Louvain School of Management

Forecasting EU27 CO2 emissions until 2030 through Artificial Neural Network and scenario analysis

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1. Coding purposes: I did use chat GPT to help me with certain errors I had in my code in RStudio.

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By signing this declaration, I affirm that the content of this master's thesis reflects my original work, augmented by the responsible use of AI.

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1 Introduction

Do we actually find ourselves in a climate urgency? Why is it that we hear about greenhouse gas (GHG) emissions anytime we put our ear to the ground? What are GHGs and why does CO_2 seem to be the main focus of our century?

Over the industrial period, human activity has been a real catalyst for greenhouse gases, especially CO_2 emissions (Ledley et al., 1999). Greenhouse gases are constituents of the atmosphere, originating from natural sources or human activities (Intergovernmental Panel on Climate Change (IPCC), 2022), which trap the heat into the atmosphere, similarly to a greenhouse, by blocking infrared radiation and creating the greenhouse effect (*Basics of the Carbon Cycle and the Greenhouse Effect.*, n.d.).

GHGs encompass water vapor, carbon dioxide, methane, surface-level ozone, nitrous oxides and fluorinated gases (Mann, 2024). While they kept Earth's temperatures sufficiently high to allow life to survive, the increased concentrations of GHGs have lead us to a radiation imbalance (*Basics of the Carbon Cycle and the Greenhouse Effect.*, n.d.). This imbalance leads to a more intense greenhouse effect, causing global warming (Kennedy & Lindsey, 2015).

Long-term shifts in temperatures and weather patterns (*What is climate change?*, n.d.), which characterize climate change, are influenced by global warming and have reached unknown levels, causing disruptions to life on a global scale, as well as inducing life-threatening temperatures (Euronews Green, 2023).

While there is no doubt about the existence of climate change (Euronews Green, 2023), climate skeptics could argue that CO_2 emissions shouldn't be the main focus of our century. In fact, the most abundant GHG in our climate system isn't CO_2, but water vapor, which causes about half of the greenhouse effect (Krol & Kerry, 2023). However, we do not have to worry about water emissions as much as CO_2 emissions, given that water molecules aren't around long enough to alter climate (Krol & Kerry, 2023). Where water lasts about 2 weeks on average in the atmosphere (Krol & Kerry, 2023), 40% of CO_2 will remain for a hundred years (*Why does CO2 get most of the attention when there are so many other heat-trapping gases?*, 2017). The focus remains on human-caused emissions. Hence why, water vapor is not taken into account when talking about GHGs in this thesis.

Extreme weather, food supply disruption, respiratory diseases, air pollution, and even increased wildfires are urgent realities of climate change we are currently facing (Nunez, 2019). Sadly, it is no longer solely an environmental issue, but rather a social and economic one.

According to NASA (2023), certain effects of climate change are irreversible for the next hundreds to thousands of years. Ranging from loss of sea ice, melting glaciers, seal level rise, more intense heat waves, and plant geographical shift, these widespread damaging effects have the potential to intensify and lead to more climate extremes (*The Effects of Climate Change*, 2023).

In addition, the rise in temperatures, driven by climate change, can have serious negative economic implications and threaten the overall economic performance of countries around the world (Colacito et al., 2018). Developing nations might be the first ones to be impacted, however, well-developed countries like the United States could also face economic damages (Colacito et al., 2018). Future increases in temperatures may impede economic growth across diverse industries and nations (Colacito et al., 2018), as well as alter the physical and cognitive performance of workers creating that economic value (Chady, 2023).

Among the top 5 most at risk of climate disaster, we find countries like Somalia, Syria, the Democratic Republic of Congo, Afghanistan, and Yemen (*10 countries at risk of climate disaster.*, 2023). These countries suffer from a variety of consequences of climate change, such as drought, food insecurity, floods, and earthquakes (*10 countries at risk of climate disaster.*, 2023). Even though it is a borderless challenge, significant contributors to CO2 emissions have to serve as driving forces for change and set standards for environmentally friendly behaviors.

Within the top 5 emitting territories we find China, the United States, India, EU27, and Russia (Tiseo, 2023). These major economies have the means to shape a sustainable future and help those who lack resources to prioritize sustainability.

During the 2022 COP27, particularly vulnerable nations were at the center of discussions. These countries could potentially be eligible to receive loss and damage funds (Lo, 2022). It is the European Union that pushed to restrict the distribution of these funds to so-called vulnerable nations (Lo, 2022). Defining which country qualifies as vulnerable is a challenging task, given that climate change impacts the whole world.

While any country could be part of that list, it is clear that some of them are more prepared and have the capacity to be more resilient, especially developed nations (Lo, 2022). Seeing these resilient countries defining who can benefit from this monetary assistance prompts us to question whether they are adhering to their commitments and actively contributing to the "mitigation" of climate change.

By counteracting the current climate trends, rather than distributing funds for damages, the focus shifts towards preventing damages linked to climate change and assisting vulnerable nations in enhancing their resilience.

In this perspective, prevention involves the effective implementation of policies to meet targets set by international agreements such as the Paris Agreement or the European Green Deal. The current situation suggests that European countries are not meeting the challenges at hand (Jewkes & Landini, 2021). Europe, being the 4^{th} largest CO2 emitter in the world, needs to be an example for both sustainable practices and management of its environmental impact (European Parliament, 2023).

The central theme of this thesis revolves around forecasting CO2 emissions within the EU27 until the year 2030, using macroeconomic data. By making use of a comprehensive forecasting method and macroeconomic indicators, this quantitative research seeks to provide insights into the potential trajectories of CO2 emissions in the European Union.

In addition, this thesis also aims to provide suggestions for designing policies and shed light upon the most significant measures helping reduce CO2 emissions within the EU27. To be more specific, the European Commission has been vocal about its desire to increase the share of energy from renewable sources to 42.5% in 2030 (*Renewable energy targets*, 2023).

Based on the information outlined above, we are asking ourselves : how likely is the EU27 to meet its 2030 CO2 emission target, and are increased shares of renewable energy sources sufficient to achieve this goal during this period ?

The first section focuses on analyzing previous work related to scenario analysis, macroeconomic indicators and CO2 emissions forecasting. This in-depth literature review will establish the current context and identify the existing gaps in the literature that this thesis seeks to fill.

Following the identification of key macroeconomic indicators for the EU27 from the literature review, the data section will define the different data sets I'll be using to forecast CO2 emissions and explain why they are relevant to this research.

Next, I will provide a definition of the machine learning model used to forecast CO2 emissions, along with the specific parameters utilized to tune the model.

The fourth section will be dedicated to the interpretation of the results obtained according to two different scenarios. The first scenario, known as the "business as usual" (BAU) scenario, forecasts input variables based solely on their historical values. Under this scenario, only a few countries reach their 2030 CO2 emissions reduction target, namely Greece, Lithuania, Hungary, Romania, and Slovakia. The second scenario builds on the BAU scenario but incorporates an increased share of renewable energies in the energy mix of EU27 countries. In this second scenario, no additional country achieves its 2030 target. In fact, some countries are emitting even more CO2 emissions : Denmark, Greece, Italy, Cyprus, Luxembourg and Finland.

Following the interpretation of the different forecasts, I will address the research question, present my final conclusions, and offer policy suggestions.

The final section focuses on the different limitations linked to the making of this thesis, as well as the potential future research that could address these limitations.

2 Literature

This thesis contributes to the current literature on CO2 emission forecasts and the analysis of their trajectories via 2 different scenarios. Although this has been done for many countries, such as Russia (Gurbanov et al., 2023), Bangladesh (Hossain et al., 2017), Thailand (Kamoljitprapa & Sookkhee, 2022), Iran (Hosseini et al., 2019), India (Nyoni & Bonga, 2019), Pakistan (Tawiah et al., 2023), China (Niu et al., 2020), it has not been done for the EU27 until 2030 using a Multilayer Perceptron (MLP), to the best of my knowledge.

2.1 Scenario analysis

The benefits of performing a scenario analysis are threefold : firstly, it can shed light upon the limits of our knowledge regarding the key factors influencing CO2 emissions in the EU27 ; secondly, it can help making different perspectives come together ; and thirdly, it can assist policymakers in defining targets (Hannah & Gassner, 2008).

However, scenarios can tend to overstate how much the future will mirror the past, as highlighted by Paltsev (2017), who also suggests that scenarios should be seen as qualitative tools, helping assess and understand the risks associated with our choices.

At the moment, the political and economic context, arising from the conflict between Ukraine and Russia, asks for the European Union to seek alternative energy sources to gas (Simon, 2022), and invest in renewable energies, like suggested by European Commission. Although this conflict shouldn't prevent the European Union from achieving its goals (Simon, 2022), performing a scenario analysis can help us map the different CO2 emissions trajectories resulting from potential other crises. In this regard, Hosseini et al. (2019) have investigated the effectiveness of the policies put into place by governments in attaining their 2030 targets in Iran. According to Hosseini et al. (2019), Iran won't reach its 2030 commitment

Similar to the study conducted by Niu et al. (2020), this thesis aims to assess the feasibility of the EU27 carbon emission reduction commitment. By adopting a scenario-based analysis, Niu et al. (2020) determined that under the Business As Usual (BAU) scenario, China's 2030 commitment would not be achieved.

As pointed out by Tang et al. (2023), scenario analysis is often used to map the different trends of carbon emissions. Other studies have pointed out policy interventions needed to achieve targets to reduce CO2 emissions by using scenario analysis, such as the one from Gurbanov et al. (2023).

My scenario analysis will be based on the share of renewable energies in the countries of the EU27. The first scenario will depict what will happen without additional measures, while the second scenario will focus on the impact of increased shares of renewable energies throughout the years in the EU27.

2.2 Macroeconomic indicators

Regarding the macroeconomic indicators, I decided to select them based on previous work. In fact, several studies analyzing Europe have highlighted the significance of certain features in predicting CO2 emissions.

Nguyen et al. (2021) as well as Shpak et al. (2022) pointed out the significance of trade openness (volume of imports and exports), the GDP, the inflation rate, the unemployment rate, and the financial development in forecasting the trajectory of future CO2 emissions in developed nations.

Jianu et al. (2022) found a positive correlation between real GDP per capita, households' final consumption per capita, waste generation per capita, and greenhouse gas emissions per capita, while the impact of the share of renewable energy in gross final energy consumption was small and negative.

González-Sánchez and Martín-Ortega (2020) found that only GDP and final energy intensity were the main drivers for the reduction of GHG emissions in Europe.

Marotta et al. (2023) estimated GHG emissions in Europe according to different scenarios, using 3 independent variables : GDP, population, and renewable energy shares, and determined that EU member states can use this model to forecast the amount of GHGs generated and plan GHG management strategies.

In light of these results, I decided to keep 9 features : the energy intensity, the exports and imports of goods & services as % of GDP, the financial development index, the inflation rate, the population, the real GDP, the share of energy from renewable sources and the total unemployment rate.

2.3 Forecasting model

As for the forecasting model, many options were available : autoregressive (AR) model, autoregressive integrated moving average (ARIMA) model, autoregressive conditional heteroskedasticity (ARCH) model, multilayer perceptron (MLP) model, support vector regression (SVR) model, and so on. These models can be seperated into 2 categories : classical methods (AR, ARIMA, ARCH), and machine learning methods (MLP, SVR) (James et al., 2022).

Within machine learning, we can distinguish several types of algorithms : support vector machines (SVM), naïve bayes, linear logistic regression, decision trees, neural networks, and many more (*Common machine learning algorithms*, 2022). Thanks to my researches, I came to the conclusion that an Artificial Neural Network (ANN) seems to be the best candidate for this forecasting task.

An artificial neural network is a type of deep learning algorithm, mimicking the structure and functioning of the human brain (James et al., 2022). Its predictions or classifications are based on large amounts of data from which the model learned the patterns and trends (James et al., 2022). I came across several articles attesting that neural networks are generally considered highly effective for complex time series data with non-linear patterns.

In fact, Aydin & Cavdar (2015), pointed out that the predictive ability of the ANN approach outperforms that of the Vector Autoregressive (VAR) method, indicating that the ANN model yields more precise estimations and accurate results.

A comparative study published by Alam & AlArjani (2021), as well as a study from Chen et al. (2018), also determined that the ANN model stands out as the most suitable choice in terms of forecasting.

More specifically, the Multilayer Perceptron (MLP) algorithm has shown very satisfying results in many studies forecasting CO2 emissions like the ones from Ağbulut (2022), Safa et al. (2016), and El Haj Assad et al. (2021). I'll delve into the architecture and functioning of this algorithm in the model section of this thesis.

2.4 Literature review summary

The below table summarizes the main characteristics of the studies mentioned in this literature review. It'll give you an overview of the different sources that I used.

Reference	Country	Forecasting model	Dataset	Input variables	Output variable
Gurbanov et al. (2023)	Russia	Multipath search algorithm, until 2030	1990 - 2020	GDP per capita, oil, natural gas, coal intensities	CO2 em.
Hossain et al. (2017)	Bangladesh	ARIMA, HWNS, ANN, until 2025	1972 - 2013	Annual CO2 emissions, liquid fuel consumption, solid fuel consumption	CO2 em.
Kamoljitprapa & Sookkhee (2022)	Thaïland	ARIMA, until 2030	2001 - 2020	Historical CO2 em.	CO2 em.
Hosseini et al. (2019)	Iran	MLR, MPR, until 2030	1971 - 2014	Total population, CO2 intensity, per capita GDP, electricity production from fossil fuels, per capita energy use	CO2 em.
Nyoni & Bonga (2019)	India	ARIMA, until 2030	1960 - 2017	Historical CO2 em.	CO2 em.
Tawiah et al. (2023)	Pakistan	ARIMA, naïve, TBATS, ETS, NNAR, MLP, until 2028	1960 - 2018	Historical CO2 em.	CO2 em.
Niu et al. (2020)	China	GRNN, until 2030	1990 - 2015	Annual GDP growth rate, GDP, GDP per capita, fixed assets investment, trade openness, urbanization rate, urban population, total population at the end of year, ratio of population aged 15 - 64 over the total population, ratio of population aged 0 - 14 over the total population, ratio of population aged over 65 over the total population, contribution ratio of primary industry to GDP, contribution ratio of secondary industry to GDP, contribution ratio of tertiary industry to GDP, ratio of industry sector value and service sector value, energy consumption per unit GDP, per capita energy consumption, total energy consumption, proportion of fossil fuels in total energy consumption, proportion of coal in total energy consumption, contribution of renewables to total primary energy supply, total primary energy consumption, electricity consumption, proportion of thermal power generation, policy stringency indicator	CO2 em.
Shpak et al. (2022)	EU region	none	1970 - 2020		
González-Sánchez & Martín-Ortega (2020)	Europe	none			
Jianu et al. (2022)	EU27	none			
Marotta et al. (2023)	EU	Multifactor algorithm, until 2050	2010 - 2020	GDP, population, renewable energy sources	GHG em.
Aydin & Cavdar (2015)	USA & Turkey	ANN, VAR, until 2017	2000 - 2014	USD/TRY exchange rates, BIST 100 index, gold prices	USD/TRY exchange rates, BIST 100 index, gold prices
Alam & AlArjani (2021)	Gulf countries	ARIMA, ANN, HWES, until 2025	1960 - 2014	Historical CO2 em.	CO2 em.
Chen et al. (2018)	World	BPNN, GRNN, MNLR, MLR	/	Latitude, age, potential net primary productivity, mean depth, of reservoirs	CO2 em. from reservoirs
Ağbulut (2022)	Turkey	DL, SVM, ANN, until 2050	1970 - 2003	GDP per capita, population, vehicle kilometer, year	Energy demand & CO2 em.
Safa et al. (2016)	New-Zealand	ANN, MLR	/	Plough passage numbers, the proportion of wheat area on farms, irrigation frequency, number of cows, age of fertilizer spreader and farm inputs, nitrogen input, insecticide input, phosphate input, age of sprayer, tractor power index	CO2 em. from wheat farms
El Haj Assad et al. (2021)	Middle Eastern countries	MLP	1990 - 2019	Consumptions of different energy sources, GDP	CO2 em.
Tang et al. (2023)	China	LASSO-SSA-LSTM, until 2036	2007 - 2019	Passenger turnover, GDP per capita, total GDP, freight turnover, proportion of natural gas and electricity, total energy consumption, renewable energy	CO2 em. from transportation

Table 1: Literature review summary

3 Data

In order to select my input variables I relied on the studies I cited in my literature review, which focused on the EU27. These studies had already performed a battery of tests, pointing out the significance of the variables they decided to keep in their forecasting models.

3.1 Variables and Countries

Following my literature review, I decided to make an exhaustive list of the variables relevant to forecast my target variable. The features outlined in the table below are pertinent to the EU27 countries :

Input variable	Source	Time frequency	Unit of measure
Energy intensity	Eurostat	Annual	Kilograms of oil equivalent (KGOE) per thousand euro
Exports of goods & services as % of GDP	Eurostat	Annual	Percentage of gross domestic product (GDP)
Imports of goods & services as % of GDP	Eurostat	Annual	Percentage of gross domestic product (GDP)
Financial Development Index	International Monetary Fund	Annual	Unit-free
Inflation rate	Eurostat	Annual	Annual average rate of change
Population on the 1st of January	Eurostat	Annual	Number of persons
Real GDP	Eurostat	Annual	Chain linked volumes (2010), euro per capita
Share of energy from renewable sources	Eurostat	Annual	Percentage
Total unemployment rate	Eurostat	Annual	Percentage of population in the labour force
Target variable	**Source**	**Time frequency**	**Unit of measure**
Net greenhouse gases emissions	EEA	Annual	carbon dioxide equivalent, kilo tonnes

Table 2: Input and target variables summary

These variables were used as input variables, spanning from 2013 to 2022, to forecast net GHGs emissions until 2030.

To ensure consistency in the measurement of these variables, I have limited the analysis to include the data from 27 countries that have been members of the European Union between 2013 and 2022. The United Kingdom left the EU in 2020, hence why it is not taken into account in this thesis.

The beneath table summarizes several relevant key statistics about these countries.

The most prominent countries in terms of GHG emissions are Germany, Italy, France, Poland and Spain. While the ones who contribute the less to total GHG emissions are Malta, Sweden, Cyprus, Luxembourg and Lithuania.

Country	% GHG of EU	GHG in kt eq. CO2	Rank GHG em.	Population	GDP per capita, in million €
Belgium	3.34	108 464	8	11 617 623	37 040
Bulgaria	1.53	49 543	16	6 838 937	7 680
Czechia	3.75	121 878	7	10 516 707	18 460
Denmark	1.35	43 862	17	5 873 420	51 660
Germany	24.07	781 762	1	83 237 124	36 010
Estonia	0.45	14 464	22	1 331 796	16 250
Ireland	2.08	67 633	11	5 060 004	77 430
Greece	2.37	76 852	9	10 459 782	18 710
Spain	8.06	261 869	5	47 432 893	24 910
France	12.05	391 233	3	67 871 925	33 180
Croatia	0.66	21 391	19	3 862 305	14 660
Italy	12.26	398 268	2	59 030 133	28 180
Cyprus	0.29	9 273	25	904 705	27 490
Latvia	0.48	15 513	20	1 875 757	13 280
Lithuania	0.40	12 893	23	2 805 998	15 100
Luxembourg	0.29	9 497	24	645 397	86 130
Hungary	1.65	53 529	14	9 689 010	14 350
Malta	0.08	2 648	27	520 971	24 650
The Netherlands	5.17	168 060	6	17 590 672	43 800
Austria	2.17	70 352	10	8 978 929	38 080
Poland	10.71	347 790	4	37 654 247	14 620
Portugal	1.68	54 656	13	10 352 042	19 310
Romania	1.96	63 526	12	19 042 455	10 040
Slovenia	0.48	15 507	21	2 107 180	21 860
Slovakia	0.92	29 958	18	5 434 712	16 340
Finland	1.59	51 785	15	5 548 241	37 670
Sweden	0.18	5 857	26	10 452 326	46 280

Table 3: European countries key statistics (2022)

3.2 Data preparation

Prior to applying my algorithm, I performed a couple of pre-processing steps, which were necessary to be able to use my data. These steps were considered as the standard procedure throughout the papers that I read during my literature review.

Firstly, I had to check the availability of my variables. Fortunately, all of my data was available between the years 2013 and 2022 from the different sources (Eurostat, IMF, EEA). Secondly, I had to scale my features. Since I had data sets with different scales, I normalized them, meaning they had a unit variance and a mean of zero. Lastly, I had to split my data into a training and test set. In order to train my model, I used the first 7 years (2013-2019) as training data and the last 3 years (2020-2022) as test data.

I did not apply other steps such as a principal component analysis, as I already had small data sets with few data points. If my analysis focused only on a few countries, without considering their adherence to the European Union, I would've had more data points, and such dimension reduction techniques would've come in handy.

4 Model

This section depicts the usefulness of machine learning in time series forecasting, as well as how and which algorithm is used in this thesis. More specifically, how a deep learning algorithm, such as an artificial neural network, can model the relationship between a target variable and given features (Boehmke & Greenwell, 2020).

4.1 Artificial Neural Networks

4.1.1 Description

Artificial neural networks aim to simulate the biological mechanism behind learning (Aggarwal, 2018). In living organisms, the learning mechanism is determined by the change in strength of synaptic connections between two neurons (Aggarwal, 2018). In artificial neural networks (ANNs), the strength of these connections can be modeled as computational units linked together with weights (Aggarwal, 2018). Each time these weights connecting the neurons change, learning occurs (Aggarwal, 2018).

External stimuli required by biological organisms to trigger learning can be analogized to the examples of input-output pairs found in the training data of ANNs (Aggarwal, 2018). During training, the weights between neurons are adjusted in response to the accuracy of predictions made by the inputs for forecasting outputs, so as to make the predictions more accurate in future iterations (Aggarwal, 2018). This process is similar to an adjustment in the synaptic strengths due to a disagreeable feedback in a living organism (Aggarwal, 2018).

The ability of the model to apply its learned knowledge from training data to unseen data is called model generalization (Aggarwal, 2018). These neural networks allow us to model complex nonlinear relationships, which traditional regression models might not be able to do (Hyndman & Athanasopoulos, 2021).

Neural networks can consist of a single-layer, or multi-layers. These ANNs are feedforward neural networks (FNNs), information is only processed forward (Jaiswal, 2024).

In single-layer models, there is one layer of neurons, which directly connects the inputs to the output (Aggarwal, 2018). A single-layer model is the simplest form of neural network and is a called a perceptron (Aggarwal, 2018).

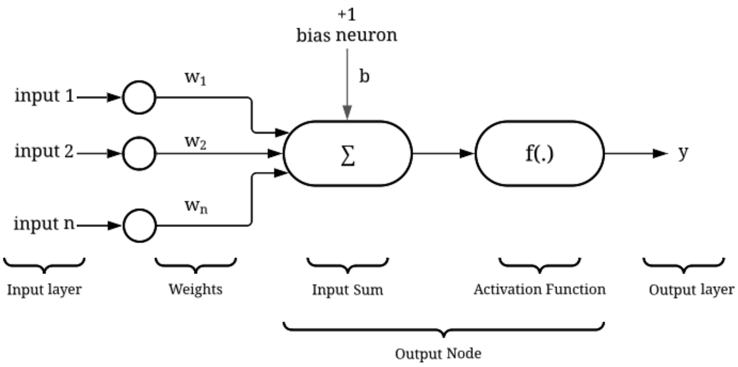


Figure 1: Single-layer neural network architecture

We consider a vector $\overline{X} = [x_1, x_2, \ldots, x_n]$ of inputs, or features, and a weight vector $\overline{W} = [w_1, w_2, \ldots, w_n]$. The bias, b, allows for more flexibility, and better classification ability. A perceptron contains one computational layer, at the output node (Aggarwal, 2018). No computations are done within the input layer.

At the output node, the first step consists of an input sum, which is given by the linear function : $\overline{W} \cdot \overline{X} = \sum_{i=1}^{n} w_i x_i + b$. Next, a sign function, or activation function, is applied as a means to convert the sum value into a class label (Aggarwal, 2018). The activation function acts as a threshold, which determines the output : if the value of the sum exceeds the threshold, the neuron generates an output signal (Bento, 2021).

According to what needs to be predicted, certain activation functions might be more fitting than others. For example, if $\hat{y}$ refers to a probability, a sigmoid function can be used, since it ranges from 0 to 1 (Aggarwal, 2018).

The prediction of $\hat{y}$ is given by :

$$\hat{y} = \text{sign}\left\{\overline{W} \cdot \overline{X} + b\right\} = \text{sign}\left\{\sum_{i=1}^{n} w_i x_i + b\right\}$$

(Aggarwal, 2018).

The goal of the perceptron is to minimize the prediction error, or missclassifications (Aggarwal, 2018). The error of prediction is given by $E(\overline{X}) = y - \hat{y}$, where $\hat{y}$ is the predicted value and y the observed value (Aggarwal, 2018).

The learning occurs based on the weights which minimizes the distance between the miss-classified points and the decision boundary, using a stochastic gradient descent (Bento, 2021).

We won't be using a Perceptron to forecast CO2 emissions, as it can't model non-linear relationships (Bento, 2021). However, it is useful to understand the basic principles of a Perceptron to understand the workings of a more complex model.

In multi-layer models, there can be multiple layers of neurons between the inputs and the outputs, also called hidden layers (Aggarwal, 2018). Due to these additional layers, we call this model a multilayer perceptron (MLP). It has the ability to model non-linear relationships and is more fitting for forecasting complex patterns (Bento, 2021). The next subsection delves into the architecture of the MLP.

4.1.2 Multilayer Perceptron architecture

Multilayer neural networks differ from perceptrons due to their multiple hidden layers of neurons. The computations performed within these layers are not visible to the user (Aggarwal, 2018).

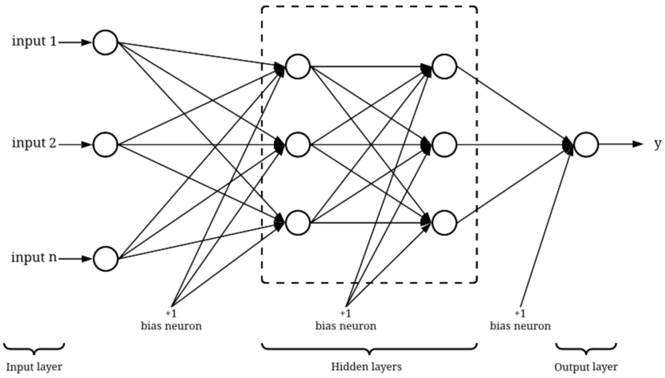


Figure 2: Multi-layer perceptron architecture

Our input layer will have as much neurons as there is input data. In our model, we have 9 input variables, so 9 neurons connected to the input layer. No computation are done within these neurons. Next, the number hidden layers, connecting the input layer to output layer, will have to be determined during the coding phase. Finally, the output layer, which its number of neurons will also have to be determined during the coding phase. The weights connecting the layers to each other will be determined during the training process.

The training process allows the model to adjust the weight and minimize the number of missclassifications, as mentioned previously.

If a neuron is given by the combination of a sum function and an activation function :

$$y = \text{sign}\left\{\sum_{i=1}^{n} w_i x_i + b\right\},$$

for a kth hidden layer, denoted $h_j^{(k)}$, we have :

$$
\begin{aligned}
h_i^{(1)} &= \operatorname{sign}\left\{\sum_{i=1}^{n} w_{n,i}^{(1)} x_i + b_n^{(1)}\right\} = \operatorname{sign}\left\{\overline{W}^{(1)} \cdot \overline{X} + \overline{B}^{(1)}\right\} \\
h_i^{(2)} &= \operatorname{sign}\left\{\sum_{i=1}^{n} w_{n,i}^{(2)} h_i^{(1)} + b_n^{(2)}\right\} = \operatorname{sign}\left\{\overline{W}^{(2)} \cdot \overline{H}^{(1)} + \overline{B}^{(2)}\right\} \\
h_i^{(k)} &= \operatorname{sign}\left\{\sum_{i=1}^{n} w_{n,i}^{(k)} h_i^{(k-1)} + b_n^{(k)}\right\} = \operatorname{sign}\left\{\overline{W}^{(k)} \cdot \overline{H}^{(k-1)} + \overline{B}^{(k)}\right\} \\
y_i &= \operatorname{sign}\left\{\sum_{i=1}^{n} w_{n,i}^{(k+1)} h_i^{(k)} + b_n^{(k+1)}\right\} = \operatorname{sign}\left\{\overline{W}^{(k+1)} \cdot \overline{H}^{(k)} + \overline{B}^{(k+1)}\right\}
\end{aligned}
$$

where $\overline{W}^{(k)}$ is the weight matrix for each layer, $\overline{H}^{(k)}$ is an activation vector for each layer, and $\overline{B}^{(k)}$ is the bias vector for each layer (Grosse, 2018).

The non-linear activation function of an MLP can be a sigmoid, tanh, ReLU (Rectified Linear Unit), or softmax (Jaiswal, 2024). The choice of the activation function will be made during the coding phase as well, according to the accurateness of the obtained results.

4.2 Model parameters

The first parameter to determine was the number of hidden layers, along with the number of neurons per layer. During my literature review, I did not find a clear methodology describing how to determine this parameter. This question seems to divide researchers.

I decided to refer myself to Sachdev (2020), a senior data scientist, to set the number of hidden layers and neurons. His method consists of choosing between 1 and 2 hidden layers for less complex data, with fewer features, and a number of neurons between the size of the input and output layer.

All 27 countries' MLPs share the same architecture, consisting of two hidden layers, with 5 neurons in the first layer, and 3 neurons in the second. The second parameter to be defined was the activation function. As I mentioned in the model section, there are several activation functions available. However, the one which gave me the best results in terms of error was the logistic function, given by :

$$\phi(z) = \frac{1}{1 + e^{-z}}$$

Finally, to determine the quality of my model, I defined the error function as the sum of squared errors. Once the model attained an error of less than 0.01, it stopped and picked this model as the best one. The amount of times the model had to repeat itself to reach this threshold is given by the number of steps.

The table below summarizes the error and number of steps of each model :

Countries	**SSE**	**Steps**
Belgium	0.00056	55
Bulgaria	0.00169	38
Czechia	0.00113	62
Denmark	0.00131	51
Germany	0.00052	73
Estonia	0.00124	51
Ireland	0.00016	118
Greece	0.00093	55
Spain	0.00306	55
France	0.00475	55
Croatia	0.00134	54
Italy	0.00073	48
Cyprus	0.00209	64
Latvia	0.00059	127
Lithuania	0.00073	32
Luxembourg	0.00414	42
Hungary	0.00399	28
Malta	0.00012	53
The Netherlands	0.00782	20
Austria	0.00912	32
Poland	0.00045	50
Portugal	0.00010	69
Romania	0.00012	53
Slovenia	0.00134	67
Slovakia	0.00228	39
Finland	0.00023	50
Sweden	0.00023	47

Table 4: MLPs sum of squared errors and steps

During the coding phase, I encountered a trade-off between selecting a computationally inexpensive model and choosing a model with a smaller SSE. In fact, I could define a threshold for the SSE to stop searching for another model once this threshold was attained. This parameter allowed me to improve my prediction precision, however, it resulted in a more computationally expensive model. After having run the models several times, I chose to set the SSE threshold at 0.01, so that the steps would not exceed 100.

It appears that for Ireland and Latvia, I wasn't able to respect that constraint. The model had to go above 100 steps to achieve an SSE of less than 0.01.

5 Results

This section aims to interpret the results I obtained under the first and second scenarios. To reiterate, the first scenario seeks to forecast CO2 emissions based on the business as usual evolution of the input variables. No additional constraints were applied. The second scenario is based on the BAU, except that it alters the evolution of the share of energy from renewable sources variable.

For the record, the European Commission has set the following national objectives :

Countries	**2005 levels**	**Reduction target**	**2030 goal**
Belgium	147 261.31	47%	78 048.50
Bulgaria	46 654.74	10%	41 989.27
Czechia	142 694.80	26%	105 594.15
Denmark	75 522.95	50%	37 761.48
Germany	1 019 560.97	50%	509 780.49
Estonia	16 343.31	24%	12 420.91
Ireland	79 931.34	42%	46 360.18
Greece	135 817.78	23%	104 987.14
Spain	403 376.69	38%	251 303.68
France	513 076.64	48%	269 365.24
Croatia	23 079.67	17%	19 225.36
Italy	570 461.09	44%	321 169.59
Cyprus	9 857.82	32%	6 703.32
Latvia	5 317.43	17%	4 413.46
Lithuania	18 334.30	21%	14 484.10
Luxembourg	13 741.29	50%	6 870.64
Hungary	72 080.77	19%	58 601.67
Malta	3 257.83	19%	2 638.84
The Netherlands	231 612.43	48%	120 438.47
Austria	76 484.74	48%	39 772.07
Poland	352 291.13	18%	289 935.60
Portugal	91 851.50	29%	65 490.12
Romania	119 962.47	13%	104 727.23
Slovenia	13 427.01	27%	9 801.72
Slovakia	46 558.18	23%	35 989.48
Finland	46 162.42	50%	23 081.21
Sweden	17 582.39	50%	8 791.20

Table 5: European net GHG targets, in CO2 eq. (in kt)

(*Cutting EU greenhouse gas emissions: National targets for 2030.*, 2023). These objectives served as the foundation for my analysis.

5.1 First scenario

As previously mentioned, my first scenario is based on the forecast of my input variables in a business as usual (BAU) context. Hence, I forecasted my features based on their historical values without applying any discount factor.

In order to forecast these input variables, I used an MLP, with only one hidden layer including 5 neurons. The results of these 243 individual forecasts can be found in Tables : 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34.

Following the forecast of my target variable, net GHG emissions in CO2 equivalent, I obtained the following results :

Countries	**Figure**	**2030 goal**	**Forecast 2030**	**$CI_{95\%}$**
Belgium	3	78 048.50	120 049.89	(119 354 ; 121 287)
Bulgaria	4	41 989.27	44 664.58	(43 816 ; 45 090)
Czechia	5	105 594.15	126 267.05	(124 134 ; 128 513)
Denmark	6	37 761.48	50 826.03	(50 430 ; 53 435)
Germany	7	509 780.49	860 464.56	(822 797 ; 823 895)
Estonia	8	12 420.91	18 248.40	(16 787 ; 17 998)
Ireland	9	46 360.18	64 966.14	(64 294 ; 66 731)
Greece	10	104 987.14	91 084.88	(92 832 ; 97 419)
Spain	11	251 303.68	273 142.09	(269 471 ; 272 931)
France	12	269 365.24	397 559.14	(393 477 ; 401 899)
Croatia	13	19 225.36	20 764.89	(20 212 ; 22 151)
Italy	14	321 169.59	407 787.48	(408 429 ; 411 118)
Cyprus	15	6 703.32	9 271.60	(8 885 ; 10 573)
Latvia	16	4 413.46	5 543.37	(8 178 ; 9 797)
Lithuania	17	14 484.10	13 954.73	(13 275 ; 16 600)
Luxembourg	18	6 870.64	11 440.25	(10 728 ; 15 136)
Hungary	19	58 601.67	58 472.67	(54 614 ; 54 703)
Malta	20	2 638.84	2 753.49	(2 255 ; 3 925)
The Netherlands	21	120 438.47	191 554.13	(185 630 ; 187 723)
Austria	22	39 772.07	79 384.13	(77 149 ; 83 303)
Poland	23	289 935.60	363 220.15	(359 618 ; 362 594)
Portugal	24	65 490.12	91 169.95	(88 800 ; 92 843)
Romania	25	104 727.23	73 094.03	(65 813 ; 66 609)
Slovenia	26	9 801.72	11 597.73	(10 937 ; 13 140)
Slovakia	27	35 989.48	35 531.40	(35 265 ; 35 336)
Finland	28	23 081.21	53 453.03	(53 981 ; 58 905)
Sweden	29	8 791.20	9 123.42	(7 828 ; 12 727)

Table 6: Forecast results until 2030

As one can see, only 5 countries would reach their 2030 goal, namely Greece, Lithuania, Hungary, Romania, Slovakia. However, given the inherent uncertainties in the data and the model, I estimated a 95% confidence interval, indicating there is a 95% probability that the actual GHG emissions will fall within this range.

These confidence intervals are based on the residuals of my models. As my data did not follow a Normal distribution, I had to use bootstrapping.

Bootstrapping is a non-parametric method, used when the assumption of normality is violated (Greenwood, 2021). This robust approach empirically estimates the distribution of the forecast errors. In layman's terms, bootstrapping works by repeatedly sampling from the data we have, with replacement, to create many new datasets and build a distribution of the statistic of interest (Greenwood, 2021). By doing this, we can estimate the variability and uncertainty of our predictions more accurately, without assuming the specific distribution of our data set (Greenwood, 2021).

The 2030 forecasted value of 11 countries out of 27 fall outside the 95% confidence interval : Germany, Estonia, Greece, Italy, Latvia, Hungary, The Netherlands, Poland, Romania, Slovakia and Finland. This deviation from the confidence interval indicates that these countries either have much higher or much lower forecasted emissions compared to the expected range. This suggests that my model did not capture trends or factors influencing the emissions of these countries, other than the ones plugged in the model.

Lastly, the 2030 target of only 2 countries fall within the 95% confidence interval. This suggests that, from a policy perspective, there may be a need for a more in-depth analysis to determine what goal is feasible and realistic for the European countries.

Setting targets that are unattainable is useless, as it doesn't reflect the true potential of improvement of the European Union. Additionally, it doesn't encourage policymakers to reconsider how they define these targets until they realize they are unattainable.

5.2 Second scenario

While our first scenario doesn't take into account additional measures, our second scenario incorporates the European Commission's desire to further integrate renewable energies into its energy mix.

The European Commission has highlighted that over 75% of the EU's greenhouse gas emissions originate from the energy sector. In response, it has set a new objective for 2030 : to elevate the proportion of renewable energy to a minimum of 42.5% (*Renewable energy targets*, 2023).

In order to assess the viability of achieving the 2030 target solely through increasing the utilization of renewable energy sources, I have analyzed the historical trend of renewable energy's contribution to the overall energy mix since 2020. By using these updated projections, Table 35, I have formulated a scenario wherein each member state of the EU27 augments its adoption of renewable energy sources.

Countries reaching their 2030 target in this new scenario are Greece, Lithuania, Hungary, Romania, Slovakia. This time around, updating the share of renewable energies seems to give more precise estimations. In fact, the only country whose emissions fall outside the confidence interval is Ireland. Having linearly increasing share of renewable energies helps my model yield better results with regards to the confidence interval.

It is interesting to point out that for Denmark, Greece, Italy, Cyprus, Luxembourg and Finland, increasing the share of energy from renewable sources has the effect of increasing their forecasted value of net GHG emissions in 2030.

This trend doesn't align with the findings of Grodzicki & Jankiewicz (2022), who examined the impact of renewable energies on CO2 emissions in Europe. In fact, their study shows that increased share of renewable energies leads to less CO2 emissions.

However, the study of Wang et al. (2022), showed that not all renewable energy sources have the same impact on CO2 emissions. In fact, their research highlighted that more advanced technologies such as solar, bionenergy and wind tend to increase CO2 emissions or have no impact, while well-established renewable energies like hydropower and geothermal lower CO2 emissions. Another study from Shahnazi & Dehghan Shabani (2021), also showed that the renewable energy consumption had a negative effect on CO2 emissions in Europe.

While it may not be the focus of my thesis, I believe it would be interesting to further conduct research regarding the impact of renewable energies on CO2 emissions within European countries.

The results of the second scenario are the following :

Countries	**2030 goal**	**Updated Forecast 2030**	**$CI_{95\%}$**
Belgium	78 048.50	119 887.59	(119 354 ; 121 287)
Bulgaria	41 989.27	44 153.35	(43 816 ; 45 090)
Czechia	105 594.15	125 342.27	(124 134 ; 128 513)
Denmark	37 761.48	51 258.98	(50 430 ; 53 435)
Germany	509 780.49	823 100.00	(822 797 ; 823 895)
Estonia	12 420.91	17 120.87	(16 787 ; 17 998)
Ireland	46 360.18	62 900.02	(64 294 ; 66 731)
Greece	104 987.14	94 097.59	(92 832 ; 97 419)
Spain	251 303.68	270 425.48	(269 471 ; 272 931)
France	269 365.24	395 704.81	(393 477 ; 401 899)
Croatia	19 225.36	20 747.20	(20 212 ; 22 151)
Italy	321 169.59	409 140.19	(408 429 ; 411 118)
Cyprus	6 703.32	9 350.50	(8 885 ; 10 573)
Latvia	4 413.46	8 624.79	(8 178 ; 9 797)
Lithuania	14 484.10	14 192.02	(13 275 ; 16 600)
Luxembourg	6 870.64	11 893.52	(10 728 ; 15 136)
Hungary	58 601.67	54 638.87	(54 614 ; 54 703)
Malta	2 638.84	2 696.87	(2 255 ; 3 925)
The Netherlands	120 438.47	186 183.29	(185 630 ; 187 723)
Austria	39 772.07	78 847.30	(77 149 ; 83 303)
Poland	289 935.60	360 439.17	(359 618 ; 362 594)
Portugal	65 490.12	89 915.93	(88 800 ; 92 843)
Romania	104 727.23	66 032.58	(65 813 ; 66 609)
Slovenia	9 801.72	11 545.00	(10 937 ; 13 140)
Slovakia	35 989.48	35 284.24	(35 265 ; 35 336)
Finland	23 081.21	55 339.88	(53 981 ; 58 905)
Sweden	8 791.20	9 001.56	(7 828 ; 12 727)

Table 7: Updated forecast results until 2030

5.3 Conclusion & policy suggestions

After having conducted two different forecasts, I came to the conclusion that most countries won't reach their 2030 target, even with additional shares of renewable energies.

According to the first scenario, the only countries which will most likely sufficiently reduce their CO2 emissions are Greece, Lithuania, Hungary, Romania, Slovakia.

As for the second scenario, raising the share of renewable energy sources doesn't seems to help any country achieving their target. Unfortunately, European countries can't rely solely on the increasing share of renewable energies to hope achieving their goal. In fact, Denmark, Greece, Italy, Cyprus, Luxembourg and Finland seem to be disadvantaged by this increased share.

Considering these findings, it is clear that more research needs to be made about renewable energies and their effect on net GHG emissions in European countries. The studies of Grodzicki & Jankiewicz (2022), Wang et al. (2022), and Shahnazi & Dehghan Shabani (2021), could be the starting point of a thesis focusing on that issue. Alongside efforts to increase the share of renewable energy sources, additional measures addressing other aspects of emissions reduction seem to be necessary.

In this regard, future research could for example focus on the impact of less energy intensive technologies, and/or stricter energy regulation. By adopting a multifaceted approach, countries can better position themselves to meet their emissions targets.

6 Limitations

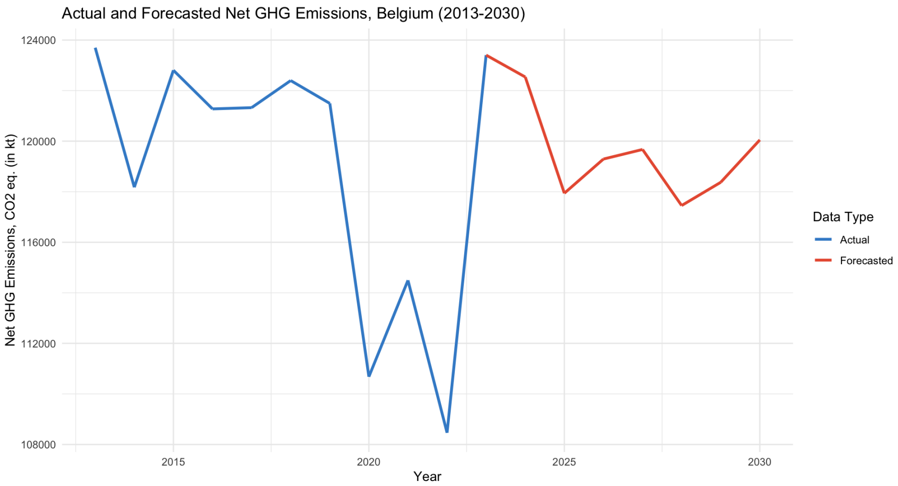
During the making of this thesis, I encountered several limitations. The first one being the lack of data. Considering that each country had its own method to collect data prior to joining the European Union, it was hard to determine a sufficiently long period of time within which these 27 countries were under the same data collection methodology.

In addition, the data which could be found on Eurostat was usually only available on annual basis, making it even more difficult to provide sufficient data to my model. Monthly data could've been more precise, and would've allowed me to apply dimension reductions techniques for example, making this thesis more interesting from a technical standpoint.

Finally, to ensure consistency, I had to use the same model across all countries. An analysis focusing on one country could've considered only the relevant variables for this country. However, I believe that replicating the same strategy for every country allowed me to make valid comparisons. Also, being limited to 40 pages prevented me from doing specific models for each country. In fact, 27 models would take more than 40 pages of explanation.

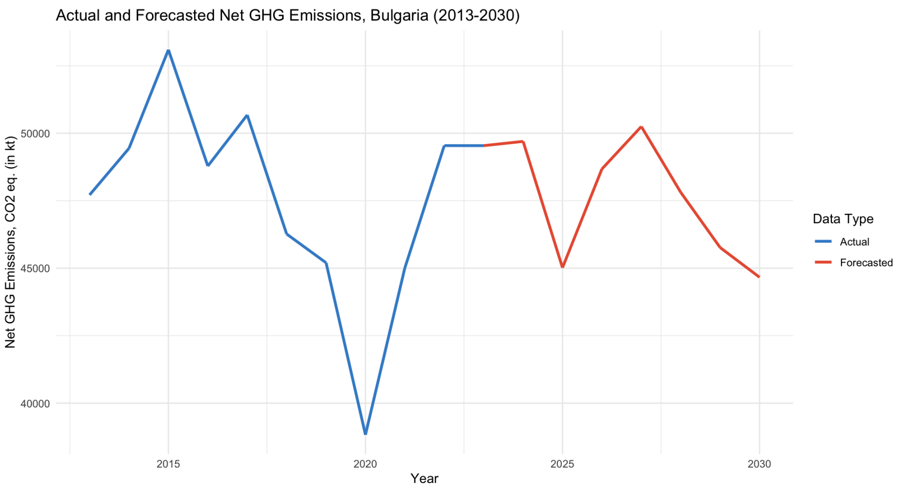
7 Appendix

7.1 Forecast per country



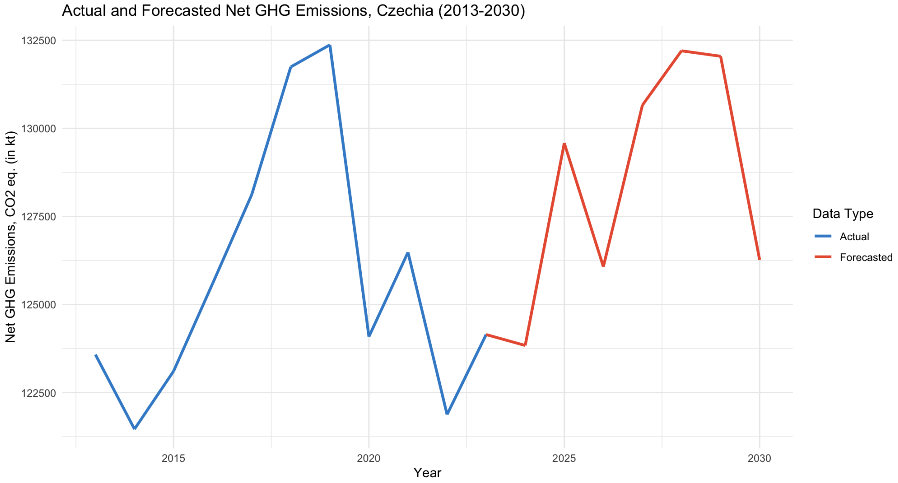
Year	Net_GHG_Emissions
2013	123696.80
2014	118175.89
2015	122804.85
2016	121276.77
2017	121325.72
2018	122397.41
2019	121494.17
2020	110680.53
2021	114494.34
2022	108463.54
2023	123404.07
2024	122538.48
2025	117940.00
2026	119292.50
2027	119671.19
2028	117453.11
2029	118372.80
2030	120049.89

Figure 3: Forecast Net GHG emissions, Belgium



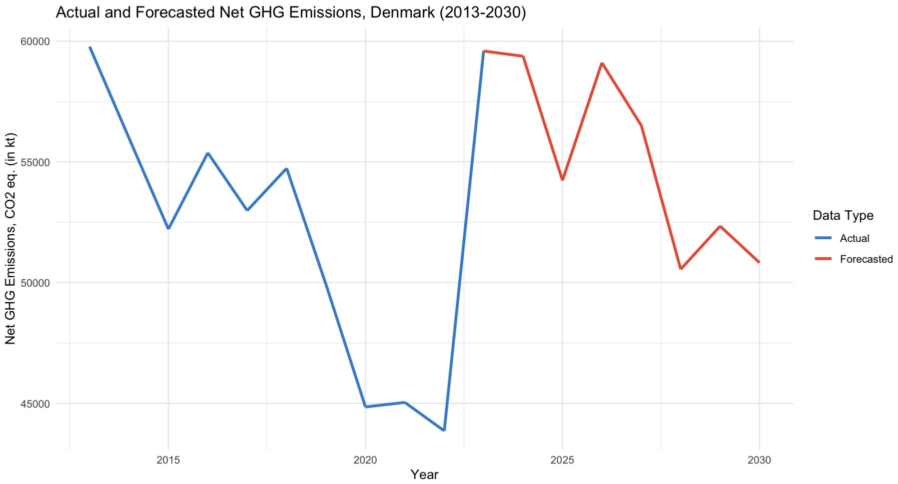
Year	Net_GHG_Emissions
2013	47714.87
2014	49441.52
2015	53094.68
2016	48784.93
2017	50677.16
2018	46267.16
2019	45202.16
2020	38829.36
2021	45012.33
2022	49542.68
2023	49540.93
2024	49698.23
2025	45018.51
2026	48675.77
2027	50248.79
2028	47810.61
2029	45765.69
2030	44664.58

Figure 4: Forecast Net GHG emissions, Bulgaria



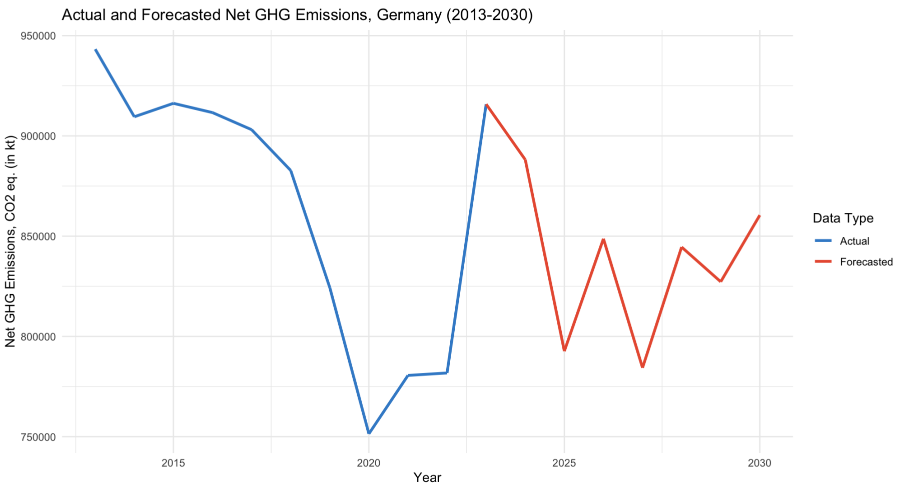
Year	Net_GHG_Emissions
2013	123580.24
2014	121464.52
2015	123107.79
2016	125596.78
2017	128118.15
2018	131743.93
2019	132369.67
2020	124089.60
2021	126482.84
2022	121878.41
2023	124147.75
2024	123839.49
2025	129580.87
2026	126074.39
2027	130659.79
2028	132201.10
2029	132046.97
2030	126267.05

Figure 5: Forecast Net GHG emissions, Czechia



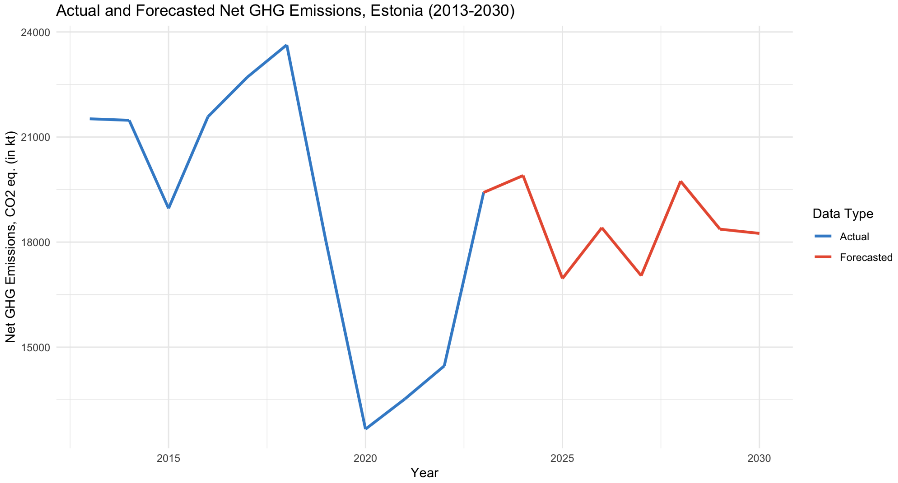
Year	Net_GHG_Emissions
2013	59775.40
2014	55988.03
2015	52217.83
2016	55378.24
2017	52985.97
2018	54735.68
2019	49917.40
2020	44854.14
2021	45039.53
2022	43862.31
2023	59593.28
2024	59376.80
2025	54235.51
2026	59106.21
2027	56508.51
2028	50555.43
2029	52341.35
2030	50826.03

Figure 6: Forecast Net GHG emissions, Denmark



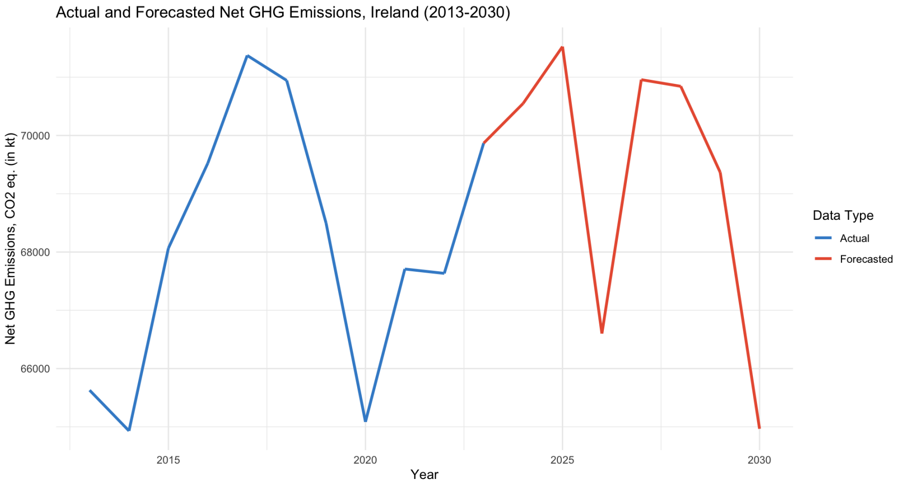
Year	Net_GHG_Emissions
2013	943260.71
2014	909547.71
2015	916252.44
2016	911633.51
2017	903110.82
2018	882774.53
2019	824349.79
2020	751411.11
2021	780543.27
2022	781761.74
2023	915819.46
2024	888142.01
2025	792654.81
2026	848701.65
2027	784351.57
2028	844550.03
2029	827251.62
2030	860464.56

Figure 7: Forecast Net GHG emissions, Germany



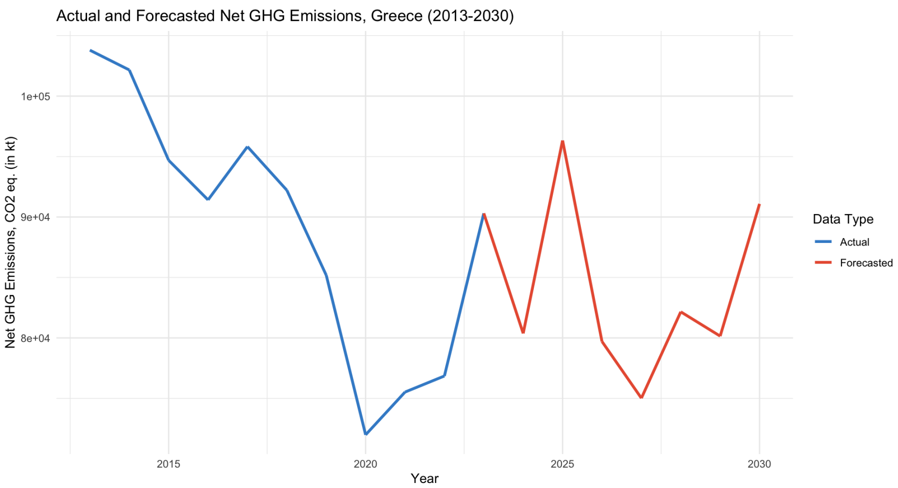
Year	Net_GHG_Emissions
2013	21520.10
2014	21477.98
2015	18963.26
2016	21578.68
2017	22710.04
2018	23631.25
2019	17999.08
2020	12658.94
2021	13520.68
2022	14464.35
2023	19416.20
2024	19899.43
2025	16959.79
2026	18409.48
2027	17040.33
2028	19738.35
2029	18369.21
2030	18248.40

Figure 8: Forecast Net GHG emissions, Estonia



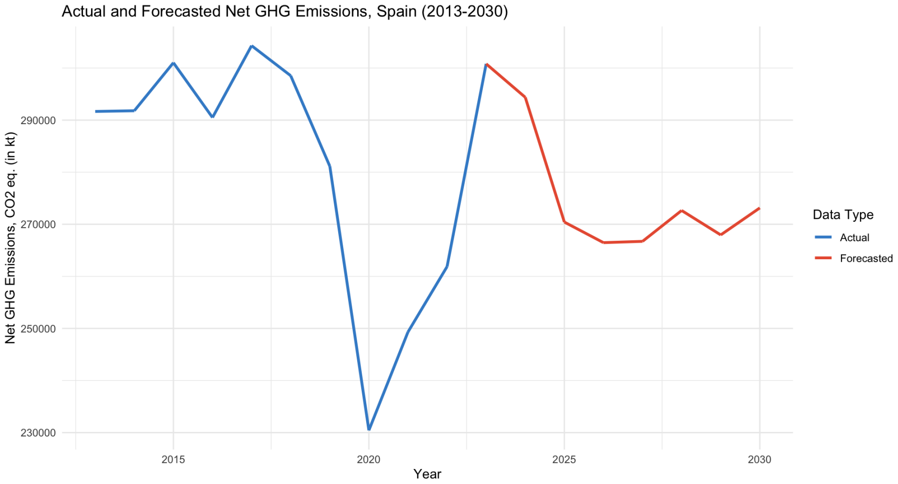
Year	Net_GHG_Emissions
2013	65628.55
2014	64930.56
2015	68065.92
2016	69524.12
2017	71373.40
2018	70945.13
2019	68496.93
2020	65084.98
2021	67707.90
2022	67633.48
2023	69868.12
2024	70548.95
2025	71524.80
2026	66600.13
2027	70957.45
2028	70843.97
2029	69368.84
2030	64966.14

Figure 9: Forecast Net GHG emissions, Ireland



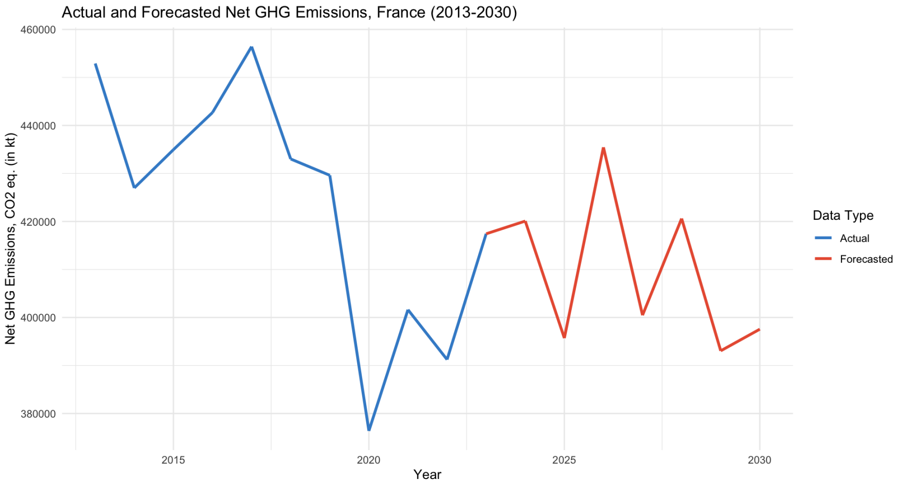
Year	Net_GHG_Emissions
2013	103797.76
2014	102162.81
2015	94690.05
2016	91415.46
2017	95821.18
2018	92215.21
2019	85185.68
2020	71986.48
2021	75521.49
2022	76852.03
2023	90303.80
2024	80372.99
2025	96329.23
2026	79703.50
2027	75017.05
2028	82158.31
2029	80149.83
2030	91084.88

Figure 10: Forecast Net GHG emissions, Greece



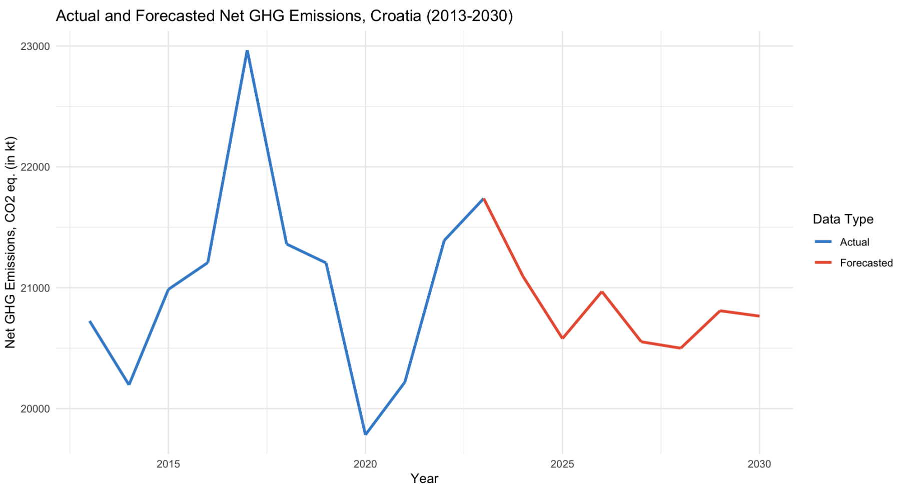
Year	Net_GHG_Emissions
2013	291665.59
2014	291797.83
2015	301021.36
2016	290498.06
2017	304293.32
2018	298527.73
2019	281150.76
2020	230436.93
2021	249310.37
2022	261868.81
2023	300802.05
2024	294380.99
2025	270425.48
2026	266474.06
2027	266721.02
2028	272648.16
2029	267955.84
2030	273142.09

Figure 11: Forecast Net GHG emissions, Spain



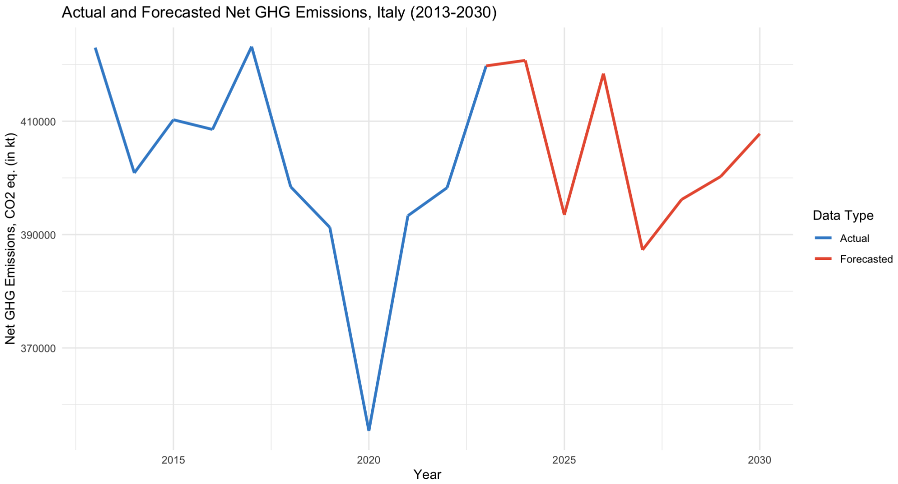
Year	Net_GHG_Emissions
2013	452900.51
2014	426983.11
2015	434947.06
2016	442688.89
2017	456415.62
2018	433014.90
2019	429611.52
2020	376380.31
2021	401618.70
2022	391232.80
2023	417426.94
2024	420075.98
2025	395704.81
2026	435440.41
2027	400473.08
2028	420605.78
2029	393055.77
2030	397559.14

Figure 12: Forecast Net GHG emissions, France



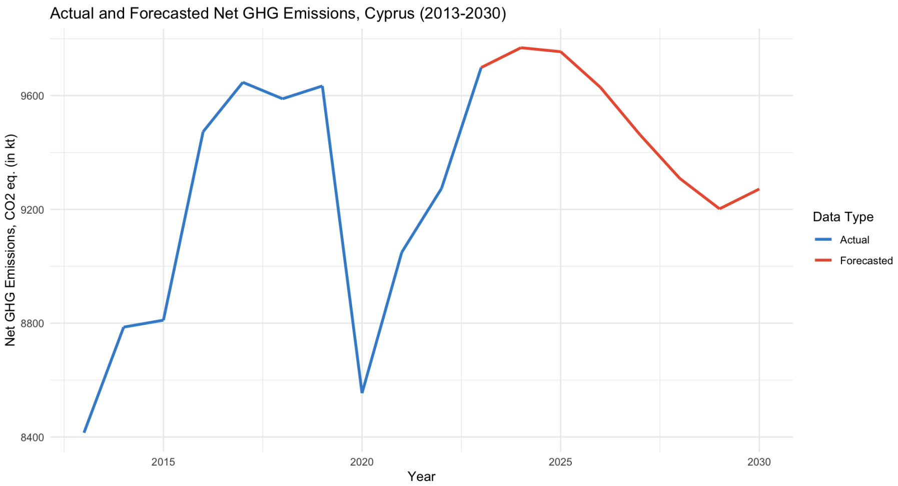
Year	Net_GHG_Emissions
2013	20724.63
2014	20195.85
2015	20986.05
2016	21207.56
2017	22965.27
2018	21361.03
2019	21205.27
2020	19782.70
2021	20218.57
2022	21390.94
2023	21738.16
2024	21092.26
2025	20579.09
2026	20968.39
2027	20552.54
2028	20499.46
2029	20809.13
2030	20764.89

Figure 13: Forecast Net GHG emissions, Croatia



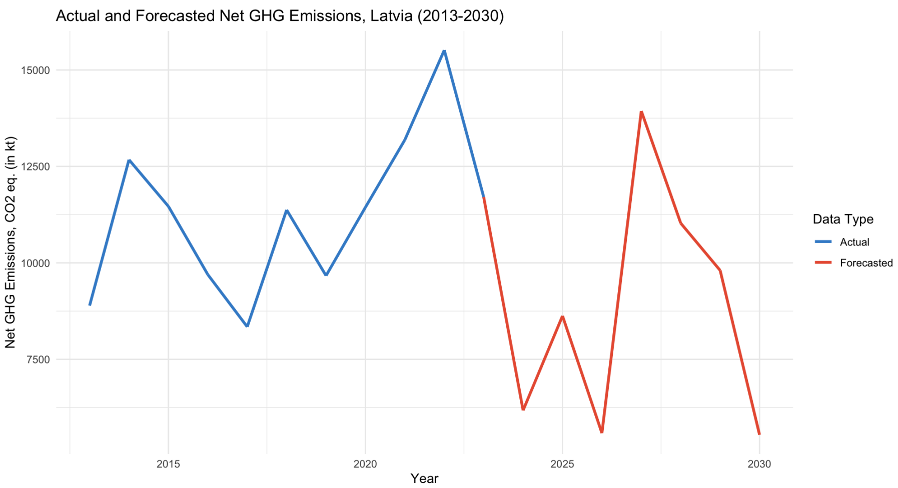
Year	Net_GHG_Emissions
2013	422978.61
2014	400874.28
2015	410260.00
2016	408551.10
2017	423162.66
2018	398430.08
2019	391278.79
2020	355368.74
2021	393337.36
2022	398267.78
2023	419768.65
2024	420734.87
2025	393487.38
2026	418415.93
2027	387303.55
2028	396192.80
2029	400250.94
2030	407787.48

Figure 14: Forecast Net GHG emissions, Italy



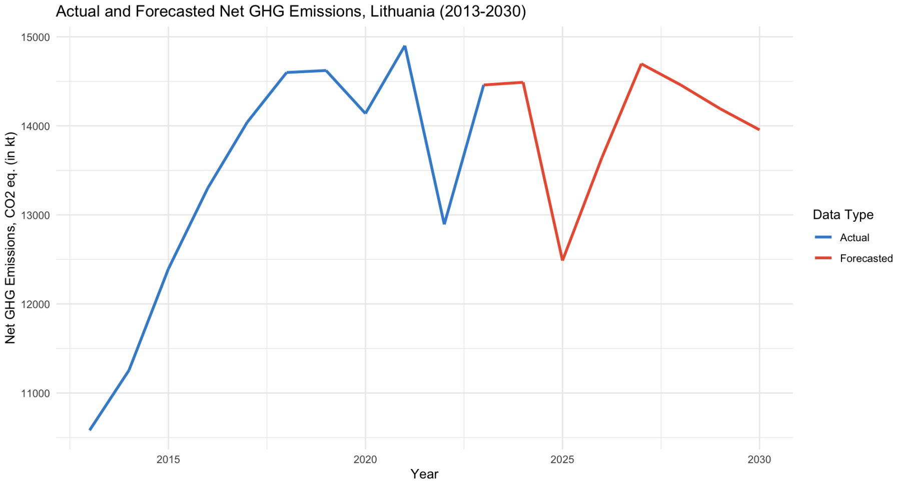
Year	Net_GHG_Emissions
2013	8414.92
2014	8786.16
2015	8810.62
2016	9473.04
2017	9646.69
2018	9588.78
2019	9633.71
2020	8554.10
2021	9049.38
2022	9273.39
2023	9698.59
2024	9768.20
2025	9754.28
2026	9628.97
2027	9461.89
2028	9308.73
2029	9201.98
2030	9271.60

Figure 15: Forecast Net GHG emissions, Cyprus



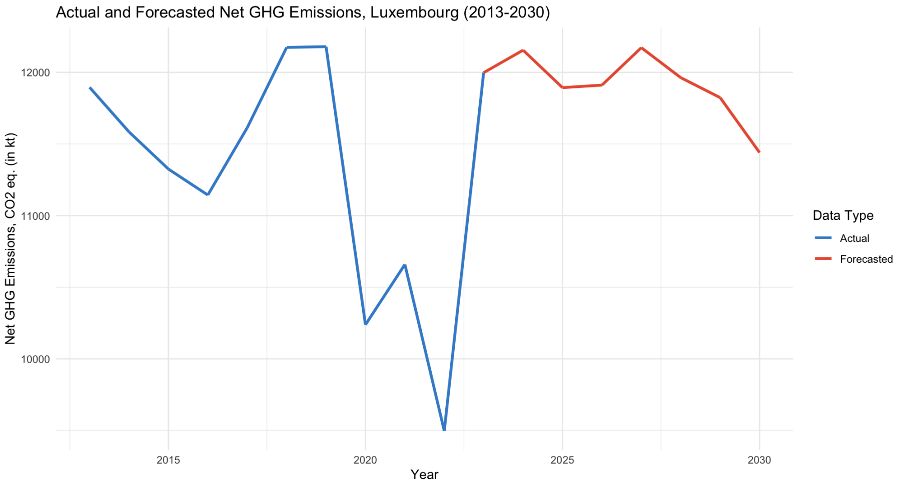
Year	Net_GHG_Emissions
2013	8891.32
2014	12673.39
2015	11464.82
2016	9696.12
2017	8343.07
2018	11373.10
2019	9668.09
2020	11441.74
2021	13189.39
2022	15513.08
2023	11706.20
2024	6177.14
2025	8624.79
2026	5587.08
2027	13935.31
2028	11028.73
2029	9804.90
2030	5543.37

Figure 16: Forecast Net GHG emissions, Latvia



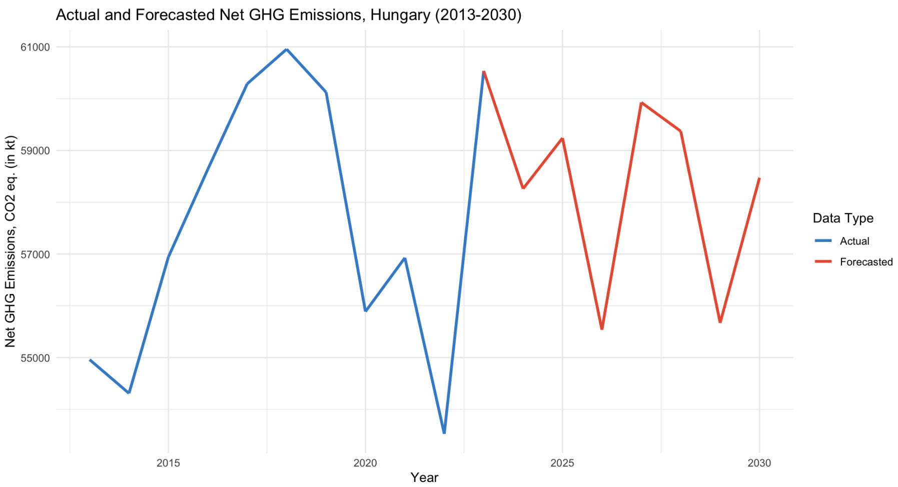
Year	Net_GHG_Emissions
2013	10581.02
2014	11255.55
2015	12394.42
2016	13301.81
2017	14040.59
2018	14598.98
2019	14621.46
2020	14138.11
2021	14900.03
2022	12893.30
2023	14458.97
2024	14488.63
2025	12486.51
2026	13643.29
2027	14696.26
2028	14458.97
2029	14192.02
2030	13954.73

Figure 17: Forecast Net GHG emissions, Lithuania



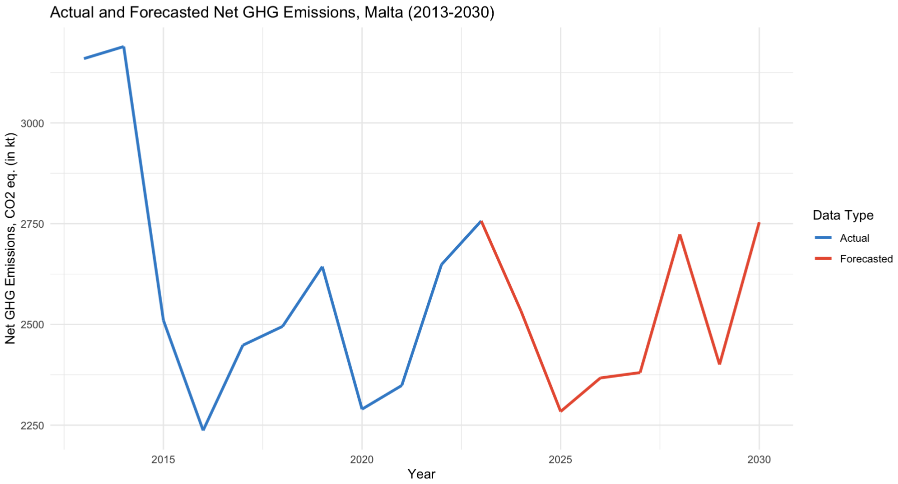
Year	Net_GHG_Emissions
2013	11895.46
2014	11584.67
2015	11324.88
2016	11143.68
2017	11613.64
2018	12174.13
2019	12179.76
2020	10238.25
2021	10658.96
2022	9497.06
2023	11998.12
2024	12155.03
2025	11893.52
2026	11910.96
2027	12172.46
2028	11963.26
2029	11823.79
2030	11440.25

Figure 18: Forecast Net GHG emissions, Luxembourg



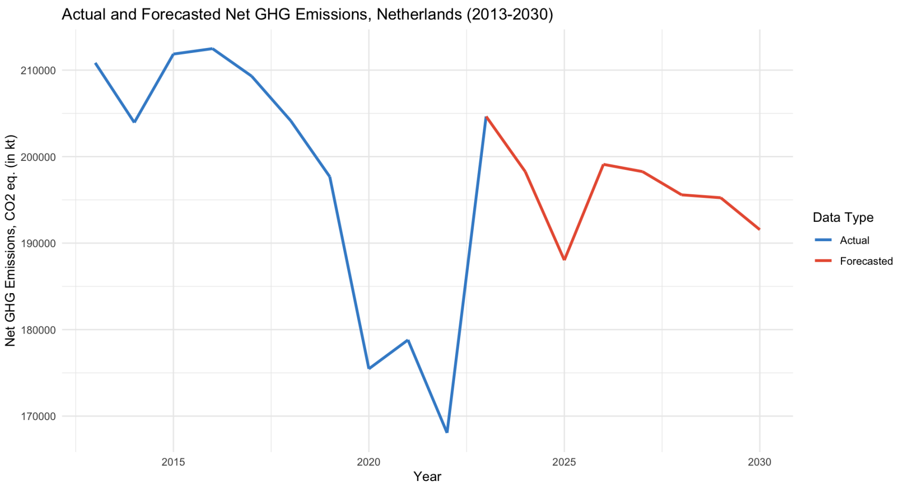
Year	Net_GHG_Emissions
2013	54961.46
2014	54310.80
2015	56943.45
2016	58636.02
2017	60287.25
2018	60955.33
2019	60125.31
2020	55888.72
2021	56927.05
2022	53528.89
2023	60534.99
2024	58261.15
2025	59239.43
2026	55537.83
2027	59926.87
2028	59371.63
2029	55670.03
2030	58472.67

Figure 19: Forecast Net GHG emissions, Hungary



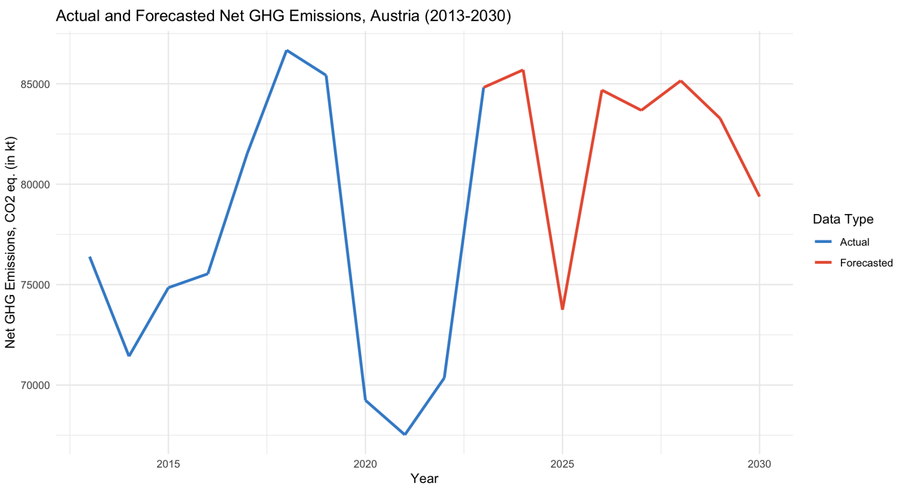
Year	Net_GHG_Emissions
2013	3159.63
2014	3189.49
2015	2510.06
2016	2236.89
2017	2448.38
2018	2495.09
2019	2643.38
2020	2289.63
2021	2348.42
2022	2648.49
2023	2756.82
2024	2533.66
2025	2283.87
2026	2367.13
2027	2380.46
2028	2723.51
2029	2400.44
2030	2753.49

Figure 20: Forecast Net GHG emissions, Malta



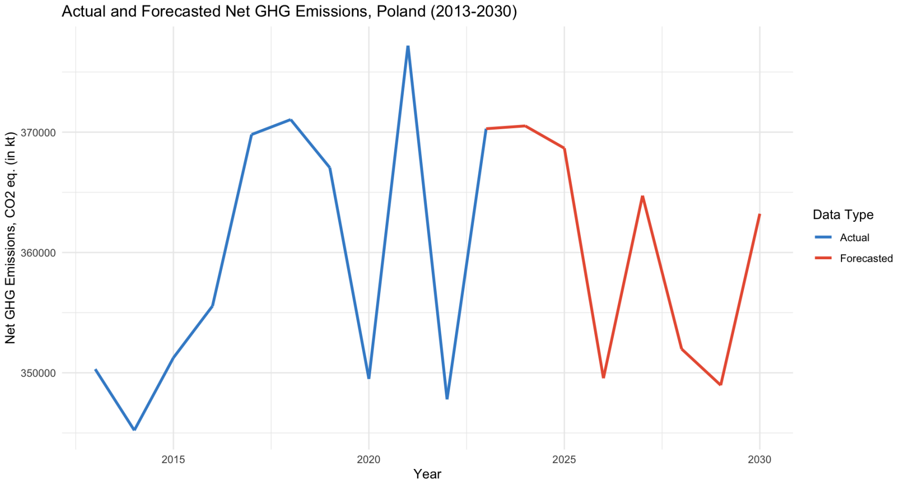
Year	Net_GHG_Emissions
2013	210841.59
2014	203942.43
2015	211860.16
2016	212488.45
2017	209309.33
2018	204156.69
2019	197675.85
2020	175464.95
2021	178807.09
2022	168059.95
2023	204645.55
2024	198267.68
2025	188029.52
2026	199106.88
2027	198267.68
2028	195582.26
2029	195246.59
2030	191554.13

Figure 21: Forecast Net GHG emissions, The Netherlands



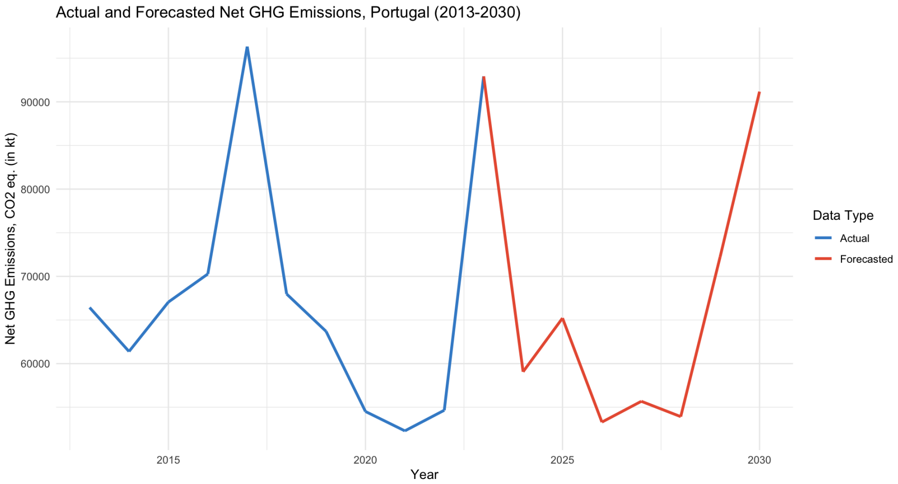
Year	Net_GHG_Emissions
2013	76393.05
2014	71431.17
2015	74847.46
2016	75537.96
2017	81528.23
2018	86673.98
2019	85423.58
2020	69238.66
2021	67521.07
2022	70351.95
2023	84819.57
2024	85691.92
2025	73747.38
2026	84685.36
2027	83678.80
2028	85155.09
2029	83276.17
2030	79384.13

Figure 22: Forecast Net GHG emissions, Austria



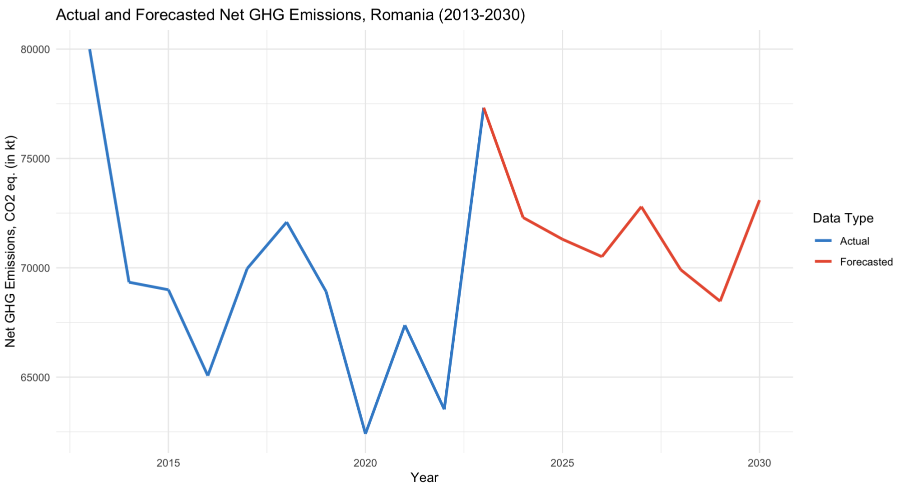
Year	Net_GHG_Emissions
2013	350302.24
2014	345218.96
2015	351248.01
2016	355550.87
2017	369803.44
2018	371047.57
2019	367052.28
2020	349490.27
2021	377189.76
2022	347789.71
2023	370288.47
2024	370520.21
2025	368666.23
2026	349547.01
2027	364726.51
2028	351980.36
2029	348967.64
2030	363220.15

Figure 23: Forecast Net GHG emissions, Poland



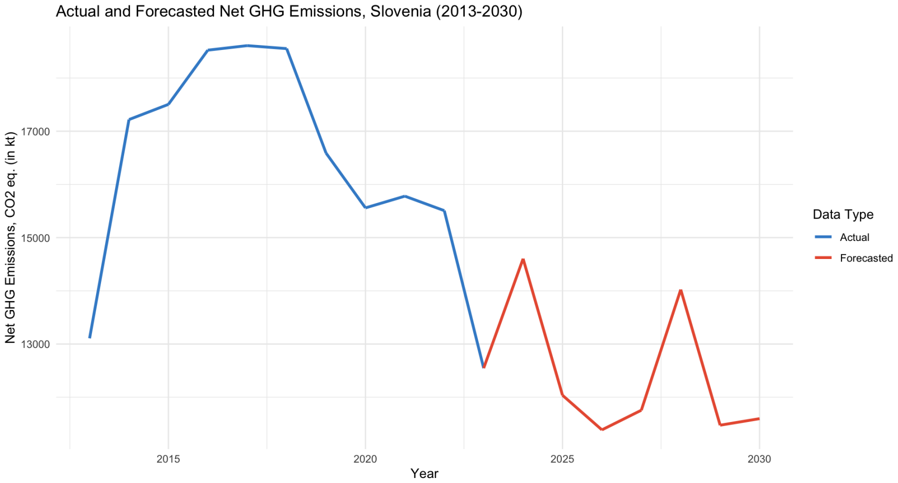
Year	Net_GHG_Emissions
2013	66430.73
2014	61392.33
2015	67056.93
2016	70271.81
2017	96327.85
2018	67978.96
2019	63700.71
2020	54515.74
2021	52293.08
2022	54656.39
2023	92925.59
2024	59066.93
2025	65211.65
2026	53298.42
2027	55681.06
2028	53925.43
2029	72234.18
2030	91169.95

Figure 24: Forecast Net GHG emissions, Portugal



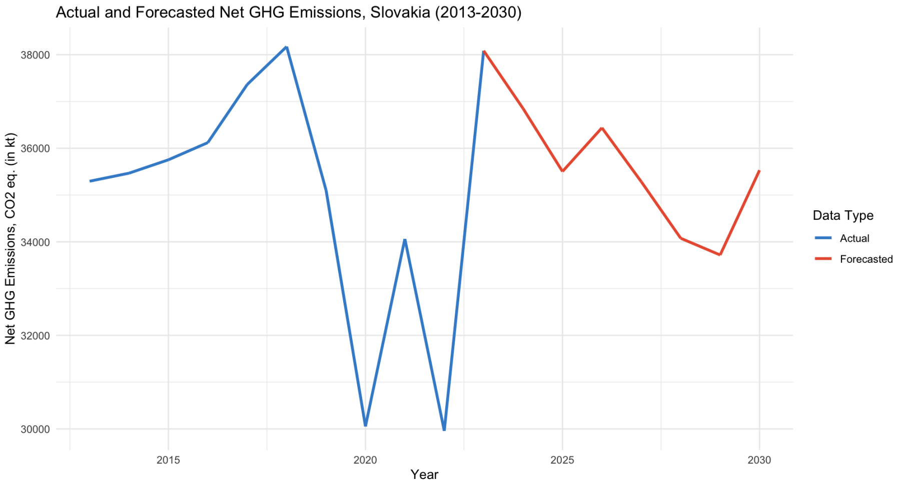
Year	Net_GHG_Emissions
2013	79997.19
2014	69339.82
2015	68994.25
2016	65063.86
2017	69967.74
2018	72089.64
2019	68916.63
2020	62407.64
2021	67373.41
2022	63526.27
2023	77320.95
2024	72298.37
2025	71303.80
2026	70508.14
2027	72795.65
2028	69911.40
2029	68469.27
2030	73094.03

Figure 25: Forecast Net GHG emissions, Romania



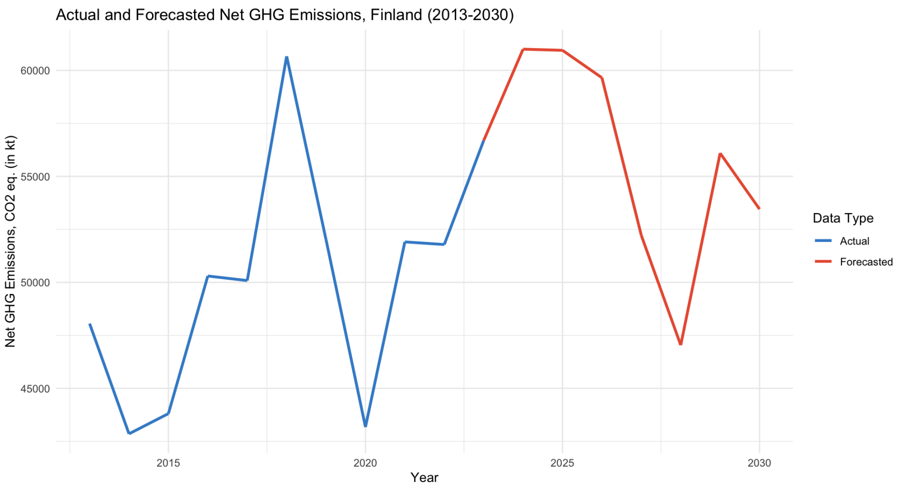
Year	Net_GHG_Emissions
2013	13107.62
2014	17218.85
2015	17504.52
2016	18523.58
2017	18608.65
2018	18552.61
2019	16589.04
2020	15559.00
2021	15779.63
2022	15507.29
2023	12546.89
2024	14603.41
2025	12037.16
2026	11386.81
2027	11755.92
2028	14023.37
2029	11474.69
2030	11597.73

Figure 26: Forecast Net GHG emissions, Slovenia



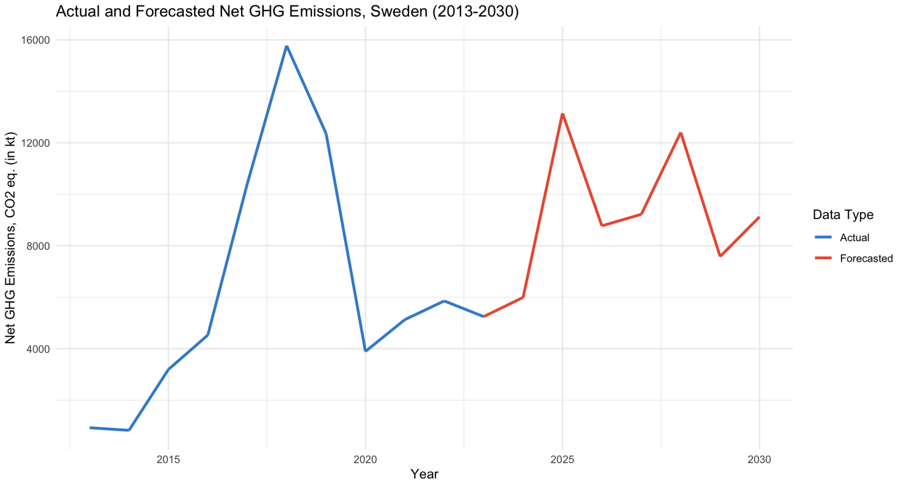
Year	Net_GHG_Emissions
2013	35295.74
2014	35467.45
2015	35753.71
2016	36121.13
2017	37363.90
2018	38173.48
2019	35103.15
2020	30052.99
2021	34060.39
2022	29958.04
2023	38085.38
2024	36849.59
2025	35503.94
2026	36437.65
2027	35284.24
2028	34075.90
2029	33718.90
2030	35531.40

Figure 27: Forecast Net GHG emissions, Slovakia



Year	Net_GHG_Emissions
2013	48052.72
2014	42854.65
2015	43807.53
2016	50299.70
2017	50084.60
2018	60664.08
2019	52005.75
2020	43174.94
2021	51908.04
2022	51784.69
2023	56687.64
2024	61000.46
2025	60946.55
2026	59652.70
2027	52213.09
2028	47037.71
2029	56094.63
2030	53453.03

Figure 28: Forecast Net GHG emissions, Finland



Year	Net_GHG_Emissions
2013	930.10
2014	829.75
2015	3193.55
2016	4529.29
2017	10402.16
2018	15775.07
2019	12364.65
2020	3895.17
2021	5130.53
2022	5856.99
2023	5247.10
2024	5992.55
2025	13148.83
2026	8775.55
2027	9222.81
2028	12403.38
2029	7582.83
2030	9123.42

Figure 29: Forecast Net GHG emissions, Sweden

7.2 Input variables

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	8.60	167.61	78.50	79.30	1.20	7.67	11137974	0.6586	33490
2014	8.70	155.42	79.00	79.80	0.50	8.04	11180840	0.6630	33870
2015	8.70	153.60	76.40	77.80	0.60	8.06	11237274	0.6404	34360
2016	7.90	160.97	78.20	79.40	1.80	8.74	11311117	0.6846	34620
2017	7.20	160.35	82.10	83.20	2.20	9.14	11351727	0.6486	35050
2018	6.00	157.70	83.40	83.10	2.30	9.47	11398589	0.6957	35510
2019	5.50	154.94	81.80	82.40	1.20	9.93	11455519	0.6602	36110
2020	5.80	147.10	76.60	78.60	0.40	13.00	11522440	0.6578	34060
2021	6.30	153.26	86.20	87.90	3.20	13.01	11554767	0.6275	36250
2022	5.60	138.52	97.40	95.70	10.30	13.76	11617623	0.6320	37040
2023	8.12	145.54	81.06	82.00	2.68	12.74	11598112	0.6507	36094
2024	7.90	161.61	80.47	81.65	1.59	14.17	11645711	0.6672	36591
2025	6.93	167.13	82.89	83.54	2.09	14.66	11651572	0.6322	35529
2026	6.50	158.48	82.00	82.90	3.79	14.73	11668273	0.6622	37011
2027	6.23	156.59	77.48	79.71	2.04	14.87	11669397	0.6556	35829
2028	5.26	148.73	83.27	84.31	2.05	14.66	11660271	0.6509	36829
2029	6.10	147.11	85.51	86.21	3.83	15.11	11665296	0.6570	36291
2030	6.62	138.28	85.94	86.31	3.07	14.87	11638511	0.6415	35990

Table 8: Input variable forecast summary, Belgium

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	13.90	438.49	65.10	64.60	0.40	18.90	7284552	0.3633	5390
2014	12.40	454.10	65.70	64.60	-1.60	18.05	7245677	0.3698	5470
2015	10.10	459.04	62.90	63.80	-1.10	18.26	7202198	0.3506	5700
2016	8.60	436.15	59.00	63.90	-1.30	18.76	7153784	0.3639	5910
2017	7.20	439.38	62.70	67.00	1.20	18.70	7101859	0.3710	6120
2018	6.20	426.23	63.20	65.70	2.60	20.58	7050034	0.3743	6330
2019	5.20	405.48	60.70	63.90	2.50	21.55	7000039	0.3718	6630
2020	6.10	400.82	54.20	56.10	1.20	23.32	6951482	0.3747	6400
2021	5.30	405.10	59.60	61.40	2.80	19.45	6916548	0.3778	6950
2022	4.30	394.95	69.00	69.20	13.00	19.09	6838937	0.3787	7680
2023	8.67	449.27	64.64	65.28	6.81	20.94	6999366	0.3648	7101
2024	8.98	442.58	61.50	63.12	3.73	20.81	6935911	0.3716	7440
2025	6.99	427.71	62.56	65.32	2.50	20.93	7023588	0.3764	7154
2026	7.14	420.02	60.21	61.63	2.91	19.88	6927437	0.3711	7603
2027	6.27	410.18	56.25	59.02	2.69	20.79	6981466	0.3691	7417
2028	4.68	394.54	58.10	60.30	2.40	19.61	6977379	0.3726	7433
2029	5.48	418.41	61.34	62.00	2.13	21.05	6994830	0.3684	7474
2030	6.26	421.41	64.14	63.60	2.89	20.50	7041261	0.3722	7069

Table 9: Input variable forecast summary, Bulgaria

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	7.00	272.62	70.40	76.10	1.40	13.93	10516125	0.4627	15160
2014	6.10	257.79	75.60	82.00	0.40	15.07	10512419	0.4758	15480
2015	5.10	244.84	74.60	80.60	0.30	15.07	10538275	0.4729	16290
2016	4.00	236.55	71.50	79.10	0.60	14.93	10553843	0.4762	16670
2017	2.90	234.66	71.50	79.00	2.40	14.80	10578820	0.4700	17490
2018	2.20	228.26	71.00	76.90	2.00	15.14	10610055	0.4704	17990
2019	2.00	217.98	67.90	73.90	2.60	16.24	10649800	0.4665	18460
2020	2.60	216.63	63.20	69.90	3.30	17.30	10693939	0.3260	17400
2021	2.80	221.78	69.80	72.70	3.30	17.67	10494836	0.3188	18020
2022	2.20	212.22	75.50	76.50	14.80	18.20	10516707	0.3169	18460
2023	4.75	242.64	73.93	79.93	8.30	17.32	10587396	0.4366	18723
2024	4.74	248.96	71.67	78.35	4.78	18.34	10589058	0.3759	18678
2025	3.15	235.36	71.32	77.46	2.57	18.21	10586229	0.3607	18453
2026	3.09	230.30	66.62	75.06	2.66	18.71	10516740	0.4156	18767
2027	2.73	223.85	65.53	74.40	3.50	18.59	10568002	0.4768	18525
2028	1.48	207.92	66.42	72.65	2.74	18.48	10528496	0.3893	18834
2029	2.16	220.04	69.49	75.33	2.57	18.77	10600530	0.4457	18675
2030	3.14	231.57	72.90	77.77	2.74	18.43	10546293	0.3979	18675

Table 10: Input variable forecast summary, Czechia

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	7.40	75.81	48.20	54.80	0.50	27.17	5602628	0.7173	44410
2014	6.90	71.37	47.70	54.60	0.40	29.31	5627235	0.7180	44890
2015	6.30	69.56	48.60	55.40	0.20	30.47	5659715	0.7015	45630
2016	6.00	68.81	46.70	53.40	0.00	31.71	5707251	0.7006	46720
2017	5.80	66.87	47.90	55.10	1.10	34.39	5748769	0.6679	47740
2018	5.10	65.90	50.40	56.60	0.70	35.16	5781190	0.6937	48450
2019	5.00	63.57	51.60	58.60	0.70	37.02	5806081	0.6737	48970
2020	5.60	59.65	48.60	55.10	0.30	31.68	5822763	0.6873	47680
2021	5.10	58.81	52.00	58.70	1.90	41.01	5840045	0.6775	50740
2022	4.50	56.38	58.90	70.00	8.50	41.60	5873420	0.6646	51660
2023	6.10	64.78	50.05	58.58	3.29	40.19	5873439	0.6900	50973
2024	6.37	64.81	48.49	55.20	3.23	40.77	5887895	0.6968	51197
2025	5.67	63.14	50.26	56.13	2.01	39.22	5888792	0.6635	50945
2026	5.70	63.33	49.73	57.38	2.84	42.95	5896573	0.6896	51995
2027	5.36	62.12	48.66	54.18	2.35	40.11	5898433	0.6829	51445
2028	4.83	58.15	51.23	56.73	2.05	42.62	5897432	0.6733	51942
2029	4.99	59.92	51.33	59.89	3.15	40.11	5899185	0.6911	51388
2030	5.33	60.07	52.10	60.40	3.45	40.31	5890192	0.6685	51100

Table 11: Input variable forecast summary, Denmark

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	5.00	123.91	39.70	45.40	1.60	13.76	80523746	0.7370	33330
2014	4.70	116.06	39.00	45.60	0.80	14.38	80767463	0.7166	33920
2015	4.40	114.95	39.30	46.90	0.70	14.90	81197537	0.7182	34130
2016	3.90	113.26	38.70	46.10	0.40	14.88	82175684	0.7437	34610
2017	3.60	110.79	40.10	47.20	1.70	15.47	82521653	0.6880	35410
2018	3.20	107.11	41.20	47.30	1.90	16.66	82792351	0.6809	35650
2019	3.00	103.61	41.20	47.10	1.40	17.27	83019213	0.6981	35950
2020	3.70	99.62	37.70	43.50	0.40	19.09	83166711	0.6698	34550
2021	3.70	100.46	41.90	47.30	3.20	19.39	83155031	0.7121	35630
2022	3.10	94.03	49.00	50.90	8.70	20.80	83237124	0.7021	36010
2023	4.05	112.49	41.27	47.33	5.19	19.48	83626401	0.6885	35931
2024	4.14	113.85	40.04	46.21	3.16	20.83	83532168	0.7174	36011
2025	3.44	109.23	40.90	47.07	3.74	20.84	83691644	0.6995	35579
2026	3.47	107.61	39.94	46.15	2.70	21.27	83642357	0.6812	36250
2027	3.55	103.81	38.39	45.57	2.68	21.35	83758051	0.7139	35618
2028	3.31	96.77	41.18	46.67	2.80	21.03	83775557	0.6902	36283
2029	3.41	103.34	41.78	47.59	2.60	21.44	83766067	0.6904	35918
2030	3.66	104.93	42.47	47.92	2.82	20.87	83842735	0.7145	35975

Table 12: Input variable forecast summary, Germany

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	8.60	380.10	81.90	84.60	3.20	25.36	1320174	0.3019	12540
2014	7.30	345.88	78.40	81.90	0.50	26.13	1315819	0.2934	12960
2015	6.40	295.58	73.50	77.40	0.10	28.99	1314870	0.2778	13230
2016	6.80	351.10	73.40	77.00	0.80	29.23	1315944	0.2873	13620
2017	5.80	328.79	71.80	75.80	3.70	29.54	1315635	0.2816	14410
2018	5.40	306.11	71.60	74.30	3.40	29.97	1319133	0.2722	14920
2019	4.50	249.12	69.30	73.40	2.30	31.73	1324820	0.2817	15450
2020	6.90	236.26	69.80	69.20	-0.60	30.07	1328976	0.2633	15260
2021	6.20	225.78	81.30	80.30	4.50	37.44	1330068	0.2795	16350
2022	5.60	238.55	86.30	85.80	19.40	38.47	1331796	0.2524	16250
2023	6.25	303.68	76.50	78.82	10.39	35.37	1329912	0.2650	16809
2024	7.24	359.20	76.13	77.79	7.86	36.55	1333709	0.2949	16678
2025	5.44	336.15	73.23	76.26	4.28	35.71	1333521	0.2635	16840
2026	5.73	300.14	69.80	72.51	4.25	39.08	1334164	0.2563	16984
2027	5.84	260.77	68.31	71.67	3.66	37.24	1333561	0.2873	16770
2028	6.97	240.25	74.35	76.06	2.70	38.10	1332974	0.2729	16996
2029	6.02	226.04	80.95	79.40	3.11	37.63	1333254	0.2792	16495
2030	6.34	254.89	83.54	81.08	2.90	37.17	1331499	0.2765	16629

Table 13: Input variable forecast summary, Estonia

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	13.80	78.49	85.30	104.10	0.50	7.52	4609779	0.6754	37080
2014	11.90	72.58	91.90	109.90	0.30	8.52	4637852	0.7107	40070
2015	9.90	61.70	93.10	121.90	0.00	9.08	4677627	0.6961	49420
2016	8.40	63.97	106.20	121.90	-0.20	9.19	4726286	0.6714	49730
2017	6.70	58.04	98.70	120.70	0.30	10.52	4784383	0.6740	53750
2018	5.80	53.82	94.10	122.50	0.70	10.94	4830392	0.6914	57610
2019	5.00	51.27	124.50	128.00	0.90	11.98	4904240	0.6695	59840
2020	5.90	44.29	114.10	132.90	-0.50	16.16	4964440	0.6601	63120
2021	6.20	39.94	93.70	133.70	2.40	12.38	5006324	0.6393	72110
2022	4.50	37.35	97.20	137.10	8.10	13.11	5060004	0.6245	77430
2023	9.02	57.78	93.80	123.04	4.06	12.95	5038782	0.6967	71266
2024	9.96	61.82	87.12	121.00	2.14	15.12	5088293	0.6529	76133
2025	7.05	57.83	103.85	123.29	2.73	14.68	5086539	0.6453	75687
2026	6.61	55.70	109.91	126.99	2.22	14.26	5103433	0.6819	79642
2027	6.44	50.05	107.39	128.66	1.49	15.29	5098343	0.6566	79275
2028	5.01	40.48	106.26	132.48	1.56	13.17	5090864	0.6623	79493
2029	5.40	40.06	97.65	129.86	2.39	15.41	5090940	0.6729	79943
2030	6.77	43.44	88.88	129.68	2.60	14.25	5063622	0.6552	79105

Table 14: Input variable forecast summary, Ireland

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	27.80	143.58	32.70	30.20	-0.90	15.33	11003615	0.5378	16630
2014	26.60	141.10	34.00	32.50	-1.40	15.68	10926807	0.5873	16830
2015	25.00	141.45	33.20	32.10	-1.10	15.69	10858018	0.6154	16900
2016	23.90	139.41	32.70	31.30	0.00	15.39	10783748	0.5492	16890
2017	21.80	144.18	36.50	35.00	1.10	17.30	10768193	0.5218	17110
2018	19.70	139.11	41.20	39.00	0.80	18.00	10741165	0.5267	17430
2019	17.90	136.80	41.80	40.10	0.50	19.63	10724599	0.4915	17780
2020	17.60	127.73	39.80	32.10	-1.30	21.75	10718565	0.4967	16150
2021	14.70	124.50	48.70	40.90	0.60	22.02	10678632	0.4928	17600
2022	12.50	120.18	58.90	49.10	9.30	22.68	10459782	0.4735	18710
2023	22.68	137.88	37.78	35.54	3.51	22.05	10732462	0.5507	17441
2024	22.79	143.42	36.65	34.35	2.02	23.40	10589538	0.5101	18041
2025	20.62	148.08	40.15	38.34	2.70	23.35	10771775	0.4722	17148
2026	20.58	139.65	40.13	35.35	3.77	23.48	10597745	0.5376	18470
2027	18.17	133.19	37.09	35.40	3.34	23.38	10691968	0.5116	17490
2028	14.48	120.34	44.50	38.95	2.92	22.99	10666715	0.4822	18551
2029	15.77	124.90	42.74	38.09	2.47	23.12	10691121	0.5287	18007
2030	16.35	120.79	44.89	39.62	2.99	22.46	10815902	0.4982	17562

Table 15: Input variable forecast summary, Greece

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	26.10	125.70	29.00	33.00	1.50	15.08	46727890	0.8262	21850
2014	24.50	122.15	30.40	33.50	-0.20	15.88	46512199	0.8441	22220
2015	22.10	121.66	30.60	33.60	-0.60	16.22	46449565	0.8781	23090
2016	19.60	119.01	29.90	33.90	-0.30	17.02	46440099	0.8775	23780
2017	17.20	120.59	31.50	35.10	2.00	17.12	46528024	0.8704	24440
2018	15.30	118.00	32.40	35.10	1.70	17.02	46658447	0.9015	24890
2019	14.10	112.97	32.00	34.90	0.80	17.85	46937060	0.8474	25180
2020	15.50	112.13	29.30	30.80	-0.30	21.22	47332614	0.8133	22250
2021	14.80	111.70	33.20	34.20	3.00	20.74	47398695	0.8266	23690
2022	12.90	108.02	39.70	40.90	8.30	22.12	47432893	0.8035	24910
2023	19.92	120.60	32.06	35.32	3.24	20.04	47304823	0.8753	24283
2024	20.32	122.42	31.04	33.91	2.88	22.58	47568662	0.8555	23925
2025	17.11	119.76	32.06	34.74	2.81	22.53	47605121	0.8141	23397
2026	17.11	117.06	31.87	34.29	3.50	23.01	47642756	0.8672	24238
2027	16.25	113.99	29.98	32.39	2.74	23.08	47614730	0.8737	23655
2028	13.70	110.65	32.41	34.13	2.32	22.78	47575396	0.8135	24897
2029	14.73	113.33	33.60	35.32	3.13	23.36	47632042	0.8527	23731
2030	16.12	114.23	33.88	36.06	3.41	22.95	47546658	0.8329	23866

Table 16: Input variable forecast summary, Spain

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	10.30	130.49	30.40	29.40	1.00	13.88	65600350	0.7691	31170
2014	10.30	124.19	30.80	29.70	0.60	14.36	66165980	0.7546	31320
2015	10.30	124.81	31.20	30.60	0.10	14.80	66458153	0.7664	31540
2016	10.10	121.30	30.90	30.20	0.30	15.45	66638391	0.8000	31770
2017	9.40	118.65	32.00	30.90	1.20	15.85	66809816	0.8009	32360
2018	9.00	116.04	32.70	31.70	2.10	16.38	67026224	0.8284	32800
2019	8.40	112.55	32.50	31.60	1.30	17.17	67290471	0.8155	33250
2020	8.00	107.84	29.50	27.30	0.50	19.11	67485531	0.8149	30630
2021	7.90	109.63	31.90	30.00	2.10	19.20	67656682	0.8102	32490
2022	7.30	97.16	38.60	34.70	5.90	20.26	67871925	0.8149	33180
2023	9.43	119.71	32.58	31.03	4.19	19.25	67859950	0.8016	32695
2024	9.64	125.79	31.34	30.02	2.90	20.48	68051369	0.8098	32658
2025	9.19	120.20	32.43	31.24	2.45	20.59	68084314	0.8035	31879
2026	9.00	116.04	31.39	29.76	3.28	20.86	68170355	0.8149	33119
2027	8.62	112.75	29.78	29.09	3.04	20.94	68174390	0.8141	31972
2028	7.79	106.33	32.28	30.65	2.10	20.61	68182206	0.8016	33486
2029	7.96	110.33	32.64	30.75	2.02	20.99	68196154	0.8086	32102
2030	8.06	110.37	33.42	31.36	2.62	20.49	68144570	0.8194	32538

Table 17: Input variable forecast summary, France

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	17.30	192.03	41.70	39.70	2.30	28.04	4262140	0.4956	10480
2014	17.30	183.76	43.00	42.60	0.20	27.82	4246809	0.4902	10480
2015	16.20	186.98	45.30	45.60	-0.30	28.97	4225316	0.4905	10810
2016	13.10	182.13	45.60	46.70	-0.60	28.27	4190669	0.4827	11290
2017	11.20	182.41	48.40	49.00	1.30	27.28	4154213	0.4970	11800
2018	8.50	173.58	50.10	49.30	1.60	28.05	4105493	0.4969	12250
2019	6.60	170.14	50.90	50.50	0.80	28.47	4076246	0.4845	12740
2020	7.50	175.77	48.40	41.40	0.00	31.02	4058165	0.4871	11700
2021	7.60	161.80	52.50	49.70	2.70	31.29	4036355	0.4856	13610
2022	7.00	148.64	65.40	59.20	10.70	29.35	3862305	0.4682	14660
2023	13.34	181.72	49.72	48.50	7.01	30.53	4078640	0.4917	13619
2024	12.40	181.45	47.22	46.83	3.85	29.98	3975040	0.4843	14107
2025	10.04	176.15	48.83	49.37	3.14	32.00	4119997	0.4777	13555
2026	10.00	177.32	50.14	47.64	2.48	30.96	4001916	0.4906	14628
2027	8.67	170.21	45.79	47.32	1.51	31.46	4067238	0.4811	14122
2028	6.04	158.84	49.57	48.54	2.28	31.13	4057518	0.4805	14472
2029	8.59	163.18	52.35	49.73	3.39	31.01	4069439	0.4895	14234
2030	9.43	162.23	53.50	50.49	2.55	31.81	4169204	0.4804	13777

Table 18: Input variable forecast summary, Croatia

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	12.40	103.91	26.20	28.60	1.20	16.74	59685227	0.7587	25620
2014	12.90	98.21	26.20	29.10	0.20	17.08	60782668	0.7403	25620
2015	12.00	101.22	26.70	29.70	0.10	17.52	60795612	0.7647	25860
2016	11.70	99.21	26.00	29.30	-0.10	17.41	60665551	0.7769	26240
2017	11.30	100.90	27.90	30.70	1.30	18.27	60589445	0.7569	26730
2018	10.60	98.67	28.90	31.40	1.20	17.80	60483973	0.7946	27030
2019	9.90	97.20	28.30	31.60	0.60	18.18	59816673	0.7704	27230
2020	9.30	97.29	25.80	29.40	-0.10	20.36	59641488	0.7697	24910
2021	9.50	97.58	29.80	32.10	1.90	19.16	59236213	0.7863	27120
2022	8.10	90.21	38.10	36.60	8.70	19.01	59030133	0.7670	28180
2023	11.47	98.37	29.27	31.09	4.89	19.16	59773009	0.7652	27016
2024	11.69	101.94	27.65	30.57	3.56	19.85	59443664	0.7707	27419
2025	10.65	101.74	28.23	31.45	3.12	20.04	59881501	0.7592	26413
2026	10.45	98.36	27.99	30.50	3.18	20.05	59335453	0.7785	27977
2027	10.02	98.33	25.05	29.82	2.13	20.30	59753915	0.7721	26708
2028	8.87	94.82	27.95	31.60	3.23	20.06	59587158	0.7557	28181
2029	10.07	95.17	29.85	31.57	3.81	20.38	59859871	0.7748	27135
2030	10.27	93.51	30.45	32.10	4.26	20.34	59847468	0.7748	27047

Table 19: Input variable forecast summary, Italy

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	15.90	138.46	59.60	61.30	0.40	8.43	865878	0.5533	20450
2014	16.10	143.08	64.90	66.00	-0.30	9.14	858000	0.4931	20310
2015	15.00	141.97	67.30	70.00	-1.50	9.90	847008	0.4811	21120
2016	13.00	144.14	68.50	70.50	-1.20	9.83	848319	0.4688	22410
2017	11.10	140.11	74.20	73.80	0.70	10.48	854802	0.4684	23470
2018	8.40	136.17	73.60	75.00	0.80	13.87	864236	0.5483	24500
2019	7.10	129.07	75.50	76.50	0.50	13.78	875899	0.5365	25510
2020	7.60	117.73	82.00	80.70	-1.10	16.88	888005	0.5156	24360
2021	7.50	111.45	85.50	89.40	2.30	19.07	896007	0.4957	26530
2022	6.80	113.94	94.70	95.00	8.10	19.43	904705	0.5080	27490
2023	13.77	132.80	74.26	75.55	3.80	18.99	896845	0.5411	27363
2024	13.56	144.05	72.78	73.91	2.19	19.57	908033	0.5155	27482
2025	10.57	146.54	75.22	76.16	2.68	20.58	907136	0.4672	27218
2026	10.26	138.74	77.09	78.36	2.35	20.76	912420	0.5394	27879
2027	8.41	125.01	73.13	75.00	2.04	20.85	911009	0.5399	27404
2028	5.30	112.97	80.33	81.72	2.46	20.83	909833	0.4893	27710
2029	7.51	102.66	81.48	82.64	3.11	20.90	911446	0.5129	27340
2030	9.39	98.00	80.97	82.47	3.16	20.89	906550	0.5084	27006

Table 20: Input variable forecast summary, Cyprus

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	11.90	234.25	64.80	60.40	0.00	37.04	2023825	0.2773	9980
2014	10.90	228.80	64.10	61.20	0.70	38.63	2001468	0.2650	10270
2015	9.90	217.90	62.00	60.30	0.20	37.54	1986096	0.2460	10760
2016	9.70	216.18	59.30	59.60	0.10	37.14	1968957	0.2428	11110
2017	8.70	213.90	62.30	61.60	2.90	39.01	1950116	0.2482	11590
2018	7.40	206.56	62.20	61.50	2.60	40.02	1934379	0.2527	12140
2019	6.30	209.98	60.70	60.00	2.70	40.93	1919968	0.2483	12300
2020	8.10	201.24	59.40	60.80	0.10	42.13	1907675	0.2177	11940
2021	7.60	197.60	67.70	64.60	3.20	42.10	1893223	0.2103	12870
2022	6.90	180.21	76.50	72.00	17.20	43.32	1875757	0.2121	13280
2023	9.67	208.60	63.50	61.81	8.60	42.66	1916586	0.2547	13130
2024	10.68	205.39	62.50	61.08	4.52	43.88	1897481	0.2238	13159
2025	8.63	204.98	62.44	61.97	2.49	43.61	1921869	0.2237	13070
2026	8.25	208.54	61.97	63.95	3.58	43.79	1889205	0.2513	13435
2027	7.82	202.12	59.29	58.17	2.58	43.80	1910009	0.2492	13267
2028	7.22	189.55	64.90	61.62	2.15	43.48	1900771	0.2348	13396
2029	6.90	203.20	66.70	64.90	4.76	43.71	1911180	0.2549	13318
2030	8.11	197.59	67.00	64.95	3.62	42.91	1915189	0.2365	13251

Table 21: Input variable forecast summary, Latvia

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	11.80	222.21	77.20	78.70	1.20	22.69	2971905	0.2257	10810
2014	10.70	213.65	70.50	72.30	0.20	23.59	2943472	0.2195	11290
2015	9.10	215.01	69.80	68.80	-0.70	25.75	2921262	0.2147	11620
2016	7.90	217.19	66.90	67.60	0.70	25.61	2888558	0.2133	12070
2017	7.10	217.97	71.30	73.60	3.70	26.04	2847904	0.2122	12760
2018	6.20	214.01	73.40	75.20	2.50	24.70	2808901	0.2187	13400
2019	6.30	203.52	71.90	77.20	2.20	25.47	2794184	0.2118	14060
2020	8.50	198.93	63.80	73.10	1.10	26.77	2794090	0.2002	14060
2021	7.10	194.88	75.60	80.10	4.60	28.17	2795680	0.2070	14870
2022	6.00	170.37	88.90	86.80	18.90	29.60	2805998	0.1965	15100
2023	8.10	193.28	73.08	74.29	8.77	26.79	2797092	0.2119	15038
2024	7.82	213.20	71.26	72.98	4.59	28.93	2800074	0.2118	15162
2025	6.15	217.64	72.99	75.62	2.83	28.08	2792951	0.2057	15139
2026	7.32	215.98	69.52	75.04	3.16	29.98	2799801	0.2106	15343
2027	7.13	212.55	66.79	74.04	2.16	29.53	2798755	0.2185	15175
2028	7.00	193.14	73.50	76.72	2.60	29.43	2798980	0.2081	15256
2029	7.28	191.90	74.58	77.11	2.19	29.81	2799635	0.2179	15108
2030	7.48	178.61	76.34	78.11	2.03	29.11	2795237	0.2083	15019

Table 22: Input variable forecast summary, Lithuania

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	5.90	96.59	144.20	176.40	1.70	3.49	537039	0.7232	82700
2014	5.90	91.56	150.60	182.80	0.70	4.47	549680	0.7202	82880
2015	6.70	88.60	159.30	191.80	0.10	4.99	562958	0.7307	82810
2016	6.30	84.65	157.30	191.10	0.00	5.36	576249	0.7176	84840
2017	5.50	86.33	161.00	192.70	2.10	6.19	590667	0.7368	84090
2018	5.60	88.73	164.90	197.50	2.00	8.94	602005	0.7330	83510
2019	5.60	87.00	175.90	206.40	1.60	7.05	613894	0.7327	84280
2020	6.80	76.65	169.20	203.10	0.00	11.70	626108	0.7330	82130
2021	5.30	76.10	179.90	213.20	3.50	11.73	634730	0.7173	86690
2022	4.60	68.04	177.20	211.30	8.20	14.36	645397	0.7076	86130
2023	6.03	80.08	163.21	195.88	2.67	12.09	648456	0.7346	85493
2024	6.18	89.29	160.05	193.15	1.18	12.97	654446	0.7215	85150
2025	5.14	95.67	164.08	195.82	2.33	13.87	655939	0.7158	84754
2026	5.63	90.08	167.68	199.52	2.42	13.38	658459	0.7281	86602
2027	5.91	86.30	174.63	205.05	1.11	14.06	659313	0.7212	84852
2028	6.23	73.40	173.44	205.64	2.58	12.87	658579	0.7273	86208
2029	5.41	74.48	174.93	205.99	2.25	13.83	658794	0.7265	84671
2030	5.69	69.05	174.30	205.82	2.49	12.42	656398	0.7158	85388

Table 23: Input variable forecast summary, Luxembourg

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	9.80	234.11	78.90	85.40	1.70	16.20	9908798	0.4672	10330
2014	7.50	223.70	81.30	87.10	0.00	14.62	9877365	0.4722	10790
2015	6.60	228.20	79.80	87.50	0.10	14.49	9855571	0.4313	11220
2016	5.00	226.09	78.00	86.40	0.40	14.38	9830485	0.4268	11500
2017	4.00	226.48	79.30	85.90	2.40	13.56	9797561	0.4349	12020
2018	3.60	215.34	79.50	83.80	2.90	12.55	9778371	0.4343	12690
2019	3.30	205.36	79.20	81.50	3.40	12.63	9772756	0.4292	13310
2020	4.10	210.56	76.80	78.70	3.40	13.85	9769526	0.4426	12730
2021	4.10	205.92	79.80	79.90	5.20	14.13	9730772	0.4654	13690
2022	3.60	185.54	95.50	91.20	15.30	15.19	9689010	0.4644	14350
2023	6.47	221.70	82.74	86.81	12.54	13.07	9759496	0.4332	13986
2024	6.12	225.44	79.15	84.67	10.86	14.39	9734188	0.4488	14273
2025	4.50	218.62	79.57	84.65	4.43	13.47	9782622	0.4611	14016
2026	4.48	215.38	81.48	82.17	5.40	15.09	9723711	0.4513	14437
2027	4.03	210.92	75.26	78.42	3.52	14.35	9754961	0.4461	14186
2028	2.82	204.59	79.18	82.73	2.44	14.25	9735633	0.4435	14347
2029	3.42	209.28	83.33	83.08	2.89	14.68	9765318	0.4519	14260
2030	4.41	205.40	84.40	85.84	2.25	13.53	9769067	0.4640	13994

Table 24: Input variable forecast summary, Hungary

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	6.10	275.11	148.40	156.00	1.00	3.76	422509	0.5341	17650
2014	5.70	261.39	137.80	149.80	0.80	4.74	429424	0.5409	18610
2015	5.40	258.64	144.90	154.60	1.20	5.12	439691	0.5303	19920
2016	4.70	269.36	145.20	157.80	0.90	6.21	450415	0.5412	20130
2017	4.00	291.03	138.80	158.10	1.30	7.22	460297	0.5152	21700
2018	3.70	279.59	142.00	160.70	1.70	7.91	475701	0.5571	22510
2019	3.60	270.38	145.60	163.80	1.50	8.23	493559	0.5297	23180
2020	4.40	274.19	159.40	173.80	0.80	10.71	514564	0.5227	20830
2021	3.40	226.30	148.50	166.30	0.70	12.67	516100	0.5341	23320
2022	2.90	232.44	150.40	163.90	6.10	13.40	520971	0.5176	24650
2023	4.91	273.74	145.32	158.90	4.42	12.61	525044	0.5289	23687
2024	4.89	269.14	143.94	158.12	2.04	13.50	534224	0.5382	24413
2025	3.82	259.88	138.09	156.04	1.22	14.29	537248	0.5294	23322
2026	4.16	276.19	145.71	161.87	2.16	14.68	536609	0.5376	24786
2027	3.83	244.03	147.23	164.74	1.54	14.65	537083	0.5343	23841
2028	3.60	237.98	150.86	165.67	1.13	14.58	534317	0.5234	24631
2029	3.62	253.64	147.15	164.01	1.98	14.73	534758	0.5393	24365
2030	3.93	252.69	147.38	162.29	1.97	14.52	531749	0.5315	23888

Table 25: Input variable forecast summary, Malta

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	8.20	143.77	69.70	79.90	2.60	4.69	16779575	0.7498	38180
2014	8.40	135.13	69.50	80.60	0.30	5.42	16829289	0.7391	38580
2015	7.90	125.70	75.20	82.70	0.20	5.71	16900726	0.7296	39170
2016	7.00	129.37	69.30	79.50	0.10	5.85	16979120	0.7242	39810
2017	5.90	124.75	72.60	83.40	1.30	6.51	17081507	0.7268	40730
2018	4.90	116.02	74.10	84.70	1.60	7.39	17181084	0.7478	41450
2019	4.40	120.46	72.70	82.50	2.70	8.89	17282163	0.7365	41980
2020	4.90	119.86	68.20	78.30	1.10	14.00	17407585	0.7284	40130
2021	4.20	115.28	72.90	84.10	2.80	12.99	17475415	0.7162	42390
2022	3.50	101.52	83.00	93.80	11.60	14.97	17590672	0.7089	43800
2023	7.14	124.02	74.45	83.94	2.97	13.05	17525007	0.7461	42697
2024	7.17	127.88	71.91	82.26	1.19	16.49	17622203	0.7283	43165
2025	5.87	123.72	73.18	83.56	1.54	16.79	17620608	0.7161	42169
2026	5.76	121.07	71.31	81.45	2.91	16.99	17650506	0.7378	43571
2027	4.74	120.89	68.83	78.92	3.01	17.27	17647324	0.7292	42752
2028	3.45	114.00	72.81	83.40	2.02	16.72	17627998	0.7270	43294
2029	4.16	115.55	74.08	84.35	2.61	17.76	17635308	0.7334	43068
2030	4.84	114.52	74.82	85.31	.10	17.01	17578622	0.7230	42528

Table 26: Input variable forecast summary, The Netherlands

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	5.70	111.30	50.60	53.40	2.10	32.66	8451860	0.6232	36180
2014	6.00	106.69	50.10	53.40	1.50	33.55	8507786	0.6165	36130
2015	6.10	108.20	49.30	53.10	0.80	33.50	8584926	0.6046	36140
2016	6.50	107.56	48.60	52.40	1.00	33.37	8700471	0.6065	36390
2017	5.90	107.07	50.90	54.10	2.20	33.14	8772865	0.6203	36980
2018	5.20	102.15	52.50	55.50	2.10	33.78	8822267	0.6069	37690
2019	4.80	102.92	52.10	55.80	1.50	33.76	8858775	0.6292	38070
2020	6.00	102.53	48.10	51.60	1.40	36.55	8901064	0.6119	35390
2021	6.20	104.06	55.00	56.00	2.80	34.57	8932664	0.6170	36740
2022	4.80	94.07	61.60	62.10	8.60	33.76	8978929	0.6584	38080
2023	5.84	106.29	51.36	54.89	5.27	35.04	8993491	0.6051	37228
2024	5.92	106.79	50.54	53.98	2.69	34.83	9008545	0.5998	37427
2025	5.41	105.03	51.93	55.40	2.19	35.96	9018364	0.6335	36625
2026	5.17	102.71	51.57	53.56	3.68	35.10	9027053	0.6111	37727
2027	5.65	103.93	49.66	52.75	2.09	36.07	9034134	0.6220	36827
2028	5.59	99.63	52.93	55.48	2.06	35.08	9031151	0.6228	38222
2029	5.87	102.63	54.02	55.38	2.90	36.07	9032786	0.6119	37245
2030	5.56	100.37	54.39	56.09	2.23	36.12	9023836	0.6321	37285

Table 27: Input variable forecast summary, Austria

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	10.60	255.35	44.80	46.00	0.80	11.45	38062535	0.4574	10030
2014	9.20	236.77	46.10	46.50	0.10	11.61	38017856	0.4627	10420
2015	7.70	229.44	45.40	47.50	-0.70	11.88	38005614	0.4512	10890
2016	6.30	233.77	47.30	50.30	-0.20	11.40	37967209	0.4552	11220
2017	5.00	232.77	49.20	52.10	1.60	11.06	37972964	0.4528	11800
2018	3.90	229.61	50.70	52.70	1.20	14.94	37976687	0.4710	12500
2019	3.30	212.05	49.50	53.20	2.10	15.38	37972812	0.4434	13070
2020	3.20	210.14	47.30	53.00	3.70	16.10	37958138	0.4335	12810
2021	3.40	209.25	54.40	57.70	5.20	15.61	37840001	0.4538	13770
2022	2.90	189.71	61.20	62.70	13.20	16.87	37654247	0.4309	14620
2023	6.96	225.95	48.62	51.53	9.64	16.44	37949102	0.4441	14244
2024	7.01	243.60	48.37	51.05	4.34	17.16	37820512	0.4577	14609
2025	5.21	224.75	50.06	52.42	2.09	16.89	37961650	0.4440	14422
2026	4.83	223.71	48.66	53.26	3.02	16.93	37800410	0.4522	14973
2027	4.02	215.97	46.39	51.17	2.86	17.11	37897398	0.4516	14786
2028	2.04	194.74	51.23	54.12	1.54	16.83	37883228	0.4416	14873
2029	3.44	199.74	51.26	55.24	1.66	17.16	37908882	0.4531	14856
2030	4.67	218.82	52.47	55.87	1.05	16.76	38031927	0.4460	14558

Table 28: Input variable forecast summary, Poland

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	17.20	137.28	38.50	39.60	0.40	25.70	10487289	0.6457	16050
2014	14.60	137.86	40.10	40.20	-0.20	29.51	10427301	0.6836	16260
2015	13.00	140.71	39.90	40.60	0.50	30.51	10374822	0.7426	16620
2016	11.50	138.23	39.10	40.20	0.60	30.86	10341330	0.6915	17010
2017	9.20	139.80	41.70	42.70	1.60	30.61	10309573	0.7225	17650
2018	7.20	132.84	43.00	43.40	1.20	30.20	10291027	0.7057	18190
2019	6.70	129.45	43.10	43.50	0.30	30.62	10276617	0.6889	18670
2020	7.00	125.43	39.20	37.00	-0.10	33.98	10295909	0.6632	17100
2021	6.70	119.25	44.20	41.40	0.90	33.98	10298252	0.6526	18090
2022	6.20	117.08	52.00	49.60	8.10	34.68	10352042	0.6539	19310
2023	12.05	137.91	42.46	42.68	4.27	33.45	10288628	0.7149	18504
2024	12.16	138.86	41.70	40.88	3.73	35.38	10321749	0.6544	18955
2025	9.41	137.06	43.08	42.83	2.00	36.12	10279475	0.6656	18093
2026	9.19	133.42	41.01	40.84	1.40	36.62	10329206	0.7047	19154
2027	7.65	125.61	39.80	39.86	2.71	36.89	10308421	0.6684	18428
2028	5.36	117.88	43.26	42.21	1.92	36.63	10313935	0.6722	19005
2029	7.81	123.09	43.12	42.45	2.61	37.28	10315968	0.6859	18874
2030	9.30	122.77	44.08	43.48	3.19	37.19	10289969	0.6628	18431

Table 29: Input variable forecast summary, Portugal

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	9.00	232.88	41.20	40.20	3.20	23.89	20020074	0.2961	6860
2014	8.60	221.95	41.90	41.50	1.40	24.84	19947311	0.2982	7160
2015	8.40	216.86	42.20	41.30	-0.40	24.79	19870647	0.2639	7420
2016	7.20	210.24	43.50	42.40	-1.10	25.03	19760585	0.2869	7680
2017	6.10	204.91	44.80	42.30	1.10	24.45	19643949	0.2811	8360
2018	5.30	193.53	44.90	41.50	4.10	23.88	19533481	0.2830	8910
2019	4.90	184.30	44.30	40.20	3.90	24.29	19414458	0.2798	9300
2020	6.10	185.72	41.20	36.90	2.30	24.48	19328838	0.2631	9000
2021	5.60	186.92	46.30	40.60	4.10	23.87	19201662	0.2719	9600
2022	5.60	164.94	50.00	43.30	12.00	24.14	19042455	0.2753	10040
2023	8.02	209.45	44.24	41.41	8.73	23.76	19397715	0.2680	9981
2024	7.59	214.88	43.81	41.16	3.62	24.33	19262953	0.2774	10173
2025	6.11	203.80	44.76	41.20	2.57	23.97	19467512	0.2703	10047
2026	6.08	198.06	43.51	39.76	3.61	24.23	19225330	0.2680	10305
2027	5.78	190.96	41.62	39.17	2.39	23.94	19374544	0.2820	10163
2028	5.23	178.12	43.63	39.76	2.89	24.03	19326987	0.2656	10288
2029	5.76	188.71	45.10	40.74	2.77	24.16	19426886	0.2641	10199
2030	6.66	188.44	45.53	41.58	2.48	23.98	19474850	0.2833	10042

Table 30: Input variable forecast summary, Romania

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	10.10	193.65	69.50	74.20	1.90	23.16	2058821	0.4662	17160
2014	9.70	182.03	69.40	76.20	0.40	22.46	2061085	0.4389	17620
2015	9.00	176.80	69.10	77.10	-0.80	22.88	2062874	0.3864	17990
2016	8.00	178.35	69.10	77.60	-0.20	21.98	2064188	0.3623	18550
2017	6.60	175.74	74.10	83.10	1.60	21.66	2065895	0.3607	19440
2018	5.10	168.48	76.30	84.80	1.90	21.38	2066880	0.3590	20240
2019	4.40	159.26	75.00	83.60	1.70	21.97	2080908	0.3480	20780
2020	5.00	155.28	68.80	77.80	-0.30	25.00	2095861	0.3785	19770
2021	4.80	147.36	77.70	83.60	2.00	25.00	2108977	0.3387	21350
2022	4.00	138.14	91.90	94.10	9.30	22.94	2107180	0.3237	21860
2023	7.43	175.04	74.58	82.17	6.51	24.02	2105025	0.4067	21899
2024	7.22	171.59	73.65	80.82	2.79	23.54	2115373	0.3581	21920
2025	5.79	163.07	75.78	83.30	2.00	25.39	2120162	0.3180	21669
2026	6.14	166.67	72.18	82.39	1.80	24.62	2123524	0.3983	22201
2027	5.40	157.21	69.43	79.35	2.46	25.05	2120824	0.3608	21836
2028	3.98	146.57	76.13	82.20	2.60	24.41	2121824	0.3462	22152
2029	5.48	160.41	75.91	83.83	3.08	24.53	2122322	0.3940	21862
2030	5.78	159.04	77.83	85.10	3.72	25.33	2121044	0.3516	21773

Table 31: Input variable forecast summary, Slovenia

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	14.10	242.44	87.90	93.40	1.50	10.13	5410836	0.2751	13300
2014	13.10	218.20	86.60	91.40	-0.10	11.71	5415949	0.2887	13640
2015	11.50	216.73	88.60	91.60	-0.30	12.88	5421349	0.2871	14340
2016	9.60	214.54	90.60	93.50	-0.50	12.03	5426252	0.2895	14590
2017	8.10	219.19	93.00	95.10	1.40	11.46	5435343	0.2943	15000
2018	6.50	206.59	94.00	95.80	2.50	11.90	5443120	0.2923	15580
2019	5.70	195.60	91.60	91.90	2.80	16.89	5450421	0.2879	15960
2020	6.70	195.55	83.40	85.10	2.00	17.34	5457873	0.2872	15400
2021	6.80	201.89	92.10	92.10	2.80	17.42	5459781	0.2858	16200
2022	6.10	185.04	104.80	99.40	12.10	17.50	5434712	0.2804	16340
2023	10.97	216.43	92.04	92.97	9.27	16.17	5461145	0.2906	16519
2024	11.14	220.83	90.97	93.07	4.99	18.33	5447052	0.2848	16553
2025	8.28	214.93	92.78	94.05	2.70	17.19	5458549	0.2823	16572
2026	8.33	207.82	89.37	91.65	2.76	18.29	5451255	0.2898	16750
2027	7.30	201.27	87.09	88.73	2.38	17.37	5452029	0.2840	16611
2028	5.17	183.37	92.33	91.06	3.07	17.62	5456512	0.2825	16839
2029	6.49	195.87	92.83	92.33	3.07	17.86	5444088	0.2868	16675
2030	8.08	199.06	94.93	94.73	2.56	17.29	5462031	0.2818	16697

Table 32: Input variable forecast summary, Slovakia

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	8.30	179.03	39.10	38.00	2.20	36.63	5426674	0.6566	34660
2014	8.70	183.37	37.60	36.50	1.20	38.63	5451270	0.6655	34390
2015	9.40	174.52	36.00	35.40	-0.20	39.23	5471753	0.6435	34460
2016	8.90	175.88	36.10	34.80	0.40	38.94	5487308	0.6581	35330
2017	8.70	172.73	37.50	37.50	0.80	40.86	5503297	0.6471	36380
2018	7.50	173.88	39.70	38.50	1.20	41.19	5513130	0.6499	36740
2019	6.80	168.41	39.70	39.90	1.10	42.81	5517919	0.6277	37150
2020	7.70	161.92	35.70	35.80	0.40	43.94	5525292	0.6428	36220
2021	7.70	165.01	39.40	39.50	2.10	42.85	5533793	0.6492	37170
2022	6.80	156.83	47.70	45.30	7.20	47.89	5548241	0.6457	37670
2023	9.25	167.96	38.77	37.90	3.39	43.20	5549389	0.6328	37904
2024	8.88	179.50	37.87	36.40	2.03	47.09	5555269	0.6424	37816
2025	8.23	175.27	39.32	39.00	1.36	44.94	5555766	0.6477	37583
2026	7.81	170.57	37.72	37.43	1.33	47.10	5560463	0.6479	37959
2027	7.60	170.11	36.10	36.30	2.23	46.76	5562870	0.6299	37720
2028	7.00	161.46	39.70	39.14	2.24	45.71	5563189	0.6327	37960
2029	7.70	158.99	39.42	39.01	2.55	47.61	5564775	0.6575	37773
2030	7.80	164.47	40.52	39.34	2.99	44.23	5562486	0.6478	37755

Table 33: Input variable forecast summary, Finland

Year	Unemployment rate	Energy Intensity	Imports of G&S	Exports of G&S	Inflation rate	% of renewable energy sources	Population	Financial Dev. Index	Real GDP
2013	8.20	132.45	38.30	42.50	0.40	50.15	9555893	0.8050	40510
2014	8.10	127.87	39.70	43.30	0.20	51.15	9644864	0.8118	41180
2015	7.60	117.13	40.00	43.80	0.70	52.22	9747355	0.8062	42580
2016	7.10	120.02	39.60	42.70	1.10	52.60	9851017	0.8056	42920
2017	6.80	120.58	41.20	43.70	1.90	53.39	9995153	0.7904	43430
2018	6.50	118.73	43.40	45.70	2.00	53.92	10120242	0.7849	43760
2019	7.00	114.02	43.60	47.80	1.70	55.78	10230185	0.7840	44180
2020	8.50	106.54	39.40	43.80	0.70	60.12	10327589	0.7890	42910
2021	8.80	105.46	41.70	46.50	2.70	62.69	10379295	0.7800	45280
2022	7.50	98.77	49.90	53.00	8.10	66.00	10452326	0.7753	46280
2023	7.45	107.08	42.19	45.39	4.59	61.25	10477808	0.7915	44930
2024	7.14	116.62	40.91	43.94	2.29	65.24	10526688	0.7935	45705
2025	6.71	121.39	42.71	46.39	1.66	64.38	10537233	0.7779	44685
2026	6.87	118.35	41.53	44.93	2.67	67.01	10545082	0.7870	46326
2027	7.78	117.07	40.13	44.67	2.20	66.51	10542400	0.7877	45521
2028	7.99	111.27	42.59	46.86	2.46	66.12	10522563	0.7872	46199
2029	8.04	109.49	42.58	46.20	2.81	67.18	10510745	0.7917	45882
2030	7.53	104.90	43.67	46.96	1.96	66.06	10468309	0.7760	45571

Table 34: Input variable forecast summary, Sweden

Countries	2023	2024	2025	2026	2027	2028	2029	2030
Belgium	15.10	16.56	18.17	19.94	21.87	24.00	26.33	28.89
Bulgaria	19.46	19.84	20.22	20.61	21.00	21.40	21.82	22.24
Czechia	18.87	19.57	20.29	21.04	21.82	22.63	23.47	24.34
Denmark	42.62	43.66	44.72	45.81	46.93	48.07	49.24	50.45
Germany	22.03	23.35	24.74	26.21	27.77	29.42	31.18	33.03
Estonia	40.63	42.91	45.32	47.87	50.56	53.39	56.39	59.56
Ireland	13.15	13.18	13.22	13.26	13.30	13.34	13.38	13.42
Greece	23.73	24.82	25.97	27.17	28.42	29.74	31.11	32.55
Spain	23.57	25.13	26.78	28.55	30.43	32.44	34.58	36.86
France	21.33	22.45	23.64	24.88	26.20	27.58	29.04	30.57
Croatia	29.60	29.85	30.09	30.35	30.60	30.85	31.11	31.37
Italy	19.24	19.47	19.70	19.94	20.18	20.43	20.68	20.93
Cyprus	21.48	23.75	26.27	29.04	32.11	35.51	39.26	43.41
Latvia	44.12	44.94	45.78	46.63	47.50	48.39	49.29	50.21
Lithuania	31.04	32.56	34.15	35.81	37.56	39.39	41.32	43.33
Luxembourg	17.15	20.48	24.46	29.22	34.90	41.69	49.79	59.47
Hungary	16.09	17.04	18.05	19.11	20.25	21.44	22.71	24.05
Malta	14.92	16.62	18.50	20.60	22.94	25.54	28.44	31.66
Netherlands	16.75	18.74	20.97	23.46	26.25	29.37	32.86	36.77
Austria	34.35	34.94	35.55	36.17	36.80	37.44	38.09	38.75
Poland	17.37	17.88	18.41	18.95	19.51	20.08	20.68	21.28
Portugal	36.05	37.48	38.97	40.51	42.11	43.78	45.52	47.32
Romania	24.29	24.44	24.60	24.75	24.91	25.06	25.22	25.38
Slovenia	23.18	23.42	23.66	23.91	24.16	24.41	24.67	24.93
Slovakia	17.70	17.91	18.12	18.33	18.54	18.76	18.98	19.20
Finland	49.57	51.31	53.12	54.99	56.92	58.92	61.00	63.14
Sweden	68.16	70.38	72.68	75.05	77.50	80.03	82.65	85.35

Table 35: Forecast of the share of energy from renewable energy sources, in %

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Abstract :

Do we actually find ourselves in a climate urgency? Why is it that we hear about greenhouse gas (GHG) emissions anytime we put our ear to the ground? What are GHGs and why does CO2 seem to be the main focus of our century?

The central theme of this thesis revolves around forecasting CO2 emissions within the EU27 until the year 2030, using macroeconomic data. By making use of a comprehensive forecasting method and macroeconomic indicators, this quantitative research seeks to provide insights into the potential trajectories of CO2 emissions in the European Union.

In addition, this thesis aims to assess the impact of an increased share of energy from renewable sources on CO2 emissions using scenario analysis.

We are asking ourselves: how likely is the EU27 to meet its 2030 CO2 emission target, and are increased shares of renewable energy sources sufficient to achieve this goal during this period?

Under the first scenario, known as the "business as usual" (BAU) scenario, only a few countries reach their 2030 CO2 emissions reduction target, namely Greece, Lithuania, Hungary, Romania, and Slovakia. Under the second scenario, which builds on the BAU scenario but incorporates an increased share of renewable energies in the energy mix of EU27 countries, no additional country achieves its 2030 target. In fact, some countries are emitting even more CO2 emissions: Denmark, Greece, Italy, Cyprus, Luxembourg and Finland under this scenario.

Considering these findings, European countries can't rely solely on the increasing share of renewable energies to hope achieving their goal. More research needs to be made about renewable energies and their effect on net GHG emissions in European countries.

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