production factors. Studies on Chinese and Japanese regions, for example, employ data on regional GDP and the stock of labour and capital. Such studies usually find significant differences in energy efficiency across regions and indicate room for improvement in lagging-behind regions. Our study observes changes in energy and emission efficiency in much smaller territorial units (districts, LAU 1 level). Data on the stock of labour and capital are not available on the LAU 1 level. The territory size, on the other hand, allows for testing economic and environmental effects of policy interventions.

1.3. Research Gap

Previous studies used secondary data to quantify energy efficiency on a regional level (Table 1). Such studies were descriptive in their scope. They presented differences in energy efficiency and indicated room for improvement. No study attempted to establish a link between policy interventions and changes in energy efficiency on a regional level.

Table 1. Literature review.

Authors	Objective	Energy Types	Method(s)	Period	Sample Size
[8]	Total-factor energy efficiency of regions in China	conventional energy (coal, petroleum, natural gas) and biomass energy (proxied by total sown area of farm crops).	total-factor energy efficiency / CCR DEA	1995–2002	29 administrative regions
[4]	Total-factor energy productivity growth of regions in Japan	electricity (industrial, private), gasoline, kerosene, oil (gas, heavy) gas (city, butane, propane), coal, coke.	total-factor energy productivity / CCR DEA	1993–2003	47 prefectures
[14]	Regional industrial energy efficiency in China	coal, coke, gasoline, kerosene, oil (diesel, fuel), gas (natural, liquefied petroleum, refinery gas, gas), other petroleum products, heat, electricity.	CCR and BCC DEA models	2000–2006	28 administrative regions
[5]	Sources of energy productivity growth in China's provinces	total energy consumption.	Shephard output distance functions / CCR DEA	1990–2005	29 provinces
[4]	Energy productivity of sunflower production	chemical fertilisers, biocides, diesel fuel, electricity, farmyard manure, irrigation water, human labour and machine power.	BCC DEA model	2009–2010	95 randomly selected farms
[13]	Total-factor Energy Efficiency for Regions in Taiwan	electricity (domestic, commercial, industrial), gasoline, diesel.	CCR DEA model	1999–2005	16 counties and 7 cities
[10]	Regional total-factor energy efficiency and electricity saving potential of manufacturing industry in Turkey	electricity.	radial and non-radial DEA models with undesirable outputs	2003–2012	26 regions of Turkey
[11]	Total-Factor Energy Efficiency of Regions in China	electricity.	SBM DEA	2000–2012	276 cities in China
[12]	Regional differences in energy and environmental performance in China	electricity in the industrial sectors.	geographically weighted regression / DEA–Luenberger productivity index	2010–2014	283 cities in China
[9]	Energy and environmental efficiency in Chinese cities	total energy consumption.	meta-undesirable EBM DEA model	2013–2016	31 cities in China

Source: authors' review. Notes: Notes: DEA = Data Envelopment Analysis. CCR = Charnes, Cooper and Rhodes model; BCC = Banker–Charnes–Cooper model. SBM = slacks-based measure.

This paper makes several novel contributions. It explores the contribution of economic factors (growth in gross value added) and the consumption of energy and production of emissions to energy and emission efficiency. It analyses changing patterns in energy and emission efficiency on the LAU 1 (district) level. Previous studies aimed at country level or very large regions. The third novelty of this study lies in analysing the links between policy interventions and changes in energy and emission efficiency. Any public policy is limited in its resources. Effects of policy interventions sometimes are not easy to recognise in very large territorial units. The LAU 1 level makes it easier to study the effects of public policies.

This paper combines primary and secondary data. It benefitted from a unique dataset. The primary data on policy interventions in energy and emission efficiency refer to individual projects supported by the ESCF. The data were obtained from the office of the Deputy Prime Minister for Investment and Information. It was the first time, to the best of our knowledge, that data on policy interventions were used to explore changes in energy and emission efficiency on a regional level.

1.4. Research Hypothesis, Data Sources and Research Methods

This paper examined two research questions and one hypothesis.

- Research question 1 concerns the key drivers of energy and emission efficiency: What was the key driver of energy production and emission efficiency—an increase in value added or a decrease in the consumption of energy and the production of emissions?
- Research question 2 is concerned with the regional patterns of energy and emission efficiency: What regions accounted for the highest improvements in energy efficiency, emission efficiency, and energy-eco efficiency in the long term?
- The following hypothesis on the effects of the European Structural and Cohesion Funds on energy and emission efficiency was proposed: Assistance from the European Structural and Cohesion Funds increased the energy and emission efficiency in Slovakia.

1.5. Data Sources

Some studies on energy and emission efficiency use country-level, firm-level or regional-level data. Firm-level data on energy and emission efficiency were not available in Slovakia. We opted for a regional approach. We compared the changes in energy and emission efficiency in 79 Slovak districts (LAU 1 level) between the periods of 2008–10 and 2016–18.

We clearly identified three energy types (electricity, gas and diesel) studied in our paper. The Statistical Office of the Slovak Republic (SOSR) [15] provides regional data on the consumption of electricity (MWh), natural gas (1000 m3), and diesel (tonnes) on the levels of 79 Slovak districts. Furthermore, the SOSR publishes data on the emissions of CO, NO_x, SO_2, and particulate matter. The final category of emissions covers PM10 and PM2.5 particulates. Regional data on energy consumption and emissions refer to all sectors of the national economy (industry, services, public sector, and households). A breakdown for specific sectors was not available on a regional level.

The SOSR also provides data on gross value added (GVA) in industrial enterprises (thousand Euros) on a district level. The sample, therefore, is identical to the whole population of the Slovak regions. Data on energy consumption and emission production were not available for some small districts for selected years due to individual data protection. We used period averages for 2008–2010, 2011–2015 and 2016–2018 to compensate for missing data.

We accessed the National Strategic Reference Framework database in order to obtain data on energy projects receiving support from the Structural and Cohesion Funds (SF and CF). The primary data cover the whole sample of enterprises and regions supported by the Operational Programme Competitiveness and Economic Growth (OPCEG) and the Operational Programme Environment (OPE).

National accounts and other macroeconomic variables are not available on the LAU 1 level. We approximated changes in total output via changes in GVA in the manufacturing industry on the LAU 1 level. A change in energy productivity is expressed via GVA generated per energy unit (1 kilowatt for electricity, 1 m3 for natural gas, and 1 kg for diesel). Meanwhile, a change in emission efficiency is expressed via GVA generated per kilogramme of emissions (CO, NO_x, SO_2, and particulate matter).

Three policy measures supported industry transformation:

- The Operational Programme Competitiveness and Economic Growth (OPCEG) implemented Policy Measure 1.1 'Innovation and Technology Transfers'. The policy measure allocated €369.30m to the purchase of new technologies. The policy measure aimed at a 'growth in competitiveness and value added, and decrease in energy consumption and undesirable ecological impacts of manufacturing'. The policy measure was implemented in all 79 Slovak districts.
- OPCEG Policy Measure 2.1 'Increase in Efficiency in Production and Consumption of Energy' targeted 'increasing efficiency of primary energy resources' and 'increasing share of renewable resources in the total energy consumption'. The policy measure allocated €94.71 m in 53 out of a total of 79 Slovak districts.

- The Operational Programme Environment (OPE) implemented several green initiatives. OPE Policy Measure 3.1 supported projects aimed at decreasing emissions in industry. The policy measure allocated €142.43 m in 50 out of a total of 79 Slovak districts.

1.6. Research Methods

A number of methods is used in studies on energy efficiency and decrease in pollution, from qualitative [16] to quantitative ones. This paper takes a quantitative route.

Energy and environmental studies often face problems of multidimensionality and, subsequently, a data aggregation method. Such problems occur when market prices for the quantities involved do not exist. DEA models apply linear optimisation methods in order to derive shadow prices as well as the measure of efficiency related to the frontier. The frontier is constructed from the best-performing subjects (DMUs). The slacks-based model of data envelopment analysis (SBM DEA) was applied in order to examine regional patterns in energy and emission efficiency.

Evaluation studies usually compare the performance of supported versus unsupported economic agents in pre-intervention and post-intervention periods. A standard policy evaluation tool (the difference-in-differences method (DiD)) with propensity score matching) is applied in order to analyse potential effects of the EU-assisted policies on a regional level. The DiD method is often is used for the evaluation of energy efficiency policies (see, for example, [17,18]. The DiD method was chosen for the evaluation of potential effects of policy interventions on energy and emission efficiency in Slovak regions. The *t*-test is applied to examine differences in performance of supported versus unsupported regions in post-intervention period.

2. Energy and Emission Efficiency of the Slovak Regions

2.1. Drivers of Energy and Emission Efficiency

Data on GVA, energy consumption and emission production indicate that the increase in energy and emission efficiency is a result of the increase in total GVA, rather than a decrease in fuel consumption and/or emissions. Total GVA increased by 61.9% at constant prices while the total consumption of electricity increased by 19.2% and gas by 18.4% between the periods of 2008–2010 and 2016–2018 (Appendix A, Table A1). The total consumption of diesel decreased by 9.3% in the same period. Some regions accounted for an increase in energy consumption and/or emission production.

2.2. Regional Patterns of Energy and Emission Efficiency

During the course of the 40 years of research, a number of DEA models have been developed. The first radial models [19] handled input or output invariables in a proportional way. Later on, the non-radial slacks-based model (SBM) approach [20] was suggested to account for nonzero slacks and avoid the overestimation of efficiency levels. Reference [21] proposed further improvement to the SBM. Recently, Reference [9] reaffirmed that non-radial slacks-based models fail to consider some characteristics of the radial model, and suggested application of the epsilon-based measure (EBM). Table 2 provides an overview of the most commonly used constant-returns-to-scale DEA models in empirical literature.

Table 2. DEA optimisation programmes.

CCR	SBM	EBM
$\underset{\lambda, s_i^-, s_i^+}{min}\ \theta - \varepsilon \sum\left(s_i^- + s_i^+\right)$	$\underset{\lambda, s_i^-, s_i^+}{min}\ \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{s}\sum_{i=1}^{s}\frac{s_i^+}{y_{i0}}}$	$\underset{\theta, \eta, \lambda, s_i^-, s_i^+}{min}\ \frac{\theta-\varepsilon_x\sum_{i=1}^{m}\frac{w_i^- s_i^-}{x_{i0}}}{\eta+\varepsilon_y\sum_{i=1}^{s}\frac{w_i^+ s_i^+}{y_{i0}}}$
s.t. $\theta x_0 - X\lambda - s^- = 0$	$x_0 - X\lambda - s^- = 0$	$\theta x_0 - X\lambda - s^- = 0$
$y_0 - Y\lambda + s^- = 0$	$y_0 - Y\lambda + s^- = 0$	$\eta y_0 - Y\lambda + s^- = 0$
	$\theta, \eta, \lambda, s^-, s^+ \geq 0$	

Source: The authors´ elaboration. CCR = Charnes, Cooper and Rhodes model; SBM = slacks-based measure; EBM = epsilon-based measure

We examined the performance of alternative DEA models (Table 3). Slovak regions (districts) act as DMUs. The efficiencies of each district are to be determined. We focus on energy and emission efficiency in two separate models and formulate a comprehensive, "energy-eco-efficient" model thereafter.

Table 3. Overview of the models.

Model	Type	Variables							
		Outputs				Inputs			
energy efficiency	SBM	ELECT	GAS	DIES		1			
emission efficiency	SBM	CO	SO_2	NO	PM	1			
energy-eco efficiency	SBM	ELECT	GAS	DIES		CO	SO_2	NO	PM

Source: The authors´ elaboration.

The energy and emission efficiencies are computed as DEA-based performance indices (Table 3). The two models feature unified fixed inputs. Measures of GVA per unit of specific energy carrier (electricity, gas and diesel) or pollutant (CO, NO_x, SO_2, and particulates) are considered to be outputs. In such a setting, higher GVA corresponds to a higher efficiency score of the model. Evaluating the 'overall' energy eco-efficiency performance, the energy model is augmented by undesirable outputs from the emission model. We consider the fully fledged DEA model. The model is conceptually devised as the fraction of aggregated energy over pollution content of the GVA. It is simplified to the amount of (aggregated) emissions per unit of (aggregated) energy. A greener transformation of energy (e.g., with lower pollution) translates to a lower value of the proposed indicator energy-eco. It should be noted that the term "efficiency" in the model's energy and emission refers to the transformation of materials to economic value, whereas the complex model captures only the relation between resources and by-products.

This study focuses on intertemporal comparisons. The DEA model has to be implemented in an intertemporal framework. We refer to the literature review in Table 1 and opt for the Malmquist productivity index (MPI):

$$MPI = \frac{d^2(\boldsymbol{x}_0, \boldsymbol{y}_0)^2}{d^1(\boldsymbol{x}_0, \boldsymbol{y}_0)^1}\left[\frac{d^1(\boldsymbol{x}_0, \boldsymbol{y}_0)^1}{d^2(\boldsymbol{x}_0, \boldsymbol{y}_0)^1} \times \frac{d^1(\boldsymbol{x}_0, \boldsymbol{y}_0)^2}{d^2(\boldsymbol{x}_0, \boldsymbol{y}_0)^2}\right]^{1/2}. \quad (1)$$

The MPI was introduced by Reference [22]. We adopt a notation from Reference [23]. Upper Scripts 1 and 2 refer to Periods 1 and 2 (i.e., d^1 and d^2) and denote efficiency scores with respect to the distance to the frontier from Periods 1 and 2 respectively. The performance of DMU_0 during these periods is labelled as $(\boldsymbol{x}_0, \boldsymbol{y}_0)^1$ and $(\boldsymbol{x}_0, \boldsymbol{y}_0)^2$. The performance is composed of the change in efficiency (a change in the distance from the frontier) and the shift of the frontier itself. Some authors (e.g., [12] (p. 3) argue that the MPI overestimates productivity changes in comparison to the Luenberger productivity index. There is, however, no sound consensus as to the use of a multiplicative (MPI) or additive measure.

We explore properties of the specific DEA models listed in Table 4. As the EBM model nests both CCR and SBM models, we analyse the results for all of these models so as to find the most parsimonious approach. We used data from the latest period of 2016–18 to calculate efficiency *ccr*, *sbm* and *ebm* scores. We found a higher correlation between *sbm* and *ebm* (0.856) than between *ccr* and *ebm* (0.756) models.

Table 4. Score and rank correlations of DEA models.

	scores			ranks		
	ccr	***sbm***	***ebm***	***rccr***	***rsbm***	***rebm***
ccr	1					
sbm	0.756	1				
ebm	0.756	0.856	1			
rccr	–0.968	–0.688	–0.744	1		
rsbm	–0.692	–0.883	–0.889	0.686	1	
rebm	–0.703	–0.768	–0.936	0.739	0.937	1

Source: The authors´ calculation. Note: All correlations with p-values of 0.00.

Scores for specific models may account for nonlinear relations. A linear correlation may not work well for nonlinear dependencies. So as to rule out nonlinearities, we do not inspect score values generated by the three specific models, but rather score rankings (labelled *rccr*, *rsbm* and *rebm*). A rank correlation of 0.937 confirms that the *sbm* and *ebm* models generate nearly identical rankings. More detailed results show that the *sbm* and *ebm* models identify the same set of efficient DMUs. We favour the SBM model for its higher parsimony and employ it in further analysis. Table 4 exhibits pairwise rank and score correlations. Ranks and scores clearly are related in a negative manner.

Figure 1 presents patterns of regional changes in energy, emission and energy eco-efficiency in 2016–18 compared to 2008–10. Districts are labelled by their codes (Table 5).

The belt of industrial districts in the west and north of Slovakia accounted for major improvements in energy efficiency. These districts accounted for more than a twofold increase in GVA over the periods compared. The absolute consumption of energies increased as well, albeit by slower rates in the same regions. This is, for example, the case with the Bratislava IV district, which constitutes the seat of the Volkswagen plant.

The map on emission efficiency combines four different stories: (1) Districts in the west (Bánovce nad Bebravou (BA), Malacky (MA), Topoľčany (TO)) and northwest (Bytča (BY), Púchov (PU), Námestovo (NO)) improved their energy efficiency via an above-average increase in GVA and a decrease in absolute volumes of emissions. The improvement in emission efficiency in some cases was motivated by more stringent environmental regulations. A decrease in emissions was a necessary condition for further operations and/or extension of manufacturing production. Meanwhile, the story of underdeveloped districts in the south and east of Slovakia is mixed: (2) Some districts benefitted from decreases in the absolute volume of emissions and stagnation or mild growth in GVA (Levice (LV), Mezdilaborce (ML), and the machinery district of Košice okolie (KS)). (3) A decline in key regional industries manifested in significant decreases in emission volumes and a decline or stagnation in GVA (the mining district of Rožňava (RV) and Gelnica (GE), the glass-making district of Poltár (PT), the leather-processing district of Bardejov (BJ)). (4) There are some notable outlier districts. The steelworks in the city of Košice (KE I–IV), for example, produced one third of the total SO_2 and CO emissions in the period of 2016–2018 in Slovakia. Other major polluting plants include a paper mill in Ružomberok (RK), an aluminium factory in Žiar nad Hronom (ZH), and coal mines and a coal power station in Prievidza (PD). All of these plants achieved a decrease in emissions and an increase in GVA, but their relative distance to the efficiency frontier increased in the period of 2016–18 compared to 2008–10.

The last map displays changes in energy eco-efficiency. The highest improvements were recorded both for some developed districts in the west and for underdeveloped districts in the east of the country. Legislative measures for decreasing pollution were key to improvement in energy eco-efficiency in the developed districts in the west. The highest improvement was recorded for the district of Prievidza (PD), which constitutes the seat of the largest Slovak coal mine, two coal power stations, and a big chemical plant. The Prievidza district accounted for 51.6% of the total SO_2 emissions in 2008–10 in Slovakia. SO_2 emissions dropped by 81% in 2016–18 compared to 2008–10. Significant decreases in SO_2 emissions were also reported for the Bratislava I–V districts (70.0%), cement-making plants in Považská Bystrica (PB, 82.9%) and the shoe-making district of Partizánske (PE, 80.0%). Decreases in emission volumes, albeit on a smaller scale, were also reported for NO_x, CO and particulates. Some poor districts in the south and east of Slovakia were affected by economic stagnation and the closure of mining and metal-processing plants (Revúca (RA), Gelnica (GE)) or leather processing (Bardejov (BJ)).

All three maps display diverging developmental pathways for relatively prosperous industrial districts in the west and north, as well as declining regional economies in the south and east of Slovakia.

Table 5. Changes in GVA and efficiency scores for energy, emission and energy eco-efficiency models: 2016–2018 compared to 2008–2010.

District	Code	Change in GVA	Energy Efficiency	Emission Efficiency	Energy Eco-Efficiency
Bánovce nad Bebravou	BN	2.201	9.523	2.640	1.004
Banská Bystrica	BB	1.690	1.306	2.216	0.809
Banská Štiavnica	BS	0.324	0.254	0.226	1.167
Bardejov	BJ	2.457	1.951	3.403	0.326
Bratislava I	BA1	1.911	6.361	0.577	1.761
Bratislava II	BA2	0.957	0.874	1.568	1.355
Bratislava III	BA3	1.328	3.828	4.366	0.649
Bratislava IV	BA4	2.798	10.141	2.241	3.922
Bratislava V	BA5	1.693	5.059	1.197	4.444
Brezno	BR	1.558	1.365	1.981	1.174
Bytča	BY	4.268	4.098	2.638	2.208
Čadca	CA	2.222	1.788	1.162	1.704
Detva	DT	1.751	1.460	1.782	1.205
Dolný Kubín	DK	2.179	1.729	2.030	0.838
Dunajská Streda	DS	1.600	1.408	1.037	1.124
Galanta	GA	1.339	1.050	0.942	1.404
Gelnica	GL	2.076	1.929	1.209	18.868
Hlohovec	HC	0.909	1.026	0.652	1.242
Humenné	HE	1.436	1.471	1.446	1.859
Ilava	IL	1.881	2.347	2.181	1.083
Kežmarok	KK	2.008	1.703	2.999	0.756
Komárno	KN	1.938	2.896	1.521	0.808
Košice-okolie	KS	2.161	1.991	3.508	0.816
Košice I	KE1	1.233	0.974	2.305	0.066
Košice II	KE2	1.583	1.251	1.708	0.086
Košice III	KE3	1.676	1.325	0.855	0.476
Košice IV	KE4	1.566	1.238	2.504	0.650
Krupina	KA	2.628	2.039	2.796	1.095
Kysucké Nové Mesto	KM	2.266	8.982	1.771	1.653
Levice	LV	2.018	1.776	3.528	0.637
Levoča	LE	0.190	0.151	0.141	1.587
Liptovský Mikuláš	LM	1.927	1.832	2.422	0.913
Lučenec	LC	1.550	1.252	2.265	0.747
Malacky	MA	2.328	13.270	2.749	0.984
Martin	MT	1.651	1.405	2.078	0.979
Medzilaborce	ML	2.251	1.663	6.136	1.022
Michalovce	MI	1.766	2.714	2.580	2.404
Myjava	MY	2.125	1.851	2.033	1.650
Námestovo	NO	4.361	3.430	2.863	2.463
Nitra	NR	1.629	1.848	1.235	2.105
Nové Mesto nad Váhom	NM	1.670	5.207	1.990	1.111
Nové Zámky	NZ	1.547	1.382	2.324	1.005
Partizánske	PE	2.561	3.685	2.322	1.656
Pezinok	PK	2.396	2.352	3.547	0.820
Piešťany	PN	1.429	1.920	1.425	1.068
Poltár	PT	0.733	0.632	6.082	0.169
Poprad	PP	2.710	11.342	2.658	1.353
Považská Bystrica	PB	2.137	2.643	0.485	6.757
Prešov	PO	2.569	7.022	3.611	0.833
Prievidza	PD	1.460	7.181	1.832	43.478
Púchov	PU	3.534	9.534	3.948	1.558
Revúca	RA	1.466	1.508	1.427	1.524
Rimavská Sobota	RS	1.375	1.555	2.441	0.540
Rožňava	RV	1.378	1.286	3.030	0.919
Ružomberok	RK	1.327	1.064	4.254	0.382
Sabinov	SB	1.590	1.263	1.531	1.284
Senec	SC	1.806	2.170	1.524	1.357
Senica	SE	1.172	0.926	1.077	0.523
Skalica	SI	1.527	3.702	2.536	0.832
Snina	SV	1.821	1.471	1.626	1.595
Sobrance	SO	1.563	1.160	1.434	1.056
Spišská Nová Ves	SN	1.083	1.435	1.102	1.318
Stará Ľubovňa	SL	1.798	1.412	1.696	1.304
Stropkov	SP	2.556	2.233	1.794	1.653
Svidník	SK	1.349	1.059	1.670	20.408
Šaľa	SA	1.811	6.229	1.292	1.326
Topoľčany	TO	2.266	6.701	2.950	0.560
Trebišov	TV	1.010	0.812	1.552	0.532
Trenčín	TN	1.588	1.535	1.935	0.942
Trnava	TT	1.084	0.999	0.779	1.572

Table 5. *Cont.*

District	Code	Change in GVA	Energy Efficiency	Emission Efficiency	Energy Eco-Efficiency
Turčianske Teplice	TR	2.820	2.134	2.597	1.427
Tvrdošín	TS	2.029	3.247	2.186	1.099
Veľký Krtíš	VK	1.725	1.436	1.991	1.531
Vranov nad Topľou	VT	3.193	3.415	3.041	2.070
Zlaté Moravce	ZM	1.700	1.948	1.588	1.212
Zvolen	ZV	2.364	2.208	2.155	1.488
Žarnovica	ZC	2.635	2.120	2.063	1.464
Žiar nad Hronom	ZH	1.133	0.895	1.038	0.884
Žilina	ZA	2.132	8.265	1.973	1.898
Average	SK	1.619	2.907	2.127	1.305

Source: Authors' computations.

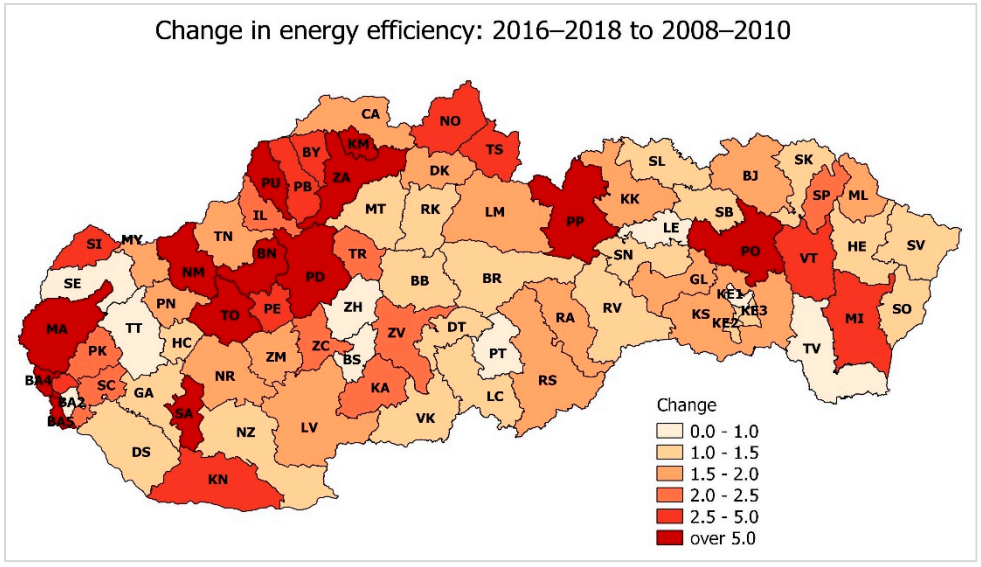


Figure 1. *Cont.*

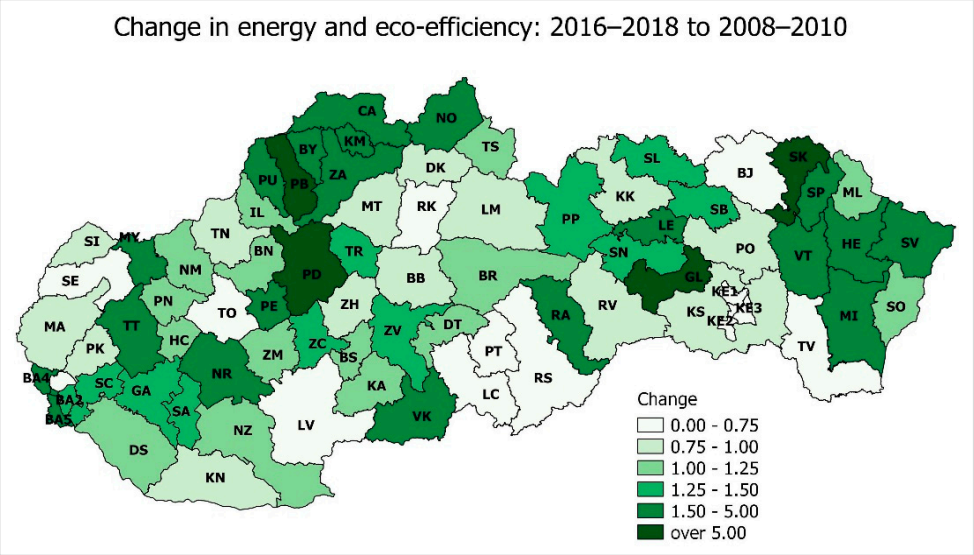


Figure 1. Patterns of regional changes in energy, emission and eco-energy efficiency.

3. Impact of Policy Interventions on Energy and Emission Efficiency

The evaluation of programmes on energy and emission efficiency benefits from experimental settings and applies a randomised controlled trial framework [24]. The DiD method first defines the appropriate time period, selects the appropriate variables and constructs treatment and control groups. Thereafter, the performance of treatment and control groups in pre-intervention and post-intervention periods is analysed via standard comparison methods (such as the *t*-test).

The DiD method was applied only to the OPCEG 2.1 and OPE 3.1 Policy Measures. OPCEG Policy Measure 1.1 was implemented in all 79 Slovak districts. It was not possible to construct the control group of unsupported districts. Potential economic effects of the latter measure were examined via correlation analysis. Descriptive statistics on regional allocations of the European support are reported in Appendix A, Table A4.

3.1. Pre-Intervention and Post-Intervention Periods

The first calls for energy and emission efficiency projects were launched in 2009. OPCEG Policy Measure 2.1 accounted for 28.3% and OPE Policy Measure 3.1 for 9.1% spending rates by the end of 2010. The first energy and emission efficiency projects started to operate after 2010. The period of 2008–10, therefore, is considered the period with no or minimal intervention. The majority of projects were completed in 2015 and their effects became fully visible in the period of 2016–18. The period of 2011–15 is considered the intervention period.

Two periods were chosen to compare the development of energy and emission efficiency in the treatment and control groups over time: 2008–2010 (pre-intervention period) and 2016–2018 (post-intervention period).

3.2. Construction of Treatment and Control Groups

Quantitative approaches mostly rely on econometric methods, such as a matching design, in time series [25]. There is an option to use some statistical techniques, such as propensity score matching (PSM), and match each agent from the treatment group with a 'mirror agent' from the control group (for further details on a 'matching design', see [26,27]. The PSM method increases comparability of the treatment and control groups in respect of the observable variable. A propensity score allows one to design and analyse an observational (nonrandomised) study so that it mimics some of the particular characteristics of a randomised controlled trial. Propensity scores are generated by logistic regression.

A propensity score is a balancing score: contingent on the propensity score, the distribution of observed baseline covariates will be similar between treated and untreated subjects [28].

There are diverse opinions on the minimum sample size for a PSM procedure. Some authors recommend a minimum sample of 100 units in order to produce reliable estimates of the treatment effect [29]. Meanwhile, other authors indicate that smaller samples are acceptable. Reference [30] conducted a series of Monte Carlo simulations so as to evaluate the influence of a sample size on the performance of a PSM procedure. They found that decreasing the sample size from 1000 to 40 subjects did not alter the type I error rate substantially, and led to relative biases below 10%. We do not underestimate the importance of the sample size for the reliability of estimates. We point to a data limitation in the concluding part of the paper.

3.3. Computation of Propensity Scores: Selection of Covariates

PSM attempts to reduce the bias due to confounding variables that could be found in an estimate of the treatment effect obtained from simply comparing outcomes amongst units that received the treatment versus those that did not. If one, for example, compares districts with and without specific support from the ESCF, the comparison is likely to generate biased results.

Districts benefitting from the OPCEG 2.1 and OPE 3.1 Policy Measures may differ from those receiving no support. Participating districts likely have a different population density, a higher business density and/or a higher share of urban population. Moreover, districts with a higher density of businesses may have higher average wages. In this evaluation, districts in the control group should have similar characteristics to those of districts in the treatment group (i.e., those supported by OPCEG Policy Measure 2.1).

Some of the abovementioned covariates (wages, business density, urban population) may be interrelated. The inclusion of interrelated covariates may cause potential problems with respect to multicollinearity. Multicollinearity testing is needed in order to eliminate the potential risk of biased estimations. One solution is that of dropping one of the correlated variables so as to reduce multicollinearity [31]. The following variables were tested for inclusion in the PSM score: (1) population density (population per 1 square kilometer), (2) the share of urban population out of the total population of the district, (3) the share of population with higher education out of the total population aged 35+, (4) average annual real wages (adjusted for changes in consumer prices) in firms with 20+ employees, and (5) numbers of firms (legal persons) per 1000 population. The multicollinearity statistics (variance inflation factor (VIF)) were obtained via conducting a linear regression analysis (OLS) with the same dependent variable and predictors. Variable (5) showed potential problems with regard to multicollinearity and was dropped from further computations. Four independent variables were retained after three steps: population density, share of urban population, share of population with tertiary education, and average real wages. Various thresholds are suggested to detect multicollinearity, e.g., VIF values above 10 [32] (p. 260). We applied multicollinearity tests to the predictor variables. No variable had a VIF value above 4.0.

The four covariates were used as inputs for the binary logistic regression in order to construct the PSM score. Participation in the OPCEG 2.1 or OPE 3.1 Policy Measure constituted the dependent variable. The Nagelkerke R-squared was 0.300 for OPCEG 2.1 and 0.157 for OPE 3.1 (Appendix A, Table A2).

Predicted probabilities were saved and used for the propensity scores. The nearest-neighbour matching procedure was used to match districts supported by the OPCEG 2.1 and OPE 3.1 Policy Measures with districts receiving no support. The effect of policy interventions upon energy and emission efficiency of the Slovak industry was analysed via the *t*-test. The *t*-test determines whether there is a significant difference between the means of two groups (i.e., treatment group and control group). The *t*-test works well even with small samples as long as the effect size is large [33].

Energy efficiency was computed via the amount of GVA generated via the consumption of an energy unit (electricity, gas and diesel). Deflators for GVA in the manufacturing sector were used for the price adjustments in the period of 2008–18. The GVA values were deflated to the 2008 levels.

Three separate *t*-tests were performed for energy efficiency in (1) electricity consumption, (2) natural gas consumption, and (3) diesel consumption (Table 6):

The average GVA per kilowatt/hour increased by 1.251 times in districts with no support, and by 1.641 times in districts supported by OPCEG Policy Measure 2.1.

The average GVA per m3 of natural gas increased by 1.679 times in districts with no support, and by 2.386 times in districts supported by OPCEG Policy Measure 2.1.

The average GVA per kilogramme of diesel increased by 1.380 times in districts with no support, and by 1.481 times in districts supported by OPCEG Policy Measure 2.1.

Energy productivity rose higher in supported districts than in unsupported ones for all energy types, but differences between supported and unsupported districts remained insignificant in the period of 2016–18. There was high heterogeneity in energy efficiency across the 79 districts. The majority of variation coefficients (the ratio of the standard deviation to the mean) were above 1. High heterogeneity lowered the significance level of the *t*-test.

Emission efficiency was computed via the amount of GVA generated per kilogramme of emissions (CO, NO_x, SO_2, and particulate matter). Four separate *t*-tests were performed for emission efficiency in (4) CO emissions, (5) NO_x emissions, (6) SO_2 emissions, and (7) pollution by particulate matter (Table 6):

The average GVA per kilogramme of CO increased by 1.235 times in districts with no support, and by 0.908 times in districts supported by OPE Policy Measure 3.1.

The average GVA per kilogramme of NO_x increased by 2.006 times in districts with no support, and by 2.338 times in districts supported by OPE Policy Measure 3.1.

The average GVA per kilogramme of SO_2 increased by 3.314 times in districts with no support, and by 2.772 times in districts supported by OPE Policy Measure 3.1.

The average GVA per kilogramme of particulate matter increased by 2.737 times in districts with no support, and by 2.088 times in districts supported by OPE Policy Measure 3.1.

The difference in emission efficiency between supported and unsupported districts was insignificant on the 0.1 level for both periods and all emission types. There was substantial regional heterogeneity in emission efficiency. Variation coefficients for the efficiency of CO and particulates, for example, were above 2. High heterogeneity made it difficult to observe statistically significant policy effects on emission efficiency.

Table 6. Results for the DiD with propensity score matching.

Energy Source	Period	Support	Descriptives			*t*-Test		
			N	Mean	Std. Dev.	t	df	Sig. (2-Tailed)
Energies								
electricity: GVA per kilowatt/hours	2008–2010	no	20	1.70	1.66	1.011	71	0.323
		yes	53	1.31	0.73			
	2016–2018	no	20	2.13	1.35	−0.073	71	0.938
		yes	53	2.15	1.17			
natural gas: GVA per m3	2008–2010	no	20	14.06	17.67	1.491	71	0.151
		yes	53	8.00	6.90			
	2016–2018	no	20	23.61	28.86	0.836	71	0.406
		yes	53	19.07	16.68			
diesel: GVA per kg	2008–2010	no	20	32.41	38.78	0.933	71	0.124
		yes	53	23.94	19.43			
	2016–2018	no	20	44.71	56.23	0.701	71	0.490
		yes	53	35.47	28.83			

Table 6. *Cont.*

Energy Source	Period	Support	Descriptives			*t*-Test		
			N	**Mean**	**Std. Dev.**	**t**	**df**	**Sig. (2-Tailed)**
Emissions								
pollution source	period	support	descriptives			*t*-test		
			N	Mean	Std. Dev.	t	df	Sig. (2-tailed)
CO emissions: GVA per kg	2008–2010	no	12	472.80	1024.18	1.087	60	0.300
		yes	50	149.55	223.15			
	2016–2018	no	12	583.67	1486.85	1.042	60	0.320
		yes	50	135.76	176.88			
NOx emissions: GVA per kg	2008–2010	no	12	455.43	547.46	0.540	60	0.598
		yes	50	364.47	413.75			
	2016–2018	no	12	913.68	1181.36	0.168	60	0.869
		yes	50	852.26	912.83			
SO_2 emissions: GVA per kg	2008–2010	no	12	1734.44	2234.01	0.608	60	0.552
		yes	50	1310.55	1863.68			
	2016–2018	no	12	5748.38	6799.77	1.016	60	0.327
		yes	50	3633.04	4917.91			
particulate matters: GVA per kg	2008–2010	no	12	1069.42	2559.62	1.044	60	0.337
		yes	50	324.90	444.05			
	2016–2018	no	12	2927.01	7317.85	1.063	60	0.310
		yes	50	678.44	692.65			

Source: authors' computations. Notes: * significant on the 0.1 level.

3.4. Correlation Analysis

The substantial increase in GVA (and the subsequent increase in energy and emission efficiency) may have been assisted by OPCEG Policy Measure 1.1. Policy support from OPCEG Policy Measure 1.1 (€369.30 m) was higher than the combined support from the OPCEG 2.1 and OPE 3.1 Policy Measures (€237.15 m). OPCEG Policy Measure 1.1 was implemented in all 79 districts and it was not possible to design control and intervention groups. We applied simple correlation analysis in order to explore the relation between changes in energy and emission efficiency and the relative amount of support to regional businesses (Appendix A, Table A3). The relative support was computed as the ratio of total GVA in the period of 2016–18 to the total support from OPCEG Policy Measure 1.1.

The respective Pearson correlation coefficients for electricity efficiency (r = 0.217; $p = 0.054$) and gas efficiency ($r = 0.248$; $p = 0.027$) were significant on the 0.1 and 0.05 levels (Appendix A, Table A3). Correlation, of course, is not causation. We conclude that support from OPCEG Policy Measure 1.1 may have assisted the increase in labour productivity and, indirectly, energy and emission efficiency as well, but the sample size and structure did not allow for testing causality.

4. Discussion

We tested the hypothesis that the financial support received from the ESCF helped to increase energy and emission efficiency in the districts supported. The DiD method found no support for the hypothesis regarding the positive impact of the ESCF upon the increase in energy and emission efficiency. There are several mutually non-exclusive explanations for the statistical insignificance of the policy support to energy and emission efficiency:

OPCEG Policy Measure 2.1 was aimed at energy saving and OPE Policy Measure 3.1 at emission cutting. The increase in energy productivity and emission efficiency was driven primarily by the substantial increase in GVA and not energy saving and/or emission cutting.

The increase in GVA was induced by firm investments in product and process innovations. New machinery, equipment and software tend to be more productive, more energy-efficient and cleaner than the incumbent ones. Combined support from three policy measures (€606.44 m) was substantial, albeit much lower than firms' own resources allocated to productivity-boosting, energy-saving and pollution-decreasing investments. According to the Reports on Innovation Activities of the Slovak

Enterprises [34], Slovak firms spent about €9573 m on process and product innovations in the period of 2007–15. Product innovations aim at increasing sales and GVA. The ESCF allocations to energy and emission projects provided only about 6.3% of the total firm expenditure on product and process innovations.

Our research has some important limitations related to the data availability and data structure. The most important limitation of our research relates to the structure of data on value added and energy consumption on regional levels (79 districts). Data on energy consumption were available for all sectors of the economy (industry, services, public sector, households), while data on value added referred to manufacturing industries only. Manufacturing enterprises consume about one half of the total energy in Slovakia. We assumed that energy and emission efficiency rose by similar or higher rates in manufacturing industries than those in the rest of the national economy. The assumption is corroborated by data on rapid growth in labour productivity in the manufacturing sector. Data on other production inputs (labour and capital) were not available on a regional level. Total-factor efficiency cannot be computed. The analysis indicated important and positive changes in energy productivity in respect of the consumption of electricity, natural gas, and diesel, but the statistical significance of the policy evaluation was impacted upon by the sample size and structure. Changes in standard deviations indicate increasing heterogeneity for energy and emissions on a regional level. The increase in heterogeneity refers more to overall increases in GVA than to the consumption of energy and/or the production of emissions. Slovak districts are rather small territorial units with an average population of 69,925. Productivity in manufacturing sometimes is impacted upon by the operations of a few large enterprises.

The abovementioned data limitations imply that the results of the analysis must be observed with caution.

5. Conclusions, and Directions for Further Research

The analysis suggested several potential directions for further research:

This paper analysed diverse types of energy consumption and pollutants in the 79 Slovak regions. Specific regions and industries have their own intensities of energy consumption and pollution. We conclude that it is better to evaluate each type of energy and pollution on an individual basis rather than lumping them together. Energy and environmental policies may work with higher precision when targeting specific types of energies and pollutants. Studies on specific types of energies and/or pollutants (Table 1) inform policy-making better than studies on 'total energy consumption'.

Regional patterns in energy and emission efficiency reflect the intensity of product and process innovations. Some regions were able to attract highly productive manufacturing industries, and some not. Branches of MNCs and/or large firms were responsible for the bulk of investments in product and process innovations in Slovakia. Such European support may be of higher importance to small and medium-sized enterprises in less developed Slovak districts. European assistance should be channelled to regions with the lowest improvements in energy and emission efficiency. Policymakers may direct their attention to regions with low ratios of GVA production to energy inputs.

Further research may combine regional data with firm-level data. Firms receiving support in the form of European assistance should report their annual consumption of energy. Combined data on energy consumption and value added would provide for a better understanding of the efficiency of policies aimed at energy and emission efficiency.

This paper found a significant increase in energy and emission efficiency in the Slovak districts in the period of 2016–18 compared to the period of 2008–10. Productivity-boosting technological innovations and structural changes in the Slovak economy (a shift towards industries with a lower consumption of energy but a higher production of GVA) were major drivers of trends in energy and emission efficiency. If an increase in energy (emission) efficiency, rather than energy savings (a decrease in pollution), is the major objective of sustainable development policies, then innovation-oriented

policies and changes in the structure of economic activities should be preferred to schemes supporting simple energy-saving (emission-cutting) projects.

Past schemes targeted several targets at once—decreasing energy consumption and emission production, and increasing GVA. Future support schemes should differentiate clearly between multiple targets, particularly high-pollution areas.

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Appendix A

Table A1. Descriptive statistics on GVA, energy consumption and emissions in Slovak districts.

Indicator	2008–2010	2011–2015	2016–2018	2008–2010	2011–2015	2016–2018
	Average			Standard Deviation		
gross value added (GVA), 2008 constant prices, annual averages						
average GVA, €m	153.49	185.58	249.03	299.50	304.81	360.71
GVA, EUR per 1 inhabitant	1969.52	2466.26	3370.59	2798.45	3089.19	3851.81
energy consumption, annual averages						
electricity, MWh	211,429.88	217,710.84	216,949.79	525,944.35	534,995.75	488,947.12
natural gas, 000 m3	42,507.34	38,672.49	34,414.78	129,838.34	103,269.30	91,274.05
diesel, tonnes	6788.73	7070.39	8638.58	9665.55	9302.64	13,264.47
emissions, annual averages						
NOx, tonnes	556.03	494.68	403.15	724.27	649.85	484.87
CO, tonnes	2072.50	2289.87	3142.15	4949.15	6161.98	6529.42
SO_2, tonnes	852.82	739.18	340.21	3933.45	3966.44	896.82
particle matters, tonnes	423.27	448.92	334.32	284.21	301.08	221.62

Source: Statistical office of the Slovak Republic and authors' computations. Notes: annual averages for total 79 districts. GVA and energy consumption are reported for manufacturing enterprises with 20+ employees. GVA is reported in constant 2008 prices.

Table A2. Binary logistic regression.

	B	S.E.	Wald	df	Sig.	Exp(B)
OPCEG 2.1: Nagelkere R square = 0.300						
Constant	4.414	1.991	4.914	1	0.027	82.585
Population density	−0.003	0.002	4.224	1	0.040	0.997
Real wages	−0.018	0.008	4.691	1	0.030	0.983
Population with tertiary education	0.031	0.112	0.075	1	0.785	1.031
Share of urban population	0.046	0.026	3.078	1	0.079	1.047
OPE 3.1: Nagelkerke R square = 0.157						
Constant	0.195	1.561	0.016	1	0.901	1.215
Population density	−0.002	0.001	2.399	1	0.121	0.998
Real wages	0.002	0.006	0.063	1	0.801	1.002
Population with tertiary education	−0.147	0.102	2.090	1	0.148	0.863
Share of urban population	0.043	0.024	3.188	1	0.074	1.044

Source: authors' computations.

Table A3. Correlation analysis: support to policy measure (€m) versus change in energy or emission efficiency (2016–2018 versus 2008–2010).

Change in:	CO Efficiency	NOx Efficiency	SO_2 Efficiency	Particulates Efficiency	Electricity Efficiency	Natural Gas Efficiency	Diesel Efficiency
OPCEG 1.1, €m	−0.187	−0.019	−0.130	−0.030	0.217*	0.248**	0.052
OPCEG 2.1, €m	−0.138	−0.101	−0.096	−0.133	−0.164	0.214	−0.050
OPE 3.1, €m	−0.144	−0.141	−0.129	−0.116	−0.040	−0.105	0.024

Notes: Pearson Correlation *significant on 0.1 level; significant on **0.05 level. N = 79 for the OPCEG 1.1, 53 for the OPCEG 2.1 and 50 for the OPE 3.1.

Table A4. Descriptive statistics – regional allocation of the European support (€m).

x	N	Minimum	Maximum	Mean	Std. Deviation
OPCEG 1.1	79	0.108	26.264	4.675	4.949
OPCEG 2.1	53	0.039	7.496	1.787	1.872
OPE 3.1	50	0.028	25.550	2.849	4.695

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