Sustainability versus the Dynamic Eco-Efficiencies of EU Countries[1]

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Abstract

In this study, the sustainable efficiencies of 25 EU countries are analyzed, and practicable paths for improvement are offered on a country-by-country basis. Dynamic eco-efficient production is not necessarily sustainable, and countries must therefore ensure the fulfillment of endogenously determined targets through additional measures. As the goals of maximizing production and avoiding pollutants seem to oppose each other, an optimization program with multiple simultaneous objective functions enlarges the dynamic eco-data envelopment analysis concept. The countries' economies and their impacts on the environment are described in Eurostat and ECB data on the countries' flow and stock inputs, output, resources for environmental protection, and emissions from 2014 to 2022. The examination reveals that the development of each EU country is far from sustainable. The countries that performed best were those that introduced carbon taxes early on, allowing their economies to largely adapt. The usage of the term "sustainable efficiency" is thus misleading, being used to measure static/dynamic eco-efficiency, without analyzing whether efficient production processes are indeed sustainable. To the best of the author's knowledge, this is the first measurement of sustainable efficiency. To distinguish the approach developed in this article from traditional models, this study uses the term "conserving efficiency".

Keywords: *data envelopment analysis, dynamic optimization, multiple objective functions, sustainability definition, sustainable efficiency, targets*

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Introduction

With the first United Nations Climate Change Conference in Berlin in 1995, the topic of protecting the world's climate once again appeared on the international political agenda. One way to reduce harmful effects of human activities on the environment and the climate is cutting consumption, but this would lead to a reduction in global production; this could in turn, lead to a reduction in living standards, the number of jobs, and even prosperity, if measured exclusively or predominantly in *value added per capita* or a similar way.[2] Most of the world's population is unlikely to support this approach; for some parts of the world, it would simply be unacceptable and impossible. Another way to reduce harmful effects on the environment is to increase the productivity of the production processes of various goods. Productivity can be enhanced by improving technical efficiency (based on existing technologies) but also through technical progress. Various methods have been developed to measure efficiency. However, most of this literature is based on static models, which ignore the fact that parts of companies' and national economies' expenditures often have a delayed effect on production (e.g., investments), and only in this way do they enable the implementation of technical progress and productivity improvements.

The long-term economic consequences of pollution are difficult to assess as the pricing for many pollutants is either inadequate or very volatile. Consequences may occur decades later and affect subsequent generations, which may have different preferences concerning the status of the environment and the economy. A complete internalization of these external costs at the time of emission fails due to political realities and imperfect markets, and, consequently, business and economic costs differ significantly.

Prior studies' usage of the term *sustainable efficiency* has been misleading. This term is usually used to measure static/dynamic eco-efficiency, without analyzing whether efficient production processes are indeed sustainable. To the best of the author's knowledge, the approach in this article is the first measurement of sustainable efficiency. To distinguish the approach developed in this article from traditional models, this study uses the term *conserving efficiency* instead of sustainable efficiency.

Some countries (especially those in the European Union) try to transform their economies by becoming more environmentally friendly without harming their prosperity and their global economic competitiveness. This study aims to support these attempts twofold. First, a measurement method is developed with which

[2] A different approach would be the *Welfare beyond GDP* approach, which takes social, environmental and health indicators into account alongside economic indicators (section 2).

sustainable behavior and deviations of it can be captured and measured by introducing endogenous intertemporal targets that ensure a minimum growth of production and reflect the conditions of the Paris Climate Agreement. Thus, technical progress is divided between economic growth and pollution avoidance/abatement. Endogenously determined paths for bads and goods define the temporal path of the targets. Second, by evaluation of their *conserving efficiencies*, practicable paths for improvement are presented for 25 EU countries.

As sustainability is a dynamic concept and pollution must be considered a specific – undesired – output, the study is based on a dynamic and environmental version of the non-parametric efficiency measurement tool data envelopment analysis (DEA). To do this, sustainability respectively conservation must be defined and employed in the dynamic eco-DEA framework to enable measurement of the distance to sustainable behavior and to reveal the potential to reach a sustainable production path. Additionally, the model is transformed into a program with multiple separated objective functions to enable it to consider how fulfilling different sustainability goals can require opposed actions. Finally, this study examines how much must be sacrificed in achieving one goal (production) in order to achieve an additional unit of another goal (pollution reduction) to remain on the same indifference curve of the country under consideration. Thus, if less renunciation is possible, the country changes to a higher indifference curve. The chosen approach is a non-parametrical technical benchmarking method. The results are not derived causally.

The objects of investigation were the EU27 countries because of their joint attempts to make their economies greener. The period of analysis was 2014 – 2022. The data for the empirical analysis was downloaded from Eurostat and the European Central Bank and consists of five dimensions, two flow inputs (*number of working hours*, *environmental protection expenditures*), one stock input (*net capital stock*), and one desired (good, *gross domestic product*) and one undesired (bad, *air emissions with international transport*) output. Poland and Ireland were excluded from the analysis to avoid biases; Poland because of implausibly low net capital stock – which is applied in the model as stock input; Ireland because of its significantly diverging trend in real GDP and consumption (presumably due to the European branches of large American IT companies). Thus, the data set for empirical investigation consists of 225 observations (25 countries, nine periods).

The empirical examination reveals that the economic and environmental development of each EU country is far from sustainable – no country developed conserving efficient. The countries that performed best were those that introduced carbon taxes early on, allowing their economies to largely adapt. For example, Sweden introduced carbon tax in the early 1990s, earlier than any other country.

Although Sweden's economy is not sustainable, it performs the best of the countries measured. Therefore, Sweden can function as role model for most other countries in the EU. For the given data and the assumptions made,[3] Europe's economy emitted by 17.3% too much (country-specific ranges from 4.2% to 51.5%) and produced by 8.2% too few (country-specific ranges from 1.3% to 34.7%) in aggregate in the analyzed period to be sustainable. Though the inefficiencies in pollution are more pronounced than the inefficiencies in production in aggregate, in 12 countries out of 25 the inefficiencies are greater in production than in pollution. As is usual in DEA models, this model identifies the sources of inefficiency and possibilities for improvement for each country; by following these recommendations, each country could ultimately be classified as conserving efficient. Furthermore, it is evident that the shortcomings in dynamical eco-efficiencies (which are calculated by country comparison) are a bigger problem than any technological gap between the technologically possible and the technologically necessary. Additionally, the new method examines how much must be sacrificed in achieving one goal (production) in order to achieve an additional unit of another goal (pollution reduction) to *remain on the same indifference curve* of the country under analysis as *if it were already behaving efficiently*; if the country is successful in renouncing less production, the country changes to a higher indifference curve. In this regard, Malta had the least latitude to reduce production for pollution reduction in the period 2014 – 2022, followed by Sweden. Croatia, Hungary, Italy, Portugal, and Spain had the highest latitude *if they were efficient*. However, this assessment must take into account that Malta, Sweden and Luxembourg, while not conserving efficient, are dynamically eco-efficient in contrast to the other countries. In other words, these countries already made a comparatively large contribution to their eco-efficiency in the past. The nearer technology comes to its maximum potential, defined by the efficiency frontier, the greater the challenge of achieving additional gains. Consequently, as a first step, each country should become efficient, which should be easier to achieve. However, ultimately, the goal should not be to remain on the same indifference curve, but to reach a higher one.

The article is structured as follows: in Section 1, concepts of sustainability are presented. Section 2 addresses dynamic eco-DEA models and the newly developed model for measuring conserving efficiency. This model is applied by analyzing the sustainable development of different EU countries in Section 3. Section 4 presents the conclusion.

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[3] Most important assumptions: equal preferences of production and pollution reduction; variable returns to scale. A brief overview of results with other assumptions is provided in appendix B.

1. Concepts of Sustainability

Leontief (1970, p. 262) argued that effects beyond economic ones, such as pollution, should be included as (negative) externalities in examinations of economic systems. Following works such as *The Limits of Growth* (Meadows et al., 1972), there has been intensive discussion of the definitions of *sustainability*, *sustainable use of resources*, *sustainable growth*, *sustainable development*, and other terms. The United Nations defined 17 goals in its *Sustainable Development Agenda* (UN, 2025) related to poverty and hunger reduction, health, education, gender equality, water and sanitation, the economy, inequality, cities, sustainable consumption and production, climate change, nature, peace and justice, and partnerships. The Brundlandt Report (UN WCED, 1987) defines *sustainable development* in very general terms and demands a holistic change in behavior from everyone: *„In essence, sustainable development is a process of change in which the exploitation of resources, the direction of investments, the orientation of technological development; and institutional change are all in harmony and enhance both current and future potential to meet human needs and aspirations"* (UN WCED, 1987, p. 46). Stiglitz et al. (2010) analyzed the possibilities to develop better measures for economic and social progress than gross domestic product alone on behalf of the French president.

Mardani et al. (2018) reviewed studies on the connection between pollution and economic growth and demonstrated that the latter must be restricted to reduce pollution. However, other researchers have assumed a transition to a *green* economy without significant loss of prosperity; Stanef-Puică et al. (2022) provided an overview. It is not clear whether *production* and *pollutant avoidance* are complementary or substitutive *in the long term*. High economic efficiency does not necessarily lead to high eco-efficiency (Halkos et al., 2015).

However sustainability is defined, it involves restrictions (certain resources must not be used too much) or reorientations (e.g., from non-renewable to renewable raw materials), which could be expedited by setting targets concerning specific dimensions. Natural resources are irreversibly lost once they reach a certain level of destruction (Pezzey, 1992, p. 15), and the substitutability between natural and *man-made* capital is limited (Barbier et al., 1990, p. 1260); thus, natural resources represent the limitative factor, and the maximum of life quantity requires the minimum rate of natural resource depletion (Georgescu-Roegen, 1971, p. 21). Cleveland and Ruth (1998) have argued that a production process is not mapped completely if the degradation of non-replaceable ecosystems or the depletion of non-renewable resources is ignored.

The concept of sustainability must be operationalized to enable its measurement and suggestions for improvement. In this article, only economics and the environment are considered for model development to examine the potential for sustainability, but in principle the developed method could be expanded to include other aspects as well, such as scientific (preservation of the biosphere, humanity), and ethical and social (justice between and within generations) perspectives. As the various components can be given in different units of measurement, DEA has been applied, for example, in the WWWforEurope project (Aiginger, 2016; Badinger et al., 2016) and in studies by Boussemart et al. (2020), Bosetti and Buchner (2009), Lábaj et al. (2014), Luptáčik et al. (2016), and Sotiroski et al. (2024). Mariano et al. (2015) summarized the use of DEA in the areas of human development and quality of life.

2. Methodology

Data envelopment analysis (DEA) models (Charnes, Cooper and Rhodes, 1978; 1979) compare production processes of different decision making units (DMUs; the observations analyzed). The observations are classified as efficient or inefficient based on Farrell's (1957) technical and price efficiency measures. They produce several outputs with several inputs; specifically, the production processes can be characterized by a multi-input, multi-output structure. No price information is required as a valuation system, and no a priori knowledge of the production structure is needed. Strengths and weaknesses, especially those of inefficient observations, are identified, and role models (*peers*) and artificial units, which are structurally similar, but efficient, are provided for each DMU. The weights are chosen endogenously so that the observation under study obtains the best possible efficiency value. A different choice of weights (even those that experts choose exogenously) does not lead to a better efficiency value for the DMU under consideration.

Numerous attempts have been made to integrate undesired outputs (*bads*) into the DEA concept. Murty and Russell (2020) provided a comprehensive overview of different eco-DEA models. One approach that has been criticized is to incorporate bads into DEA models by treating them like inputs, as both should be reduced. However, since the emissions of bads are usually calculated from the input usage and are not measured directly, this approach is a good proxy. Schnabl (2025, p. 3) presented further arguments regarding why this approach can be used.

Dynamic DEA models enable the interconnection of different production periods. Fallah-Fini et al. (2014) and Kao (2023, pp. 395 – 418) offered comprehensive overviews of such models. In the Nemoto-Goto models (1999; 2003), instead of considering *flow input* investments (the norm in DEA models), *stock input* capital stock is modeled, and investments are determined endogenously and indirectly through the determined size of the stock input. The intertemporal transferable components are fundamentally different from the outputs intended for sales and externally purchased inputs. Contrary to most models, the Nemoto-Goto models describe the dynamics via the optimal development paths of the variables. The optimality conditions of their models can be transformed into the Hamilton-Jacobi-Bellman equation of dynamic optimization.

Several dynamic eco-DEA models have been developed: Dakpo and Lansink (2019) integrated the environmental concepts of Murty et al. (2012) and Førsund (2009) into the dynamic network DEA model of Färe and Grosskopf (1996; 1997). Ratner (2020) introduced pollutants as inputs in the dynamic DEA model of Emrouznejad and Thanassoulis (2005). Tone and Tsutsui (2014) extended the slacks-based measure approach by considering *carry-overs* between periods and multi-level production processes in each period, which Hsieh et al. (2019) applied. In Schnabl (2025), bads were introduced into the models of Nemoto and Goto (1999; 2003).

The goal of this section is to extend the first model of Schnabl (2025, pp. 7 – 12) and further develop it into a DEA model for measuring sustainable efficiency by integrating predefined targets, under the assumption that these targets would lead to sustainable economic activities and environmental statuses and reveal the potential for sustainable development. This is done in two steps. First, the model is transformed into a program with multiple objective functions to enable consideration of the opposing goals of reducing bads and growing goods production; this step uses separated objective functions by applying Benson's (1998) algorithm which gives the dynamic eco-efficiency model (DEE). Second, targets are introduced in two ways: by using Thanassoulis and Dyson's (1992) concept of ideal targets and by setting endogenously determined intertemporal targets which produces the conserving efficiency model (CE).

2.1. The Base Model

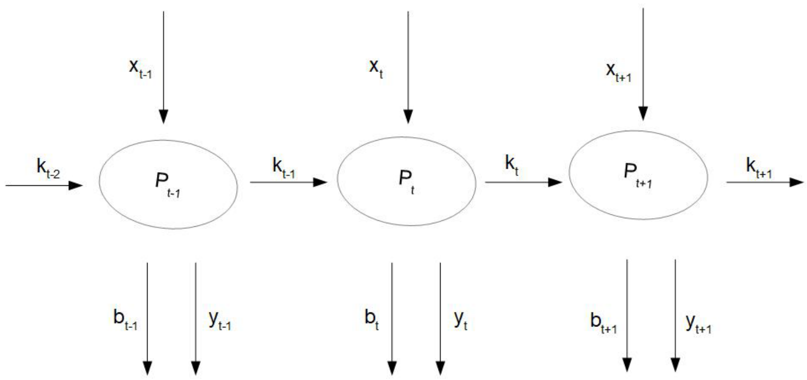
In this article, *dynamics* denotes the change in the state of the system. *Dynamic eco-efficiency* means that the production of one desired output cannot be increased (1) by shifting time, (2) without increasing the use of resources and/or environmental pollution, or (3) by reducing another desired output (Schnabl, 2025, p. 4). When applied to entire states, a changed savings or investment behavior does not lead to an increase in production without worsening environmental conditions.

In Schnabl (2025, pp. 7 – 12), bads were introduced into the models of Nemoto and Goto (1999; 2003); the idea is illustrated in the following paragraphs and in Figure 1. The corresponding constraints of this optimization model are presented in Appendix A.1.

DMU j $\left(j=1,\ldots,J\right)$ uses in period $t\left(t=1,\ldots,T\right)$ I different flow x_{tij} $\left(i=1,\ldots,I\right)$ and L different stock input factors k_{t-1lj} $\left(l=1,\ldots,L\right)$, which are carried over from the production process of the previous period $t-1$, as resources, and manufactures *R* different goods y_{trj} $\left(r=1,\ldots,R\right)$, and the stock inputs k_{tlj}, which are delivered to the process to the following period $t+1$ as products, causing *P* different bads b_{tpj} $\left(p=1,\ldots,P\right)$.[4] The DMU under assessment is assigned by j_0. The optimal flow and stock inputs $\tilde{x}_{tij_0}$ and y_{trj} $\tilde{k}_{tlj_0}$, the goods $\tilde{y}_{trj_0}$, and the bads $\tilde{b}_{tpj_0}$ are sought, contrary to the observations x_{tij}, k_{tlj}, and b_{tpj}. In this way, all optimal values can be theoretically larger or smaller than the observations. This greater flexibility compared to standard DEA models is needed to enable the expansion of the environment-related capital stock or workforce to reduce pollution, which is costly. Hence, deviations from the optimum can be both positive and negative (e.g., too few or too many investments). To avoid unrealistic trajectories for optimal bads, bads are prevented from increasing during optimization compared to their observation values; the reverse is true for goods. Decision-makers can choose between buying flow inputs for immediate production and making money or investing in stock inputs to produce more or more effectively or to produce less pollution in the future. Thus, the production system can change over time.

Figure 1

Dynamic Eco-DEA Model without Separated Abatement



Source: Schnabl (2025, p. 7).

2.2. Economic versus Environmental Views in Economic Development: Dynamic Eco-Efficiency Model (DEE)

Contrary to the standard DEA models, in the current article the opposing goals of maximizing production and avoiding pollutants are modeled with multiple simultaneous objective functions; in this way, decision-makers do not need to weigh

[4] In the current article, pollution, measured in tons of CO_2 equivalents (tCO_2e), is the only bad, but in principle any sort of undesired outcome could be a bad component.

the relative importance of the different $R + P$ goals a priori. DEA models are usually linear programming models in which several opposing goals are summarized in a single objective function, as in the study of Nemoto and Goto (1999; 2003) in which the costs are minimized by using given input prices as predetermined weights. Generally, if the weighted goods $\tilde{y}_{trj_0}$ minus the weighted bads $\tilde{b}_{tpj_0}$ are maximized, the objective function is (γ is the time preference rate, $w^b_{tpj_0}$ and $w^y_{trj_0}$ are predetermined weights):

$$C_1 = \max\left(\sum_{t=1}^{T}\gamma^t \sum_{r=1}^{R} w^y_{trj_0}\tilde{y}_{trj_0} - \sum_{t=1}^{T}\gamma^t \sum_{p=1}^{P} w^b_{tpj_0}\tilde{b}_{tpj_0}\right) \tag{1}$$

The weights $w^b_{tpj_0}$ and $w^y_{trj_0}$ can be time- and DMU-dependent. The *virtual weights* $\sum_{t=1}^{T}\gamma^t w^y_{trj_0}\tilde{y}_{trj_0}$ and $\sum_{t=1}^{T}\gamma^t w^b_{tpj_0}\tilde{b}_{tpj_0}$ reflect the relative importance of the specific objective of the DMU under consideration. However, if the weights are selected exogenously, it is not clear a priori how they should be chosen to meet the visions of the managers of the DMU under study and whether these weights lead to the best efficiency value for each DMU, which is usually the case in DEA models. If the weights are generated endogenously, the model becomes non-linear. An alternative would be to employ multiple objective functions to represent the trade-offs between these different objectives:

$$C_{b,p,1} = \min\sum_{t=1}^{T}\gamma^t \tilde{b}_{tpj_0};\forall p \tag{2}$$

$$C_{y,r,1} = \max\sum_{t=1}^{T}\gamma^t \tilde{y}_{trj_0};\forall r \tag{3}$$

A linear optimization model with multiple objective functions can be solved by Benson's (1998) outer approximation algorithm. This algorithm is a generalization of the interactive method of Zionts and Wallenius (1976). Both methods deliver Pareto-Koopmans-efficient solutions; that is, it is not possible to improve one objective value without causing another to become worse. These solutions represent compromises between the various objectives. The solutions are not unique, which is typical because of the opposing goals. The Zionts-Wallenius method implicitly assumes that the null vector is a feasible solution, which is not the case in the given problem due to the condition that the optimized goods values must not fall below the observed ones. In the Benson method, the starting point must be a feasible solution but can be otherwise arbitrarily chosen. To obtain the closest Pareto-Koopmans-efficient solution, the observation could be the starting point. The implementation of the Benson algorithm is shown in Appendix A.2.

The new method also examines how much must be sacrificed in achieving one goal (production) in order to achieve an additional unit of another goal (pollution reduction) to remain on the same indifference curve of the DMU under analysis. If the DMU is successful in sacrificing less, it changes to a higher indifference curve. This indifference curve is given by shadow prices corresponding to the deviations resulting from the dual of the Benson algorithm; for these, the results are Pareto-Koopmans-efficient. This means that the scalarized objective function value of the multiple objective linear program is maximal. The optimized variables project the DMU under study onto the efficiency frontier. Thus, at the projection point, if one goal is to be improved, the other must be worsened.

The labor force is bound by demographic circumstances as demographic trends also play a role in sustainability. Thus, additional constraints of bounded variable types (Cooper et al., 2007, p. 224) are added, such as upper and lower bounds for variable inputs, to avoid unrealistic results (Appendix A.3.1).

2.3. Conserving Efficiency Model (CE)

As dynamic eco-efficient production methods are not necessarily sustainable and mankind is currently extracting more from natural resources than can be regenerated, mankind's current behavior is not sustainable. The definition of conserving efficiency narrows the definition of dynamic eco-efficiency in Section 2.1 even further. In this study, in addition to dynamic eco-efficiency, *conserving efficiency* requires the fulfillment of targets that experts have defined concerning the paths of bads and goods that ensure the sustainable development of the economy and environment/climate, combined with the requirement that future generations be *better off* in terms of living standards and environmental conditions because of technological progress, leading to a sustainable economy and environment/climate.

For an inefficient DMU, DEA delivers a projection onto the efficiency frontier; this projection point is therefore efficient, shares similarities with the original DMU, and consists of best-practice DMUs that are efficient and form the peer group (role models) of the DMU under study. The type of projection is determined a priori by the choice of the model and is then the same for all DMUs. Even if all projection points are part of the production possibility set, they can be difficult to achieve by the corresponding inefficient DMUs in practice. The respective management may also involve different plans and objectives (Thanassoulis et al., 2008, p. 354); public bodies can also influence the targets. For example, certain environmental requirements could be set as targets. Target-setting enables projection points that make the DMUs efficient and that fulfill exogenously specified conditions. Two approaches can be distinguished. In the first, the targets are formulated *directly* in the model; in the second, the selection options of the weights chosen endogenously in the model are restricted so that the path to the targets – and, therefore, the targets – are influenced. These restrictions can be absolute: in this case, weights or the virtual multipliers must then be above or below exogenously selected minimum or maximum values. An alternative would be a relative restriction compared to other weights or virtual multipliers.

Golany and Roll (1994) presented a model of direct target-setting. They used an *engineering approach* to efficiency measurement based on total quality management (ibid, p. 315). In this approach, certain standards are specified for each input and output. These standards do not have to originate from observations and can be outside the production possibility set that the observations span. The standards are added as *artificial* DMUs; this shifts the efficiency frontier outwards, which increases potential opportunities for improvement. Another model is that of Halme et al. (1999) and is referred to as *value efficiency analysis*. In this model, each DMU can individually specify its standards; simultaneously, the weights are restricted such that a projection in the direction of these specific standards is preferred.

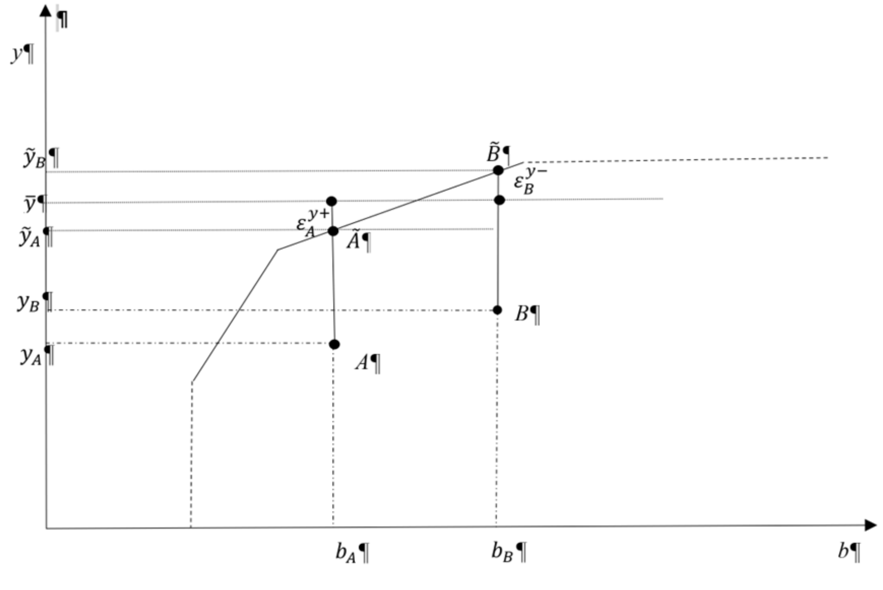
To introduce the *ideal targets* of Thanassoulis and Dyson (1992, pp. 87 – 88), additional restrictions must be appended to the constraints set, which are shown in Appendix A.3.2. The ideal targets can be outside the production possibility set and above the efficiency frontier without shifting it. If this is the case, the distance of the projection points on the efficiency frontier to the ideal target is sought. Positive and negative deviations of the projection points from the ideal targets respectively are measured for each variable by introducing further nonnegative variables.

It is not necessary to define ideal target values for each dimension; for example, only the bads could be restricted. The distance from the observation to the ideal target can be divided if the ideal target lies above the efficiency frontier for at least one variable, as shown in Figure 2 for DMU $A = (b_A, y_A)$. The first distance is from the observation A to the projection point $\tilde{A} = (b_A, \tilde{y}_A)$, as is typical in a DEA model, and the second distance is from the projection point $\tilde{A}$ to the ideal target $(b_A, \bar{y})$ defined by ε_A^{y+}. In sum, these two distances give the distance from the observation path to the sustainability path if the ideal targets lie above the efficiency frontier for at least one variable. If the ideal targets are not above the efficiency frontier, the distance to the sustainability path is given by the first distance alone.

The new type of *endogenously determined intertemporal targets* reflects that certain variables must grow or shrink at certain rates over time. Instead of (ideal) targets, the (de)growth rates of specific dimensions are predetermined. If these rates are positive, the economic and environmental conditions must constantly improve, either based on the optimal value of the previous period if the endogenous target is part of the empirical production possibility set or, if not, on the endogenous target of the previous period. This procedure leads to targets that are calculated endogenously in the model. The corresponding constraints are presented in Appendix A.3.3.

As the ideal targets and the endogenously determined intertemporal targets can lie above the efficiency frontier, they can define production processes that are not part of the empirical production possibility set and that are technologically impossible. Consequently, the efficiency frontier and the empirical production possibility set are not changed by adding these two types of targets. This contrasts with, for example, the standards approach of Golany and Roll (1994). As these two targets may not be achievable through the given technology, it is possible that no production process is evaluated as sustainably efficient, not even dynamic eco-efficient DMUs.

F i g u r e 2
Function of the Deviation Variables



Source: Author's presentation.

The deviation variables received from the constraints concerning the ideal and endogenously determined intertemporal targets describe the distances from the efficiency frontier to the necessary sustainable path. If the DMU under study is evaluated as dynamically eco-efficient *and* all these deviation variables equal zero, then this DMU is also considered *conserving efficient*. If the DMU under study is not dynamically eco-efficient *or* if any deviation variable is positive, then the DMU under study is considered sustainable *in*efficient. The dual model of the sustainable efficiency model is presented in Appendix A.4. This approach enables the pursuit of multiple objectives that are measured in different units of measurement.

Since it is thus not possible to fully capture national targets, no ideal targets are set in the empirical calculations in the current article; only endogenous targets are assumed. This research focuses on the interplay between the economy and ecology, but it should be possible in principle to generalize the model developed here to other aspects. Technological progress can occur, but this model does not analyze it.

3. A Conserving Efficiency Analysis of European Countries

The different crises in the years since 2020 – namely the COVID-19 pandemic, the Ukraine war, rising energy prices, the intensifying Middle East conflict – hit the economies of European Union countries particularly hard. This once again indicates that these countries should try to become less dependent on imports of energy and fossil energy sources, which could be achieved most easily by extending more environmentally friendly renewable energy production. This would also have the positive effect of shifting production and added value to Europe. In the following sub-sections, the models from Sections 2.2 and 2.3 are applied to the EU countries to demonstrate the potential for sustainable development. Raw data and detailed results can be requested from the author. As rising GDP is also important in the context of environmental efficiency because it can be used to finance expenditure and investments related to environmental protection, rich countries tend to spend more on environmental protection. For this reason, the objectives given are simultaneous maximization of the GDP and minimization of pollution.

3.1. The Data

The data[5] for the empirical analysis was downloaded from Eurostat and the European Central Bank. The objects of investigation were originally the EU27 countries during the 2014 – 2022 period, but Poland's data for the capital stock was implausibly low, it was removed from the analysis.[6] Additionally, as the trends in real GDP and consumption in Ireland diverge significantly from each other (2014 – 2022 +116% and +24%, respectively), presumably due to its hosting of European branches of large American IT companies, Ireland was also excluded

[5] The data mentioned in this abstract were taken from Schnabl (2025) to enable the comparison of the effects of the different models.

[6] According to Eurostat the capital stock of Poland is lower than the capital stocks of countries with much lower populations and GDP like Czechia or Portugal.

from the analysis. Thus, the data set for empirical investigation consists of 225 observations (25 countries, nine periods). For the empirical application presented, the model is five-dimensional, with two flow inputs (*number of working hours* and *environmental protection expenditures*, measured in euros) and one stock input (*net capital stock*, measured in euros), one good (g*ross domestic product*, measured in euros), and one bad (*air emissions with international transport*, measured in tons of CO_2 equivalents, tCO_2e).

As the number of working hours cannot increase indefinitely, the capacities of the variable input *working hours* are limited from above.

The *participation rate*[7] is 64%, the *part-time share*[8] 18.9%, and the *unemployment rate*[9] 8.5% in the weighted average in the EU countries. The *extended labor force*[10] was used as a proxy for the upper limit. This measure means that no one who wants to work is unemployed, which would bound the working hours enhancement by 19.1% in the weighted average. The sample descriptive statistics are presented in Table 1.

T a b l e 1

Sample Descriptive Statistics (PPP EU27 in constant 2022 prices)

		Minimum	Mean	Median	Maximum
Flow input	*Number of working hours (million)*	371	11,777	7,029	62,168
	Participation rate (%)	43.4	64.0	65.6	72.2
	Part-time share (%)	1.5	18.9	12.7	42.2
	Unemployment rate (%)	2.0	8.5	6.8	26.6
	Extended labor force (million)	410	14,026	8,014	66.536
	Potential enhancement (%)	3.1	19.1	15.2	35.0
Flow input	*Environmental protection expenditures (million EUR)*	262	11,689	3,863	77,849
Stock input	*Net capital stock (million EUR)*	27,506	1,833,212	783,283	12,847,999
Good	*Gross domestic product (million EUR)*	12,843	548,867	240.323	3,549,237
Bad	*Air emissions with international transport (thousand tCO_2e)*	7,164	136,300	60,668	931,038

Source: Author's presentation.

The monetary data was adapted by purchasing power parity (PPP) based on EU27, year 2022, and inflated to 2022 prices using the GDP deflator. These data components are highly correlated, with correlation values of 0.93, as shown in Table 2.

[7] Number of working people in relation to the comparable total population.

[8] Share of working people which are not working full time.

[9] Share of number of unemployed persons compared to the active population (= sum of people employed and unemployed).

[10] Eurostat (2025): *The extended labor force concept includes unemployment, employment and two categories of inactive persons, those available but not seeking, and those seeking but not available.*

Table 2

Correlation between Data Components

	k_t	k_{t-1}	P	G	E	W
Net capital stock k_t	1.0000	0.9996	0.9859	0.9894	0.9324	0.9369
Net capital stock k_{t-1}	0.9996	1.0000	0.9865	0.9898	0.9338	0.9383
Environmental protection expenditures P	0.9859	0.9865	1.0000	0.9895	0.9582	0.9577
Gross domestic product G	0.9894	0.9898	0.9895	1.0000	0.9707	0.9695
Emissions E	0.9324	0.9338	0.9582	0.9707	1.0000	0.9771
Working hours W	0.9369	0.9383	0.9577	0.9695	0.9771	1.0000

Source: Author's presentation.

The agreements between the European Union and the member states, the *Kyoto 2nd commitment* (2013 – 2020; European Union 2025a) and the *national energy and climate plans* (2021 – 2030; European Union 2025b) distinguish between pollution regulated by the EU Emissions Trading System (*ETS*) and other (*non-ETS*) pollution. In the latter case, individual nation states agreed to annual pollution limits. The limits for ETS pollution, however, were set for the whole European Union using the annual reduction in the total number of certificates issued, as well as those issued free of charge. As ETS certificates can be bought and sold throughout the European Union, it is difficult to isolate national limits. At the same time, enough certificates were available in total (both free and auctioned), at least in the period until 2020, that these did not represent an actual restriction in the direction of more environmentally friendly economic activity. In other words, most countries (over)fulfilled these targets in this way. Furthermore, it is unclear whether these targets are sufficient to achieve the objective of the Paris Climate Agreement. Since it is not possible to fully capture national targets, no ideal targets are set in the following empirical example; only endogenous targets are assumed.

3.2. The Models

Two model variants were calculated. In the dynamic eco-efficiency model variant, no targets were considered, contrary to the conserving efficiency model variant. In this way, the impact of the targets' insertion compared to the DMUs' projections onto the efficiency frontier can be analyzed.

3.2.1. The Dynamic Eco-Efficiency (DEE) Model

The first model is the *DEE* model, which was described in Section 2.2 and is defined by the constraints (4) to (12), as noted in Appendix A.1, representing the base model from Schnabl (2025, pp. 7 – 12) but with another objective function, and with capacity limits (16) for the variable input *working hours*. In the first run, the objective function (1) was applied with the following predetermined weights to receive starting points for the Benson algorithm. To avoid the dominance of GDP in the objective function, time- and country-dependent weights were chosen with $w_{tj_0}^{y} = 1$ and $w_{tj_0}^{b} = y_{tj_0} / b_{tj_0}$, [11] which is increasing for most countries, thus giving GDP and pollution the same importance. In the second run, the results from the first run were applied in the program with the objective functions (2) and (3) instead of (1), using the iterative process of the Benson algorithm in Appendix A.2.

3.2.2. The Conserving Efficiency (CE) Model

Adding targets according to the DEE model gives the *CE* model, which was described in Section 2.3. However, as no national targets could be identified, ideal targets were not set, and only endogenous intertemporal targets were defined. The *endogenous intertemporal targets* were introduced by adding the bads and goods intertemporal restrictions (21) to (23) in Appendix A.3.3. To ensure production growth, an annual economic growth of $g_{tj}^{y} = 0.02$ is demanded. In order to reflect the Paris Climate Agreement, which requires a global reduction in gross emissions of 87.5% between 2020 and 2050, the following weights were selected for the bads: $g_{tj}^{y} = 0.875 / \left(2050 - t\right)$. Thus, technical progress was divided between economic growth and pollution avoidance/abatement. Instead of using observed values for building targets, the endogenously determined paths for bads and goods define the additional targets. As with the DEE model, the CE model was calculated in two runs applying the same procedure.

3.2.3. The Bad-Oriented Efficiency (BO) Model

For comparison, the *bad-oriented* variant of these models was also computed (*BO*). In this variant, pollution is minimized over time; thus, the BO is given by $w_{tj_0}^{y} = 0$ and $w_{tj_0}^{b} = 1$ in the objective function (1). Since there is only one objective, it is not necessary to convert the program into a multiple objective functions problem and to perform the Benson algorithm. Because of the condition that the optimized goods values must not fall below the observed ones, the production cannot be reduced; otherwise, a bad orientation would result in null production.

3.3. Results

This study evaluates the sustainable efficiencies of 25 EU countries and offers them practicable paths for improvement. For this purpose, a measurement method was developed with which sustainable behavior and deviations thereof can be

[11] A brief overview of the results with other weights is provided in the appendix B.

captured and measured by introducing endogenous intertemporal targets that ensure a minimum growth of production (+2% in real terms) and reflect the conditions of the Paris Climate Agreement. One result of this exercise is the determination of how far each EU country is from its sustainability-consistent path under these targets.

This analysis is done in two steps. First, the DEE model from Section 2.2 delivers projection points on the dynamic eco-efficiency frontier based on a comparison of the countries among each other.

However, being static/dynamic eco-efficient is not necessarily sufficient for sustainable production. Second, the CE variant from Section 2.3 gives additional distance from these projection points to the sustainable paths, which are defined by the endogenously determined intertemporal targets. The efficiency frontiers only differ between constant (CRS) and variable returns to scale (VRS), but not between the DEE and CE models. This is because the targets endogenously determined in the CE models can lie above the efficiency frontier and can define production processes that are not part of the empirical production possibility set, which cannot be reached via the given technology. Consequently, adding the targets does not change the efficiency frontier and the empirical production possibility set. Because of these two steps, two optimized sets are delivered for each country, one from the DEE and one from the CE model. By contrasting the result sets of the DEE and CE models, the conserving inefficiencies can be divided into inefficiencies which are caused by comparison with the other countries, and inefficiencies which are caused by the additional setting of the targets, catching any technological gap.

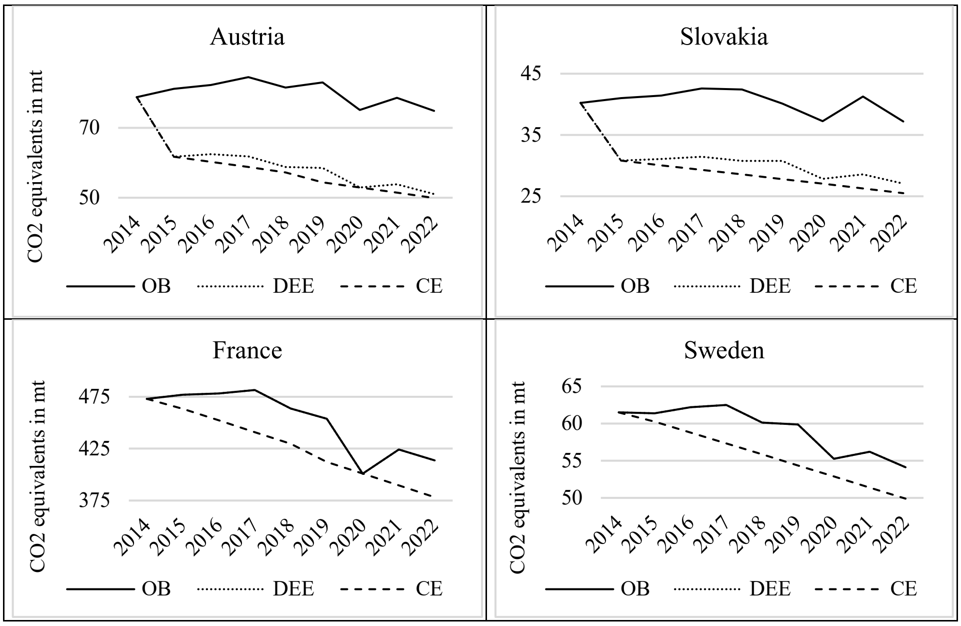
3.3.1 Country-Specific Results

If countries are efficient, then the optimized variables are identical to the observations. Three countries (Sweden, Luxembourg, and Malta) are CRS-efficient in the DEE model. Each CRS-efficient country is also VRS-efficient. Another two countries (France and Germany) are VRS-DEE-efficient but not CRS-DEE-efficient. The Netherlands and Denmark are weak VRS-DEE-efficient (i.e., at least one optimized variable is identical to the observed one, but not all). In any model, Sweden serves as a role model for most inefficient countries. Sweden introduced a carbon tax very early and performs best; its economy may already be adapted to the existence of a carbon tax and be favored for this reason.

As the targets can lie outside the production possibility set, even DEE-efficient DMUs can be CE-inefficient, and even Sweden's economy and the other DEE-efficient countries are not conserving efficient.

In Figure 3, the observed pollution paths from 2014 – 2022 are contrasted with the optimized paths resulting from the VRS-DEE and the VRS-CE models for the VRS-DEE-inefficient countries Austria and Slovakia as well as the VRS-DEE-efficient countries Sweden and France. As they are efficient, the DEE paths and the observed paths are identical for Sweden and France, but the CE paths differ. For the VRS-DEE-inefficient countries, all three paths differ. Considering Austria and Slovakia, it is obvious that the DEE-inefficiencies cause greater deviations than setting additional targets. The optimized pollution levels decrease in both model variants, decreasing the most in the CE variant.

F i g u r e 3
Comparison of the Observed (OB) Pollution Paths from 2014 – 2022 with the Optimized Paths Resulting from the VRS Dynamic Eco-Efficiency (DEE) and from the VRS Conserving Efficiency (CE) Models for Austria, Sweden, Slovakia, and France



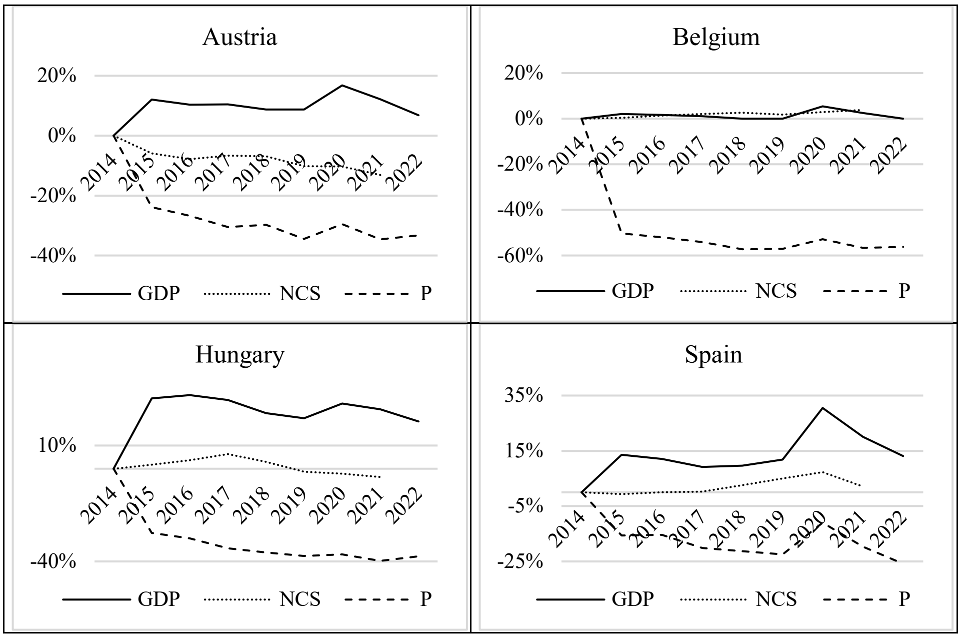
Source: Author's calculations.

Figure 4 presents the relative deviations of the VRS-CE paths of the observed paths for the variables GDP, net capital stock, and pollution for Austria, Hungary, Belgium, and Spain. Positive deviations mean that the optimized values are larger than the observed ones, while negative deviations mean the opposite. As the sole good, the GDP is considered in the objective function and is minimum constrained. Its optimized values from the VRS-DEE model are not below the observed GDP and partially show a strong deviation from the observed GDP for some countries.

The optimized values from the VRS-CE model are even higher in some cases. This happens especially in 2020 – the first COVID-19 year, in which the GDP dropped in each country – as a GDP growth of at least 2% is demanded, and the corresponding deviation values are positive. The optimized values of the net capital stock are partially above and partially below the observed values for Hungary and Spain; for example, Hungary's net capital stock was too high from 2015 to 2018, and the opposite was true from 2019 to 2022. Belgium's net capital stock was too small in general (by an average of 2.2% over time). Austria's was too large in all years (by in average of 8.7% over time); this could be interpreted as inefficient capital use because the GDP is too low, while pollution is too high at the same time. The path developments for the GDP and pollution are not symmetrical due to varying degrees of inefficiency in the GDP and pollution dimensions.

According to the CE model, in Slovakia the pollution is too high by 30.3% (DEE: 26.3%) on average over time, while GDP is too low by 45.6% (DEE: 44.3%). Since no targets relating to the net capital stock were added, the results are the same for the DEE and CE models (too low by 11.8%). Like most other inefficient countries, the main weakness of Slovakia's economy is its lack of dynamic eco-efficiency compared to the other countries. Targets are not the problem.

F i g u r e 4
Relative Deviations of the VRS-CE Paths of the Observed Paths for the Variables GDP, Net Capital Stock (NCS), and Pollution (P) for Austria, Hungary, Belgium, and Spain



Source: Author's calculations.

3.3.2. Aggregate Results

To receive costs, the variables given in volumes are valued by prices. The price for the *number of hours worked* is given by the ratio of the employees' compensation to the hours worked. For *air emissions*, the ratio of environmental taxes and levies to the CO_2 equivalents is used as the price. The price for the *net capital stock* is given by the ratio of the consumption of fixed capital to net capital stock. The prices depend on year and country.

Table 3 presents the savings potentials (–) in aggregate for the 25 countries analyzed from 2014 – 2022 by cost categories and by model, presented in real prices of 2022 and in PPP. For the 25 countries analyzed, total costs of 86.44 trillion euros were observed. Employees' compensation (58.8 trillion euros, 68% of the total) and the consumption of fixed capital (21.86 trillion euros, 25.3%) are considerably higher than the environmental taxes (3.15 trillion euros, 3.6%) and the environmental protection expenditures (2.63 trillion euros, 3%). GDP per emitted tCO_2e is 4,027 euros; this may be an important indicator of the sustainability of economic activities and production.

If all variables are optimized for the period 2014 – 2022 using the DEE model, the savings in pollution would reach 3.8 (VRS assumption) or 8.4 billion tCO_2e (CRS-assumption), or savings of 12.3% to 27.5%. At the same time, the GDP would be higher by 4.9% (VRS) to 10.6% (CRS), meaning production would be considerably higher. The VRS and CRS results differ in the instructions for action. Both outcomes indicate a necessary reduction of working time, and this is higher under the VRS assumption, leading to a weaker increase/decrease of GDP/pollution. This suggests that a workforce is needed for pollution abatement or purification, partially to compensate for the rise in economic activities. Both variants recommend more investments in capital stock. Taken together, this also means that the GDP could be higher, and pollution could be lower with lower variable inputs (the net capital stock is higher in both VRS and CRS), but a much higher GDP change is only possible with a larger workforce. Considering the detailed countries' results, the recommendations are different for each country. To reach their projection points on the DEE efficiency frontier, most Eastern European countries should reduce working hours, while the opposite is true for most Western European countries. The GDP per emitted tCO_2e would increase by 20% (4,816 euros, VRS) or 53% (6,142 euros, CRS) in the weighted average.

Compared to the DEE results, the sustainable paths resulting from the CE model would require an even lower pollution by 1.54 (–5.0pp, VRS) or by 2.0 billion tCO_2e (–6.6pp, CRS). The GDP would further increase by 3.3pp (VRS) to 6.3pp (CRS). The GDP per emitted tCO_2e would increase to 5,271 euros (+11.3pp, VRS) or 7,149 euros (+25pp, CRS). None of the countries met the sustainability requirements, and no country is considered conserving efficient. In aggregate, setting the targets had less additional impact on the results than wiping out inefficiencies. The opposite result applies for DEE-efficient and weak efficient countries as well as – under the variable return to scale assumption – for Belgium and Romania concerning the GDP inefficiencies resp. Cyprus and Latvia concerning the pollution inefficiencies. Setting targets had a stronger impact for seven from 25 countries in both dimensions and for additional four countries in one dimension.

T a b l e 3

Observed and Optimized Values 2014 – 2022, in Aggregate, Given in Real Prices of 2022 and in PPP

						Changes (in %)			
In billion euros	**Observations**	**CRS**		**VRS**		**CRS**		**VRS**	
		DEE	*CE*	*DEE*	*CE*	*DEE*	*CE*	*DEE*	*CE*
Consumption of fixed capital	21,861	21.916	21.916	22.164	22.164	0,3	0,3	1,4	1,4
Employees' compensation	58,798	61.246	61.246	55.911	55.911	4,2	4,2	–4,9	–4,9
Environmental protection expenditures	2,630	2.869	2.869	2.655	2.655	9,1	9,1	0,9	0,9
Environmental taxes	3,153	2.115	1.916	2.671	2.514	–32,9	–39,2	–15,3	–20,3
Total costs	86,442	88.146	87.947	83.401	83.244	2,0	1,7	–3,5	–3,7
CO_2 equivalents (million tons)	30,668	22,236	20,202	26,894	25,354	–27.5	–34.1	–12.3	–17.3
Working hours (trillions)	2,650	2,628	2,628	2,418	2,418	–0.8	–0.8	–8.8	–8.8
Net capital stock (average)	412,473	413,941	413,941	418,276	418,276	0.4	0.4	1.4	1.4
GDP	123,495	136,581	144,417	129,516	133,635	10.6	16.9	4.9	8.2
GDP / total costs	1.429	1.693	1.794	1.695	1.751	18,4	25,6	18,4	22,4
GDP / CO_2 equivalents	4,027	6,142	7,149	4,816	5,271	52,5	77,5	19,6	30,9

Source: Author's calculations.

T a b l e 4

Comparison of Results Relative to the Observations in Aggregate (in %)

	CRS			*VRS*		
	DEE	*CE*	*BO*	*DEE*	*CE*	*BO*
Consumption of fixed capital	0.3	0.3	–5.9	1.4	1.4	–2.1
Employees' compensation	–7.9	–7.9	–13.1	–16.0	–16.0	–18.3
Environmental protection expenditures	–4.6	–4.6	–10.2	–11.2	–11.2	–14.7
Environmental taxes	–34.0	–38.8	–39.9	–18.8	–23.0	–21.3
Total costs	–6.7	–6.9	–12.2	–11.6	–11.7	–14.2
CO_2 equivalents	–27.5	–34.1	–35.0	–12.3	–17.3	–14.8
Working hours	–0.8	–0.8	–7.7	–8.8	–8.8	–12.1
Net capital stock	0.4	0.4	–6.2	1.4	1.4	–2.4
GDP	10.6	16.9	0.0	4.9	8.2	0.0

Source: Author's calculations.

The effect of target-setting is shown by the different results of the DEE and CE models. The constraints concerning capacity limitation and the orientation of the model also have a high impact on the recommended changes of the variables. Especially in the CRS variants, a removal of the workforce bounds would lead to unrealistic suggestions of workforce necessities because of production maximization. The effect of the model orientation, with different weighting of good and bad, is shown by comparison with a bad-oriented (*BO*) objective function, which means $w_{tj_0}^{y} = 0$ for all years and DMUs.[12] Table 4 compares the results. In the bad-oriented variants, strong decreases in pollution are shown, and the net capital stock also decreases.

3.3.3. Latitude to Reduce Production for Pollution Reductions

The indifference curve of the country under study is given by shadow prices corresponding to the deviations resulting from the Benson algorithm; for these, the results are Pareto-Koopmans-efficient. Thus, the scalarized objective function value of the multiple objective linear program is maximal. The optimized variables project the country under study onto the efficiency frontier. As such, at the projection point, if one goal is to be improved, the other must be worsened. The trade-off at the projection point is given by the ratio of the shadow prices corresponding to the deviations received from the Benson algorithm. Table 5 presents these ratios which are termed *latitudes*.

The latitude indicates the number of units that would have to be sacrificed in one goal (GDP in euros) to improve another goal by one unit (pollution in tCO2e) to remain on the same indifference curve, not at the observation but at the projection point under the assumption that GDP and pollution are of same importance for the DMU under study. If the country is successful in renouncing less, the country changes to a higher indifference curve.

T a b l e 5

Latitudes, Measured in Euros per tCO_2e, Constant Returns to Scale

Austria	4,260	France	5,250	Netherlands	3,159
Belgium	3,237	Germany	3,880	Portugal	7,024
Bulgaria	2,290	Greece	2,405	Romania	3,259
Croatia	7,024	Hungary	7,024	Slovakia	3,168
Cyprus	3,110	Italy	7,024	Slovenia	3,168
Czechia	3,110	Latvia	3,646	Spain	7,024
Denmark	3,873	Lithuania	3,342	Sweden	1,000
Estonia	2,282	Luxembourg	3,374		
Finland	3,646	Malta	416		

Source: Author's calculations.

[12] A brief overview of results under other weighting sets is provided in appendix B.

Thus, from 2014 – 2022, Malta presented the lowest latitude (416), followed by Sweden (1,000). Croatia, Hungary, Italy, Portugal, and Spain had the highest latitudes (7,024) *if they were efficient*. Hence, a (much higher) carbon tax or ETS allowances could be possible.[13] However, this assessment must consider that Malta, Sweden, and the Netherlands, while not conserving efficient, are dynamically eco-efficient in contrast to the other countries. In other words, these countries already made a comparatively large contribution to their eco-efficiency in the past. The nearer technology comes to its maximum potential, defined by the efficiency frontier, the greater the challenge of achieving additional gains. Consequently, as a first step, all countries should become efficient, which should be easier to achieve. Ultimately, however, the goal should not be to remain on the same indifference curve, but to reach a higher one (and sacrifice less production).

4. Conclusions and Further Research

This study aimed to support countries attempting to transform into green economies without harming their prosperity and their global economic competitiveness by measuring their sustainable efficiencies and delivering them practicable paths for improvement. The study used the example of 25 EU countries. Based on the author's view that the usage of the term *sustainable efficiency* is misleading in existing literature, a new measurement method was developed with which sustainable behavior and deviations thereof can be captured and measured. The approach developed in this article is termed *conserving efficiency* to distinguish it from traditional models. Two model variants were calculated. In the *dynamic eco-efficiency* (DEE) variant, dynamic eco-efficiencies were measured solely by comparing the countries with one another. However, being static/dynamic eco-efficient is not necessarily sufficient for sustainable production. The *conserving efficiency* (CE) variant gives additional distances to the sustainable paths, which are defined by endogenously determined intertemporal targets. These targets ensure a minimum growth in production and reflect the conditions of the Paris Climate Agreement. Given that sustainability means the combination of at least two opposing objectives – namely minimization of the bads and maximization of the production of goods – both models were converted into a program with multiple simultaneous objective functions. The chosen approach is technical and originates from the field of non-parametrical benchmarking. The results are not derived causally.

For the given data and the assumptions made, the DEE model showed a substantial savings potential of CO_2 equivalents – 12.3% under the VRS assumption,

[13] The German Federal Environment Agency estimates the costs of one tCO_2e between 300 euros, current generation oriented, and 880 euros, current and future generations oriented (UBA, 2024, p. 8).

together with increasing GDP (+8.2%) in the weighted average of the countries considered. The GDP per emitted tCO_2e would increase by 20%. The CE model showed that the necessary sustainable paths are quite far from the observations and from the efficiency frontier formed by the DEE model. The sustainable path requires further pollution reduction compared to the optimal results of the dynamic eco-efficiency model by up to 5pp (VRS) with an even higher GDP (+6.3pp), resulting in an even higher GDP per emitted tCO_2e relation (+11.3pp). The developments of each EU country are evaluated as not sustainable. The impact of the targets' insertion is much smaller than the missing dynamic eco-efficiencies. It is therefore more important to start using the (environmentally friendly) technology that is already in use elsewhere in Europe than to argue about targets that will not be met or will be postponed anyway for various reasons.

Finally, the latitudes to reduce production for pollution reductions among the different member states were analyzed to determine how many units would have to be sacrificed for one goal (GDP) to improve another goal (pollution) per unit in order to remain on the same indifference curve.

The results presented are dependent quantitatively on the different assumptions made, which can be seen in the comparison of the results in Appendix B, but the core results do not change. First, Sweden, Malta, Luxembourg, France, and Germany are dynamically eco-efficient and can act as role models for the other countries. Sweden, in particular, introduced carbon taxes early on, allowing its economy to adapt. Second, the missing dynamic eco-efficiency measured by country comparison has a greater impact than the setting of targets. It is evident that the shortcomings in dynamical eco-efficiencies (which are calculated by country comparison) are a bigger lack than any technological gap between the technologically possible and the technologically necessary. Third, (higher) carbon taxes or ETS allowances should be manageable for each economy.

In the present paper, a composite pollution index, tCO_2e, was used as a proxy for emissions of climate-harmful substances, delivering a one-dimensional bad. Opening to include multidimensional bads by considering the diverse climate and environmentally harmful substances individually could give valuable insights into possible trade-offs between the different variables. This research focuses on the interplay between the economy and ecology, but it should be possible in principle to generalize the model developed here to include social aspects.

In another research step, further restrictions could be added. For example, to ensure that the relative importance of bads in the aggregate does not decrease solely due to smaller associated shadow prices (and not due to a decrease in quantities), these shadow prices should be non-decreasing over time. One problem with this is that limitations of the shadow prices or the virtual multipliers can make the associated optimization programs unsolvable.

The following aspects could not be included in this paper. First, possible rebound effects were not considered. These can occur, for example, if a product is manufactured or used in a more environmentally friendly way and is therefore in greater demand, resulting in an increase in the total amount of environmental pollutants emitted. One example is the increase in private transportation. Second, indirect pollution caused by the production of inputs along the entire production/value chain and by waste disposal was also not considered. Third, the generation of secondary pollutants was not considered in this research project. Secondary pollutants are not produced directly as pollutants; rather, they are only created through reactions with other substances in the atmosphere.

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Appendices

A The Mathematical Formulation of the Presented Models

A.1 The Dynamic Eco-DEA Model in Schnabl (2025, pp. 7 – 12)

In this appendix the formulae corresponding to the base optimization model mentioned in Section 2.1 (Schnabl, 2025, pp. 7 – 12) are presented. The meanings of the variables are presented in Section 2.1. Figure 1 illustrates of the temporal sequence of the dynamic production processes. Constraints (4) to (8) form the efficiency frontier restricting the production possibility set, and (10) and (11) restrict the projection possibilities onto this frontier. By searching the intensity weights λ_{tj}, a linear combination of the production processes of all DMUs forms a composite unit that is similar to the DMU under assessment but at least weakly efficient (i.e., at least one constraint of [4] to [8] is fulfilled as an equation). Optimal values of the flaw and stock inputs could be theoretically larger or smaller than the observations (constraints [4] to [8]). The combinations of the conditions (5) and (10) as well as (6) and (11) ensure that bads and goods only move in the desired direction. By applying constraints (4) to (12), CRS is assumed (the different facets constructing the efficiency frontier must go through the origin, according to the dual program). By adding the convexity condition concerning the intensity weights $\sum_{j=1}^{J}\lambda_{tj}=1, \forall t$, the assumption changes to VRS.

$$\sum_{j=1}^{J}\lambda_{tj}x_{tij}-\tilde{x}_{tij_0}\leq 0;\ \ \forall i,t \tag{4}$$

$$\sum_{j=1}^{J}\lambda_{tj}b_{tpj}-\tilde{b}_{tpj_0}\leq 0;\ \ \forall p,t \tag{5}$$

$$-\sum_{j=1}^{J}\lambda_{tj}y_{trj}+\tilde{y}_{trj_0}\leq 0;\ \ \forall r,t \tag{6}$$

$$\sum_{j=1}^{J}\lambda_{tj}k_{t-1lj}-\tilde{k}_{t-1lj_0}\leq 0;\ \ \forall l,t\geq 2 \tag{7}$$

$$-\sum_{j=1}^{J}\lambda_{tj}k_{tlj}+\tilde{k}_{tlj_0}\leq 0;\ \ \forall l,t\leq T-1 \tag{8}$$

$$\sum_{j=1}^{J}\lambda_{1j}\bar{k}_{0lj}\leq \bar{k}_{0lj_0};\ \forall l \tag{9}$$

$$\tilde{b}_{tpj_0}\leq b_{tpj_0};\forall p,t \tag{10}$$

$$-\tilde{y}_{trj_0}\leq -y_{trj_0};\ \ \forall r,t \tag{11}$$

$$\lambda_{tj},\tilde{k}_{tlj_0},\tilde{x}_{tij_0},\tilde{b}_{tpj_0},\tilde{y}_{trj_0}\geq 0\,\forall\ i,j,l,p,r,t \tag{12}$$

A.2 The Implementation of the Benson Algorithm

For the implementation of the Benson algorithm, the objective functions (2) and (3) are transformed into additional constraints on the envelopment program. The starting point $\left(x_{tij_0}^0, y_{trj_0}^0, b_{tpj_0}^0, k_{tlj_0}^0\right)$ must be a feasible solution, but apart from this condition can be arbitrarily chosen:

$$-\sum_{t=1}^{T} \gamma^t \tilde{y}_{trj_0} + \overline{d}_{rj_0}^{y} \leq -\sum_{t=1}^{T} \gamma^t y_{trj_0}^0; \forall r \tag{13}$$

$$\sum_{t=1}^{T} \gamma^t \tilde{b}_{tpj_0} + \overline{d}_{pj_0}^{b} \leq \sum_{t=1}^{T} \gamma^t b_{tpj_0}^0; \forall p \tag{14}$$

The deviations $\overline{d}_{rj_0}^{y}$ and $\overline{d}_{pj_0}^{b}$ are DMU- but not time-dependent and should be maximized using a single objective function:

$$\overline{\overline{C}}_1 = \max\left(\sum_{r=1}^{R} \overline{d}_{rj_0}^{y} + \sum_{p=1}^{P} \overline{d}_{pj_0}^{b}\right) \tag{15}$$

If $\overline{d}_{rj_0}^{y}$, $\overline{d}_{pj_0}^{b} = 0$ for all p, r, then $\left(\tilde{x}_{tij_0}^*, \tilde{y}_{trj_0}^*, \tilde{b}_{tpj_0}^*, \tilde{k}_{tlj_0}^*\right)$ is a Pareto-Koopmans-efficient solution (Benson, 1998, p. 1).

A.3 The Introduction of Targets and Bounds

A.3.1 Bounded Variables

Constraints of bounded variable types (Cooper et al., 2007, p. 224) are, for example, upper and lower bounds ($\ddot{x}_{tij_0}$ resp. $\dddot{x}_{tij_0}$) for the variable inputs:

$$\tilde{x}_{tij_0} \leq \ddot{x}_{tij_0}; \forall r, t \tag{16}$$

$$-\tilde{x}_{tij_0} \leq -\dddot{x}_{tij_0}; \;\; \forall r, t \tag{17}$$

The DEE model is given by the constraints (4) to (14), (16) and (17), and the objective fction (15).

A.3.2 Ideal Targets

To introduce ideal targets, additional restrictions must be appended to the constraints set (4) to (14), (16), and (17). Positive and negative deviations of the projection points from the ideal targets $\overline{b}_{tpj_0}$ resp. $\overline{y}_{trj_0}$ are measured for each variable by introducing further nonnegative variables ε's, namely, the deviation variables:

$$\tilde{b}_{tpj_0} - \varepsilon_{tpj_0}^{b_1-} + \varepsilon_{tpj_0}^{b_1+} = \bar{b}_{tpj_0}; \forall p, t \tag{18}$$

$$-\tilde{y}_{trj_0} - \varepsilon_{trj_0}^{y_1+} + \varepsilon_{trj_0}^{y_1-} = -\bar{y}_{trj_0}; \ \forall r, t \tag{19}$$

$$\varepsilon_{tpj_0}^{b_1-}, \varepsilon_{tpj_0}^{b_1+}, \varepsilon_{trj_0}^{y_1+}, \varepsilon_{trj_0}^{y_1-} \geq 0 \,\forall\, j, p, r, t \tag{20}$$

The constraints (10), (11), (18), and (19) must be used together, as it is possible that some predetermined ideal targets that are defined for each DMU separately are weaker than the corresponding projection points onto the efficiency frontier spanned by all DMUs.

A.3.3 Endogenously Determined Intertemporal Targets

Endogenously determined intertemporal constraints for endogenized goods and bads are given by (21) to (23). The (de)growth rates g_{trj}^{y} and g_{tpj}^{b} are predetermined:

$$\tilde{b}_{tpj_0} - \varepsilon_{tpj_0}^{b_2-} + \varepsilon_{tpj_0}^{b_2+} = \left(1 - g_{tpj}^{b}\right)\left(\tilde{b}_{t-1pj_0} - \varepsilon_{t-1pj_0}^{b_2-}\right); \forall p, t \tag{21}$$

$$-\tilde{y}_{trj_0} - \varepsilon_{trj_0}^{y_2+} + \varepsilon_{trj_0}^{y_2-} = \left(1 + g_{trj}^{y}\right)\left(-\tilde{y}_{t-1rj_0} - \varepsilon_{t-1rj_0}^{y_2+}\right); \ \forall r, t \tag{22}$$

$$\varepsilon_{tpj_0}^{b_2-}, \varepsilon_{tpj_0}^{b_2+}, \varepsilon_{trj_0}^{y_2+}, \varepsilon_{trj_0}^{y_2-} \geq 0 \,\forall\, j, p, r, t \tag{23}$$

The conserving efficiency model is given by the constraints (4) to (14) and (16) to (23) and the objective function (15).

A.4 The Dual of the Conserving Efficiency Model

The dual of the conserving efficiency model is given by

$$\bar{\bar{J}}_1 = \min \sum_{l=1}^{L} \alpha_{0lj_0} \bar{k}_{0lj_0} + \sum_{t=1}^{T}\sum_{p=1}^{P} b_{tpj_0} \varpi_{tpj_0} - \sum_{t=1}^{T}\sum_{r=1}^{R} y_{trj_0} \bar{\mu}_{trj_0} + \sum_{t=1}^{T}\sum_{p=1}^{P} \bar{b}_{tpj_0} \varpi_{tpj_0}^{1z} - \sum_{t=1}^{T}\sum_{r=1}^{R} \bar{y}_{trj_0} \bar{\mu}_{trj_0}^{1z} + \sum_{t=1}^{T}\sum_{i=1}^{I} \left(\ddot{x}_{tij_0} \ddot{v}_{tij_0} - \ddot{x}_{tij_0} \ddot{v}_{tij_0}\right) + \sum_{p=1}^{P} d_{pj_0}^{b} \sum_{t=1}^{T} \gamma^t b_{tpj_0}^{0} - \sum_{r=1}^{R} d_{rj_0}^{y} \sum_{t=1}^{T} \gamma^t y_{trj_0}^{0} \tag{24}$$

$$-\sum_{i=1}^{I} x_{tij} v_{tij_0} - \sum_{p=1}^{P} b_{tpj} \omega_{tpj_0} + \sum_{r=1}^{R} y_{trj} \mu_{trj_0} - \sum_{l=1}^{L} k_{t-1lj} \alpha_{tlj_0} + \sum_{l=1}^{L} k_{tlj} \beta_{tlj_0} \leq 0; \forall j, t \tag{25}$$

$$-\omega_{tpj_0} + \varpi_{tp} + \varpi_{tpj_0}^{1z} + \varpi_{tpj_0}^{2z} - \left(1 - g_{t+1pj}^{b}\right) \varpi_{t+1pj_0}^{2z} + \gamma^t d_{pj_0}^{b} \geq 0; \forall p, t \tag{26}$$

$$-\overline{\omega}_{tpj_0}^{2z} + \left(1 - g_{t+1pj}^{b}\right)\overline{\omega}_{t+1pj_0}^{2z} \geq 0; \forall p, t \tag{27}$$

$$\mu_{trj_0} - \overline{\mu}_{trj_0} - \overline{\mu}_{trj_0}^{1z} - \overline{\mu}_{trj_0}^{2z} + \left(1 + g_{t+1pj}^{b}\right)\overline{\mu}_{t+1rj_0}^{2z} + \gamma^t d_{rj_0}^{y} \geq 0; \forall r, t \tag{28}$$

$$-\overline{\mu}_{trj_0}^{2z} + \left(1 + g_{t+1pj}^{b}\right)\overline{\mu}_{t+1rj_0}^{2z} \geq 0; \forall p, t \tag{29}$$

$$\nu_{tij_0} + \ddot{\nu}_{tij_0} - \ddot{\nu}_{tij_0} \geq 0; \forall i, t \tag{30}$$

$$-\alpha_{t+1lj_0} + \beta_{tlj_0} \geq 0; \forall l, t \geq 2 \tag{31}$$

$$d_{pj_0}^{b} \geq 1; p \tag{32}$$

$$d_{rj_0}^{y} \geq 1; r \tag{33}$$

$$\omega_{tpj_0}, \overline{\omega}_{tpj_0}, \overline{\mu}_{trj_0}, \mu_{trj_0}, \nu_{tij_0}, \alpha_{tlj_0}, \beta_{tlj_0}, \ddot{v}_{tij_0}, \ddot{\nu}_{tij_0} \geq 0; i, l, p, r, t \tag{34}$$

$$\overline{\omega}_{tpj_0}^{1z}, \overline{\mu}_{trj_0}^{1z}, \overline{\omega}_{tpj_0}^{2z}, \overline{\mu}_{trj_0}^{2z}, d_{rj_0}^{y}, d_{pj_0}^{b} \text{ free}; \forall p, r, t \tag{35}$$

$$\beta_{Tlj_0} = 0; \forall l \tag{36}$$

The deviations $d_{pj_0}^{b}$ and $d_{rj_0}^{y}$ corresponding to the deviations $\overline{d}_{rj_0}^{y}$ and $\overline{d}_{pj_0}^{b}$ a DMU- but not time-dependent. As the shadow prices in DEA, they are dependent on the units of measurement.

The complementary slackness condition indicates that, as it can be assumed that the bads are always positive, the corresponding shadow prices are given by $\gamma^t d_{pj_0}^{b} = \omega_{tpj_0}^{*} - \overline{\omega}_{tpj_0}^{*} - \overline{\omega}_{tpj_0}^{1z*} - \overline{\omega}_{tpj_0}^{2z*} - \left(1 - g_{t+1pj}^{b}\right)\overline{\omega}_{t+1pj_0}^{2z}$ in both models in the optimum. The same applies to the goods. As the flow input working hours are restricted from above, the complementary slackness condition leads to $\nu_{tij_0}^{*} = \ddot{v}_{tij_0}^{*}$ in the optimum in all models at all times. For the net capital stock-related shadow prices, $\alpha_{t+1lj_0}^{*} = \beta_{tlj_0}^{*}$ is valid because of the complementary slackness condition in both variants. That means, if it is assumed that the stock input is always positive, then the shadow prices of the stock input produced as output and used as input are identical in the optimum. As there are no targets to the flow input environmental protection expenditures, their complementary slackness condition is $\tilde{x}_{tij_0}^{*}\nu_{tij_0}^{*} = 0$ in all models; thus, the shadow prices are zero at all times as the environmental protection expenditures are positive in each year.

B Alternative Preferences

For the results mentioned in the main text, the time- and country-dependent weights were chosen with $w_{tj_0}^{y}=1$ and $w_{tj_0}^{b}=y_{tj_0}/b_{tj_0}$, thus giving GDP and pollution the same preference *(1:1)*. In this section, aggregate results for other assumed preference schemes are presented. Table 6 lists the potentials savings, beginning in the second column with the assumption that the environment is three times as important than the economy *(3:1)* to the sixth column in which the opposite applies *(1:3)* under CRS and VRS assumptions and with the DEE and CE models. The fourth column shows the same values as in Table 6 *(1:1)*; economy and environment are equally important. The different assumptions concerning the preferences do not influence the empirical production possibility set and efficiency frontier but enforce different main thrusts of the projection and the endogenously determined intertemporal targets.[14] Comparing the results from left to right, a growing optimized production volume can be observed. In contrast, pollution decreases at a lesser rate, which is consistent with the assumed decreasing relative importance of the environment, representing the changing projection direction towards the efficiency frontier.

In the penultimate (*direct*) and last columns (*direct_bp*), the aggregate results are presented if no assumptions concerning the relative importance of the environment are set a priori. The difference between these two is the underlying model. In the *direct* case, the model presented in this article was applied. In *direct_bp*, the model type was changed concerning the treatment of the bads using the by-product approach (Murty et al., 2012), including a forced connection of the sub-technologies via the equivalence of the constructed composite units (Dakpo et al., 2017, p. 37; Førsund, 2018, p. 92), leaving everything else unchanged (several simultaneous objective functions, endogenous intertemporal targets, Benson). In these cases, the observed values are inserted as starting values for the Benson algorithm directly, meaning only the second run (Section 3.2.1) is necessary. In this case, latitudes indicate the number of units that would have to be sacrificed in production to decrease pollution by one unit to remain on the same indifference curve *at the observation* rather than the projection point. By comparing these results with the other columns, it is obvious that the economy is at least three times more important than the environment, at least in aggregate. The detailed results present more or less the same findings. The lacking efficiencies are a bigger problem than the targets, except in cases *1:3* and *direct* with CRS for pollution reduction. Since the by-product variant assumes that goods and bads are produced using two loosely connected but different technologies, the spread of inefficiencies is greater than in the approach chosen here, which assumes a common technology.

[14] As the ideal targets would have been set a priori, they cannot be changed by the calculations.

Concerning the latitudes to reduce production for pollution reductions, the relationship is not surprising – for most countries a falling latitude can be observed together with an assumed increasing importance of the economies. The latitudes do not change for the dynamical eco-efficient countries Sweden, Luxembourg, and Malta (CRS) or for France and Germany (VRS) as they lie on the corresponding efficiency frontiers.

By comparing the latitudes of the *direct* and *direct_bp* variant with the latitudes of the other scenarios, the relative importances of economy and environment can be estimated for each country. For example, for the variant *direct*, for Croatia (CRS) the latitude is 2,160, which lies between 1,000 in the case *2:1* and 7,024 in the case *1:1*. For Croatia the relative importance of the environment lies between 0.5 and 1; for France it is between 0.333 and 0.5; for Bulgaria, Cyprus, Greece, Lithuania, and Romania it is less than 0.333. The importance of the environment is not higher than the importance of the economy in any country. In the direct variant, the latitudes range from 416 (Malta) to 3,373 (Luxembourg).

T a b l e 6

Aggregate Results under Different Assumptions Concerning the Relative Importance of Pollution and Production, Given in Saving Rates (in %)

	Constant returns to scale									
	Dynamic eco-efficiency					*Conserving efficiency*				
	3:1	*1:1*	*1:3*	*direct*	*direct_bp*	*3:1*	*1:1*	*1:3*	*direct*	*direct_bp*
Environmental protection expenditures (trillion euros)	4.4	9.1	–5.3	–5.3	–6.6	4.4	9.1	–5.3	–5.3	–6.6
CO_2 equivalents (million tons)	–34.7	–27.5	–1.1	–1.1	–10.2	–38.6	–34.1	–7.6	–7.6	–14.8
Working hours (trillions)	–6.6	–0.8	–2.4	–2.5	9.9	–6.6	–0.8	–2.4	–2.5	9.9
Net capital stock (average, trillion euros)	–5.2	0.4	2.3	2.3	4.4	–5.2	0.4	2.3	2.3	4.4
GDP (trillion euros)	1.3	10.6	29.4	29.4	49.8	4.9	16.9	34.9	34.9	53.1
GDP / total costs	4.5	8.4	26.5	26.5	37.9	8.3	14.9	32.2	32.2	41.2
GDP / CO_2 equivalents	55.2	52.5	30.8	30.8	66.8	70.8	77.5	46.0	46.0	79.6
	Variable returns to scale									
	Dynamic eco-efficiency					*Conserving efficiency*				
	3:1	*1:1*	*1:3*	*direct*	*direct_bp*	*3:1*	*1:1*	*1:3*	*direct*	*direct_bp*
Environmental protection expenditures (trillion euros)	–0.5	0.9	1.8	2.3	1.3	–0.5	0.9	1.8	2.3	1.3
CO_2 equivalents (million tons)	–14.5	–12.3	–9.9	–8.5	–11.4	–19.3	–17.3	–16.8	–16.6	–18.0
Working hours (trillions)	–10.6	–8.8	–7.5	–7.4	–6.3	–10.6	–8.8	–7.5	–7.4	–6.3
Net capital stock (average, trillion euros)	–0.7	1.4	2.2	2.3	1.9	–0.7	1.4	2.2	2.3	1.9
GDP (trillion euros)	2.3	4.9	6.0	6.4	8.0	5.6	8.2	8.8	9.0	10.7
GDP / total costs	7.6	8.7	8.6	8.9	10.2	11.3	12.3	11.8	11.8	13.3
GDP / CO_2 equivalents	19.7	19.6	17.6	16.4	21.9	30.9	30.9	30.8	30.7	35.1

Source: Author's calculations.