Modelling the European Power Market through 2050: Quantifying Trends in Electricity Demand

Master's Thesis of

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I declare that I have developed and written the enclosed thesis completely by myself, and have not used sources or means without declaration in the text.

Leonberg, 14 July 2020

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Abstract

Forecasting electricity demand is essential to build long-term power market models. Current long-term forecasts are mainly politically driven analysis, excluding the underlying fundamental dynamics. Focusing on the Base Metals, Chemicals, Pulp & Paper and Non-metallic Minerals industries in Germany, France, Belgium, the Netherlands and Austria, the present thesis proposes the application of a three-factor Cobb-Douglas production function to model the output elasticities of the use of electricity consumption to capital, labour and raw materials. Different model setups are discussed and for each country and sector, one model is implemented, reflecting the most important inputs among the three factors. Applying the elasticities from the individual models and making assumptions on the development of the input variables, five scenarios for industrial electricity consumption are designed. The modelling results suggest that the Cobb-Douglas function is well suited to estimate industrial electricity consumption. Further, the analysis allows for a fundamental understanding of the most significant drivers of industrial electricity demand, and it reveals the relation between the use of the production factors and electricity consumption. Using the scenarios, strengths and weaknesses of the present approach are discussed, and perspectives for future research identified.

Keywords: Industry, Electricity Demand, Forecasting, Cobb-Douglas, Scenarios

Zusammenfassung

Die Vorhersage der Stromnachfrage ist für den Aufbau langfristiger Strommarktmodelle unerlässlich. Aktuelle langfristige Prognosen sind hauptsächlich auf politischen Maßnahmen basierte Analysen, die die zugrunde liegende fundamentale Dynamik vernachlässigen. Die vorliegende Arbeit konzentriert sich auf die Industriezweige Basismetalle, Chemikalien, Zellstoff & Papier sowie Nichtmetallische Mineralien in Deutschland, Frankreich, Belgien, den Niederlanden und Österreich, und schlägt die Anwendung einer Drei-Faktor-Cobb-Douglas-Produktionsfunktion vor, um die Elastizitäten des Stromverbrauchs bezüglich Kapital, Arbeit und Rohstoffe zu modellieren. Es werden verschiedene Modelle diskutiert, und für jedes Land und jeden Sektor wird ein Modell implementiert, das die wichtigsten Inputs unter den drei Faktoren widerspiegelt. Unter Anwendung der Elastizitäten aus den einzelnen Modellen und unter Zugrundelegung von Annahmen über die Entwicklung der Inputvariablen werden fünf Szenarien für den industriellen Stromverbrauch entworfen. Die Modellierungsergebnisse legen nahe, dass die Cobb-Douglas-Funktion gut geeignet ist, den industriellen Stromverbrauch zu schätzen. Darüber hinaus ermöglicht die Analyse ein grundlegendes Verständnis der wichtigsten Treiber der industriellen Stromnachfrage und zeigt die Beziehung zwischen dem Einsatz der Produktionsfaktoren und dem Stromverbrauch auf. Anhand der Szenarien werden die Stärken und Schwächen des gegenwärtigen Ansatzes diskutiert und Perspektiven für zukünftige Forschung aufgezeigt.

Stichworte: Industrie, Stromnachfrage, Prognosen, Cobb-Douglas, Szenarien

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Acronyms

BAU Business As Usual.

CAGR Compund Annual Growth Rate.

CEFIC European Chemical Industry Council.

EAF Electric Arc Furnaces.

EC European Commission.

ECU Electro-Chemical Unit.

EU European Union.

Eurostat European Statistical Office.

GCCA Global Cement and Concrete Association.

GDP Gross Domestic Product.

IEA International Energy Agency.

LLV Log-Likelihood Value.

Mtoe Million tonnes of oil equivalent.

NACE Statistical Classification of Economic Activities in the European Community.

OBF Oxygen Blast Furnaces.

OECD Organisation for Economic Cooperation and Development.

OLS Ordinary Least Squares.

VCI Verband der Chemischen Industrie.

1. Introduction

1.1. Motivation

In energy economics, long-term forecasts play an important role for utilities planning ahead. Given average lifetimes of 46 years for coal power plants (Cui et al. 2019) and 40 years for nuclear power plants (Cattant, Crusset, and Féron 2008), plant operators have a need for information about future electricity demand.

Further, the European Union (EU) is currently discussing the *Green Deal* proposed by the European Commission (EC), aiming for climate neutrality by 2050 (EC 2019). In order to assess the implications of its political measures, and the need to implement further policies, quantification of future energy and electricity demand is crucial.

In 2017, the industrial sector in the EU-28 countries consumed a total of 89.5 Million tonnes of oil equivalent (Mtoe) of electricity, or 37.7% of total electricity consumption. As displayed in figure 1.1.1, the share of industry in final electricity consumption has decreased since 1991; however, absolute electricity consumption is increasing. This shows very clearly the need to establish a reliable industrial electricity demand forecast on the long-term: For energy utilities to plan their power plant fleet of the future, and for politics to establish suitable policies ensuring that long-term climate goals are met.

1.2. Objectives

The present work aims to establish an industrial electricity demand forecast through 2050. To do so, historical trends will be analysed using a Cobb-Douglas production function, including data for use of capital, labour, and materials. Based on this analysis, sensitivities of electricity consumption to changes in the input variables are calculated. Applying these coefficients and making assumptions on the future development of these inputs, a forecast for future electricity demand is established. This demand forecast is then challenged by different scenarios, which are based on potential development paths towards EU climate goals.

In the following chapter 2, the geographical, industrial and timely scope and limits of the work are introduced. Chapter 3 will give an overview of scientific and other works aiming to perform demand forecasts, or implementing Cobb-Douglas production functions. Chapter

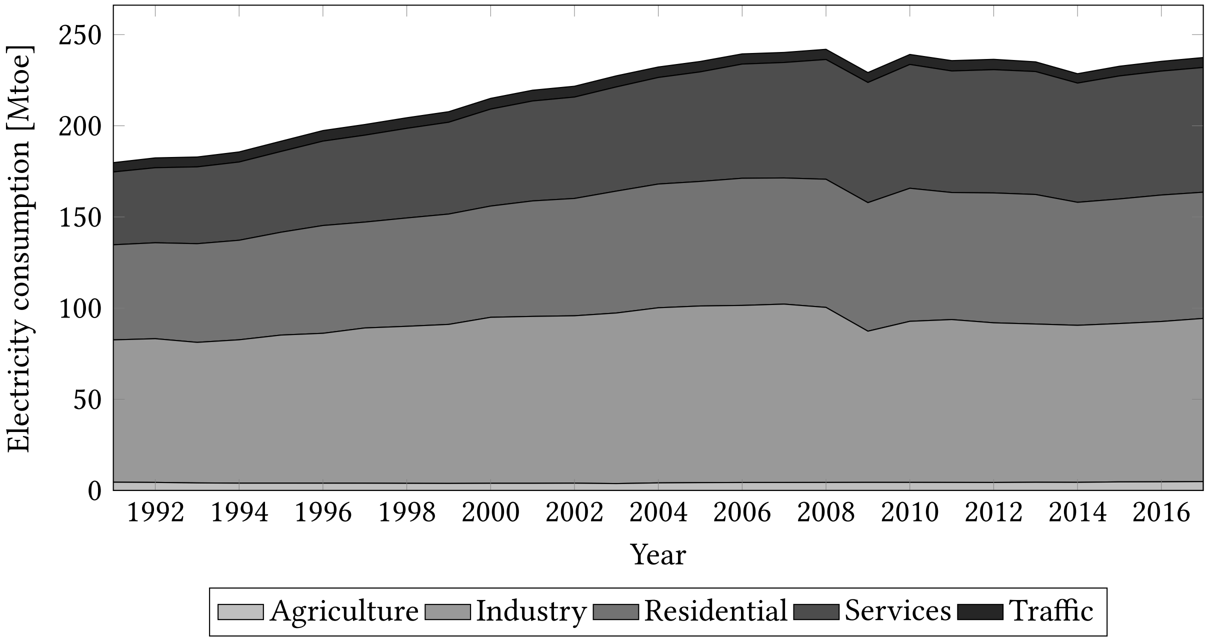

Figure 1.1.1.: Final electricity consumption by sector, EU-28 countries, based on Enerdata 2020

4 defines the theoretical model, and outlines the implementation of the model. In chapter 5, the individual models are set up by sector and country and results of the models discussed. Chapter 6 establishes the base forecasts. These base forecasts are challenged and diversified in four additional scenarios, as described in chapter 7. Finally, chapter 8 summarises the findings, discusses the limits of the work and gives an outlook on future research potential.

2. Scope of the work

The aim of this analysis is to forecast industrial electricity demand in the EU. However, given the time frame of the project, it was decided to limit the scope of the analysis to specific countries and the most important (i.e. electricity-intensive) industries.

Applying the method used in this analysis, the scope can be extended to include further countries, not only in Europe, but worldwide. However, model performance will depend on the availability of data and the structure of a given industry, which should be reflected in the model setup.

2.1. Countries

At the focus of this study are the five Western European countries Germany (DE), France (FR), Belgium (BE), Austria (AT) and the Netherlands (NL). These countries were chosen based on the assumption that the industrial sectors in these countries resembled one another more than if compared to e.g. Southern or Eastern European countries.

The analysis can be extended to more countries, applying the same methodology. However, availability of reliable historical data is an issue for many countries. Especially smaller countries tend to report with less detail. Further, European competition regulation sometimes prevents the publication of some data, especially by the European Statistical Office (Eurostat). This will have implications for the five countries in this work as well, as will be noted at a later point.

2.2. Industries

The selection of industries is designed to reflect the structure of the Odyssee Online Database[1]. The industries are classified according to their Statistical Classification of Economic Activities in the European Community (NACE) rev. 2 code (Eurostat 2008). Industries included in this

[1] The Odyssee Database is an online tool provided by the consulting firm Enerdata and co-funded by the Horizon 2020 programme of the EU. It gathers data from public sources, such as national institutions or the European Statistical Office Eurostat. The data is made available free of charge on the project website (`https://www.odyssee-mure.eu/`).

analysis are manufacturing industries (section C) from the NACE rev. 2 divisions 10-33. This includes the sectors as shown in table 2.2.1.

Industrial branch	**NACE rev. 2 division**	**Share of electricity consumption**
Food, beverage and tobacco	10-12	10.9%
Textiles, clothing, leather	13-15	2.1%
Wood, wood products	16	2.2%
Paper, pulp and printing products	17-18	10.0%
Chemicals	20-21	23.9%
Non-metallic minerals	23	6.4%
Base metals: Iron and steel, non-ferrous metals	24	19.2%
Machinery and metals products	25-28, 33	11.8%
Transport equipment	29-30	6.3%
Other manufacturing	22-23, 31-32	7.3%

Table 2.2.1.: Industrial activities according to NACE rev. 2 classification, and share of electricity consumption of the sectors analysed in this study, in DE, FR, BE, NL, AT, percentage of total from 1991-2017, according to data from Enerdata 2020

However, not all industries mentioned above are equally suitable for conduction of an analysis such as the one implemented in this work. Some sectors are very diverse (e.g. the Machinery and Metals Products sector: products range from metal tubes over computers and electrical equipment to industrial machines). Given that the electricity consumption for those sectors is reported as an aggregated figure, and not split by sub-sectors, implementation of a coherent model proved to exceed the limits of this work.

The scope was therefore reduced to the following industries: Chemicals, Base Metals, Pulp & Paper and Non-metallic Minerals, which all together account for more than 60% of historical electricity consumption in the whole industrial sector of the five countries.

3. Literature Review

Forecasting European energy demand in recent years was mostly the subject of political studies by the EU. In 2012, the EC published its Energy Roadmap 2050 (EC 2012). In seven scenarios, the Roadmap describes possible development paths of energy consumption in the EU until 2050. While the Roadmap provides a wide overview of potential scenarios, those are policy-driven, focus on decarbonisation policies without exploring the actual developments, and lack the influence of exogenous factors such as the development and implementation of new technologies. Further, the focus of the Roadmap was overall energy demand, without a specific analysis of the electricity demand.

More recently, the EC published its 2050 base case (EC 2016). The study provides a more detailed view on long-term final energy demand in different sectors of the EU economy. However, the study is again largely based on an impact assessment of individual energy policies.

While the International Energy Agency (IEA)'s World Energy Outlook 2018 (IEA 2018b) is only partly publicly accessible, the results published by the IEA suggest that the main driver of scenarios in the study remain international policies. On electricity demand in the EU, no results are available.

Scientific literature on the future of the European energy landscape so far seems to be scarce. Beneki and Silva 2013 choose a statistical time series modelling approach to estimate future energy demand in the EU countries. Their analysis however does not provide reasoning for the drivers of energy (and even less electricity) demand. Pilli-Sihvola et al. 2010 provide an analysis of the impact of increased temperatures on electricity consumption in five European countries. At the beginning of the century, Sun 2001 published a forecast of future European energy demand by 2010, using a decomposition approach.

For other geographical areas, there are examples for long-term projections of energy demand. Adams and Shachmurove 2008 in their paper modelled sensitivities of the Chinese energy balance to specific independent variables, such as Gross Domestic Product (GDP) growth, population and number of motor vehicles. Adeyemi and Hunt 2007 in their paper are closer to the geographical and sectoral scope of this work. They set up a model to forecast industrial energy demand (however not electricity demand) in the Organisation for Economic Cooperation and Development (OECD) countries, using non-linear least squares optimisation, to allow for a lagged price response. They further include data on income and a time dummy to reflect technical efficiency gains.

Other authors set up models using different modelling techniques, such as Genetic Algorithm Modelling (Ceylan and Ozturk 2004, Turkish energy demand). Notably, Chui et al. 2009 compare different modelling techniques (autoregressive, simple linear and multiple linear regression), among which multiple linear regression was found to deliver the best estimate. The input variables in their model were GDP, employment, number of dwellings, population, the year (thus a time-dummy equivalent), and Heating- and Cooling-Degree-Days.[1]

Multiple linear regression was therefore chosen to model electricity demand in the present work. The choice of input parameters, however, had to be adapted to the industrial sectors. A very wide-spread tool in economics is the use of a Cobb-Douglas production function, established in Cobb and Douglas 1928, estimating output based on a set of input parameters, mostly labour and capital. In the context of energy economics, the Cobb-Douglas function, however, has not been tested extensively; Wei 2007, based on Saunders 2000, set up a production model incorporating energy, but as an input factor (in addition to labour and capital), rather than as an output. A similar approach was used in Yuan, Liu, and Wu 2009, estimating energy intensity, i.e. energy used per output unit, in the Chinese industrial sector. The approach used in the present work, on the other hand, is fundamentally different: Energy is not considered as an input into the Cobb-Douglas production function in order to estimate production levels, but as the output variable. Von Hirschhausen and Andres 2000 used a Cobb-Douglas function to predict Chinese electricity demand, thus a similar approach to the one proposed in this work. Their method was focused on macro-economic factors, such as GDP, electricity prices and historical electricity consumption.

[1] For further reading, Suganthi and Samuel 2012 present an overview of scientific energy demand forecasting models.

4. Methodology

The forecast, as explained before, is based on a detailed (qualitative) analysis of the production processes and dynamics in a sector. In a second step, the regression models for the specific sectors are set up, according to the model described in section 4.1. The electricity forecast by sector and country is based on the results of these models and assumptions on future development of the input factors, as described in section 4.2.

4.1. Basic Model Setup

The model is set up as a three factor Cobb-Douglas production function. This setup was used e.g. by Echevarria 1998 to estimate agricultural production, using as input factors – the so-called independent variables – Capital, Labour, and Land.

Setting up the model as a Cobb-Douglas production function provides several advantages which are described below. Nonetheless, it is important to note that this model was not designed to model electricity demand, but production output. Energy, and more specifically electricity, in the original model, would be an input rather than an output. But energy and raw materials, in most cases, are not substitutes for one another, but rather complements: The transformation of input into output in all industries is related to more or less energy-intensive processes, allowing for this transformation. And the use of electricity alone does not produce outputs. Further, it seems intuitive to assume that a profit-seeking industrial would not consume more raw materials than can be transformed into products using energy - or, more specifically, he does not produce (significant amounts of) waste. It therefore seems reasonable to assume that energy (here: electricity) consumption can be modelled using a Cobb-Douglas production function, while accounting for efficiency gains as explained below. In a different context, the adapted Cobb-Douglas model was used by Von Hirschhausen and Andres 2000 to model electricity demand.

The following sections describe model design, the reasoning for using the Cobb-Douglas function, and detail the use of specific parameters.

4.1.1. Cobb-Douglas production function

The setup used in this thesis takes into account Capital (K), Labour (L), and Raw Materials (M) used in the specific industry. The basic setup of the model is as follows:

$$Y = \beta * K^{\alpha_1} * L^{\alpha_2} * M^{\alpha_3} * t^{\alpha_4}, \tag{4.1}$$

where Y denotes output, or - in this case - final electricity consumption, β is the technology level, and α_i, $i \epsilon \{1, 2, 3\}$ denote output elasticities of the independent variables Capital, Labour, Raw Materials and the time dummy t. The time dummy is a variable increasing its value with every time step (i.e. year) and will be introduced in further detail below.

Modelling using a Cobb-Douglas production function provides several advantages:

Interpretability
It seems intuitive to assume that a company - or an industry - does not produce output or use energy, when neither capital, nor labour or raw materials are used.

Complementary input factors
It is assumed that only combining the three inputs a product is produced. This might not apply in the case of energy consumption; however, in this study, it is assumed that companies self-optimise to a certain degree, i.e. if they have production capacities and use labour, they also use raw materials and consequently use energy. This assumption seems valid especially in the case of an analysis of a whole industry is analysed, and not of specific companies, which is the case for this study.

Deduction of output elasticities
The Cobb-Douglas production function allows to draw direct conclusions on output elasticities, i.e. how output - or electricity consumption - depend on the use of input factors. For example, it seems intuitive to say that, if more raw materials are used, output should increase as well, suggesting an output elasticity of $\alpha > 0$.

Note that this relation is not always obvious in the case of an analysis of energy consumption, as section 5.4 will show.. It will therefore be crucial for this study to understand the dynamics in the production processes of the different industries, and the implications for energy and electricity demand, in order to ensure a correct interpretation of model results.

Further, it should be noted that the present model does not assume constant returns to scale ($\sum \alpha_i = 1$) or any other constraint with regards to the output elasticities. These restrictions were avoided as, a priori, no assessment on economies of scale could be made, particularly with regards to the different countries and industries analysed here. In general, the model allows for negative coefficients as well, as some input factors tend to decrease electricity consumption, as the country models will show.

Applying the natural logarithm to both sides of the equation yields the so-called trans-log model:

$$ln(Y) = c + \alpha_1 * ln(K) + \alpha_2 * ln(L) + \alpha_3 * ln(M) + \alpha_4 * ln(t), \tag{4.2}$$

where $c = ln(\beta)$ denotes the intercept, or technology level.

The model coefficients α can be calculated by applying Ordinary Least Squares (OLS) regression. In this case, the Statsmodel package for Python (Seabold and Perktold 2010) was used to fit the trans-log model. The Cobb-Douglas production function yields the significant advantage of providing direct conclusions on output elasticities from model coefficients. E.g., for a positive coefficient α for raw materials, output (i.e. electricity consumption) increases with increased raw material input. This allows for high interpretability when fitting the model. Another advantage of the trans-log model is the smoothing of spikes in the historical training data.

It should be noted that only those variables which were statistically significant (p-value ≤ 0.05) were considered in the model setup. If for a given country and industry, one of the independent variables was insignificant, it was excluded from the model (unless stated otherwise). For all models, interpretability had to be given for the model to be considered valid.[1]

4.1.2. Parameters

While the basic setup of the Cobb-Douglas model is arguably straight-forward, the use of some of the parameters is more controversial. This section describes the reasoning behind the use of different parameters of the model described above.

On the use of a time dummy

Very often, it is impossible to quantify certain aspects of reality in a model. Examples can be energy efficiency measures, general electrification trends or others. Sometimes, these effects can be assumed to develop linearly over time. This can be reflected by a time dummy; it is a variable which increases by one unit for every period of the analysis time frame. When multiplied with the same coefficient in every period, the effect of the variable in- or decreases steadily over time, depending on the sign of the coefficient.

Such time dummies are not uncommon in scientific literature when setting up regression models, especially in the energy field (most often representing difficult-to-quantify energy

[1] I.e. factors represented by the model with a specific factor for which there was no logical interpretation were excluded despite potentially being statistically significant. The basic model setup in section 5.1.2 will discuss different setups.

efficiency gains). Examples from the energy sector can be found, among others, in the papers by Griffin and Schulman 2005 and Adeyemi and Hunt 2007.

That said, the interpretability of the time dummy is not always obvious, neither is it consistent for different models. For some countries and industries, “negative” (electricity consumption decreasing) effects like efficiency gains may outweigh “positive” effects like general electrification measures; for others, it may be the other around; finally, both effects might offset. Therefore, the time dummy was included in those models for which it proved to be statistically significant, independent from the sign of its coefficient.

Finally, with regards to the Cobb-Douglas function, one final note appears important: The Cobb-Douglas production function considers output elasticities to be constant over time. This assumption is called constant technology. Over time, the sensitivity to changes in the inputs does not change. Assuming constant inputs, output will therefore not change over time. This assumption is somewhat relaxed by the introduction of the time dummy. While the output elasticities are still considered constant, the impact of the time dummy is such that, given a coefficient unequal to zero, and given a constant set of inputs, output does change over time, according to the sign (positive/negative) of the time dummy.

On the use of an intercept

When setting up linear regression models, constants are usually included to represent constant effects which are not otherwise represented in the model. In the context of industrial production, this might be baseload power consumption which is independent of assets, labour and the use of raw materials. Given the difficult interpretability of the constant, it was only included in those models where it significantly improved the model fit, while being statistically significant.

The use of a constant has one advantage in setting up regression models, which is the validity of the R^2 value. When the constant is excluded from the model, it is modelled as “regression through the origin” (when all independent variables are 0, and there is no constant going into the equation, the dependent variable will be 0 and therefore in the origin of a thought multi-dimensional coordinate system). This yields an “overfit” of the model, which leads to unrealistically high values for R^2 and adjusted R^2 (T. O. Kvalseth and T. Kvalseth 2018).

However, the R^2 value is only one possible way to measure the fit of a model (even though probably the most well-known). Others include the F-Statistic of a model and its Log Likelihood Function. In the basic setup of the model, the constant was therefore excluded in order to ensure interpretability of the models. Models were then compared using their Log-Likelihood Value (LLV) (note that different models cannot be compared using the LLV; however, the same model in different configurations can be compared by their LLV).

On the use of raw material inputs

Generally, it might seem more intuitive to use production output as an indicator for electricity consumption, rather than the input of raw materials. There are however two arguments in favour of using raw materials over production.

From a theoretical point of view, the Cobb-Douglas production function tries to estimate production output. Using products as an input would therefore turn the logic of production around. Further, the consumption of raw materials in many cases is equivalent to, or at least related to, production outputs and are therefore as good an indicator as products. One example is the production of chlorine, which will be explained in detail in the section on the Chemicals sector.

From the practical point of view, it is also important to note that, in many industries, there is a multitude of different products. On the other hand, there are very often only a few main input materials used in an industry, significantly reducing the effort of selecting the most important factors. Once again, a very illustrative example is the Chemicals sector, where, from ten main raw materials, thousands of different final products are manufactured.

4.2. Forecasting and Scenarios

The forecasts are based on the results found for the country- and sector-specific Cobb-Douglas models. As these results provide output elasticities to changes in the input parameters, future electricity demand can be forecast if valid assumptions on the future development of the independent variables are made.

Therefore, for each industrial sector, a specific section will discuss the assumptions made for future development of the input variables in detail. Whenever possible, this thesis will take external sources as a base for the calculation. For all sectors, investment forecasts from OE 2020 were used to estimate development of capital (assets). Further, Eurostat 2020 projections were used for population forecasts.

Developments displayed in the Forecasting chapter 6 represent the development based on historical trends and base case assumptions for external sources, and therefore could be called the "Business As Usual (BAU)" scenario. Chapter 7 presents alternative pathways for these developments, applying the same methodology. These scenarios are then used to evaluate the strenghts and weaknesses of the applied methodology, using examples from the sectors in this analysis.

The forecast will start in the year 2018 and calculate results for every year through 2050. Up to 2017, training data (i.e. historical electricity consumption data) was available for all countries. For some input variables, data for 2018 and 2019 was available. If that was the case, the assumptions were applied only after the last year for which data was available (ergo officially reported data was used for 2018 and 2019).

Note that the forecasting method used in this work cannot or only partly reflect trends or new technologies that were not observed in the past. The introduction of new, more or less electricity-intensive production technologies is therefore not part of the forecasts. For the specific sectors, structural changes and new technologies will therefore be mentioned in the sector-specific sections.

5. Models and results

This chapter introduces the specific model setups for all industrial sectors and countries specified in the scope of the study (see chapter 2). Section 5.5 provides cross-sectoral insights into the significance of the individual inputs, comparing the relative impact of independent variables on electricity consumption.

5.1. Base Metals

The basic model was set up using the German Base Metals sector as an example. This was done for two main reasons:

- **Power consumption**: The Base Metals sector is one of the most energy- and power-intensive sectors in the countries at the focus of this study. Between 1991 and 2017, the Base Metals sector in the six countries consumed a total of 192 Mtoe, excelled only by the chemicals sector (236 Mtoe, Enerdata 2020).
- **Database**: For the Base Metals sector, an extensive database is available from different sources. This includes, among others, data on financial assets, employment and working hours, raw material consumption and production output.

It should be noted that the Base Metals sector only includes the production of primary metals (e.g. iron, steel, aluminium). More specifically, it does not include further processing of metals to produce other goods, e.g. the automotive or machine building industries. For more detailed information on the classification of industries see chapter 2.

5.1.1. Sector introduction

The Base Metals sector can be subdivided into iron and steel production on the one hand, and non-ferrous metals (incl. e.g. aluminium and copper) production on the other. It should be noted that there is no data available on assets and hours worked that distinguishes by the kind of metal produced. Therefore, with the only variable differing between the two being raw materials, splitting the sector did not seem to yield meaningful results.

Table 5.1.1 shows the share of total electricity consumption of the two parts of the Base Metals sector in each country, summed up from 1991-2017. It becomes evident that the production of ferrous metals requires most of the electricity used in the sector, apart from the Netherlands (to be explained in the country-specific analysis).

Country	**Share of electricity consumption in Base Metals sector**	
	Iron & steel	Non-ferrous metals
Austria	74.5%	25.5%
Belgium	74.6%	25.4%
Germany	61.6%	38.4%
France	60.1%	39.9%
Netherlands	34.6%	65.4%

Table 5.1.1.: Split of electricity consumption between Iron & steel and Non-ferrous metals sectors by country Enerdata 2020

Therefore, where necessary, the analysis focuses in a first step on the iron and steel production, and only in a second step considers the production of non-ferrous metals.

The steel production process

There are three fundamental production processes in the iron and steel making industry – primary steel, secondary steel and direct reduction routes –, using two different technologies: Oxygen Blast Furnaces (OBF) and Electric Arc Furnaces (EAF) (Schumacher and Sands 2007).

As displayed in figure 5.1.1, electricity as a relevant input factor is used only in EAFs (s. secondary steel route), which are highly electricity-intensive. Main raw material inputs in the secondary steel route and the direct reduction route are scrap metals, in particular scrap steel, and iron ore.

Concluding, we have learned that most of the electricity used in the Base Metals sector in most countries is used in the production of iron and steel. Secondly, the main electricity consumers in the production of iron and steel are EAFs. Therefore, the use of EAFs and scrap metals will be at the core of the models for the Base Metals sector.

Note that there was no data available on the use of the different production routes, only on the use of EAFs versus OBFs (data from Worldsteel). It is therefore not possible to distinguish whether metal ores are mostly used in the primary steel route or in the direct reduction route. It is however assumed, that direct reduction only plays an inferior role; consequently, the models will focus on scrap steel wherever possible.

On a side note, the year 2009 was excluded from the analysis for all sectors. That year, the financial crisis led to a significant decrease in industrial activity (and power consumption) in all industrial sectors in all EU countries. Including this negative peak would lead to overfitting

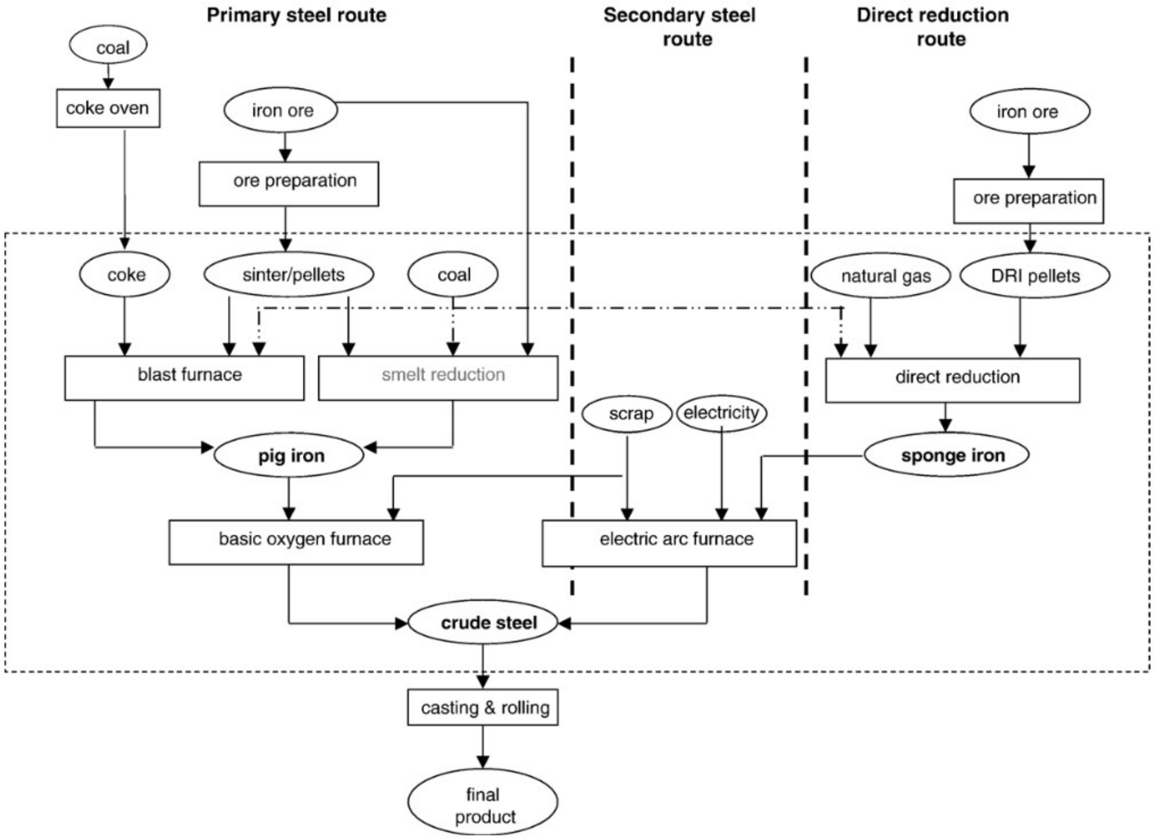

Figure 5.1.1.: Iron and steel production routes and technologies at the example of the German steel industry, taken from Schumacher and Sands 2007

of results, as the model would try and fit the input variables to the value with highest variance (i.e. this negative peak).

In the following sections, the model setup for the German Base Metals sector will be discussed, followed by the models for the other countries. It will be described which independent variables were used in the model, which of those were statistically significant and how the model was optimised to best reflect reality. Finally, an interpretation of the model coefficients will be given.

5.1.2. Basic model setup - Germany

The basic model was set up at the example of the German Base Metals sector. The statistical database for this sector is extensive and well fit to set up a basic model, allowing to identify the most important input variables and optimise the model. Note however that every model has to be adapted to the specific structure of the country and sector. The data tested to set up the basic model can be taken from table 5.1.2. Note that the data in this table exceeds the inputs into a Cobb-Douglas production function. In order to set up the basic model, these variables were tested nonetheless. It was found that the three inputs Labour, Capital and Raw Materials deliver the best results in terms of statistical significance, independence (from one another) and model performance.

Subject	**Factor**	**Source**
Energy	Energy consumption by fuel source	Enerdata 2020
Capital	Assets	Destatis 2020
	Invest	Destatis 2020
Material use	Scrap consumption	Worldsteel 2020
	Metal ores consumption	Destatis 2020, Eurostat 2020
	Coke and coked coal consumption	Kohlenstatistik 2019
Labour	Hours worked	Destatis 2020
	Employees	Destatis 2020
	Personnel costs	Eurostat 2020
Production	Steel production by technology	Worldsteel 2020
	Value added	OECD 2020
	Production index	Enerdata 2020
Foreign trade	Import values of scrap and metal ores	WTO 2020
Demand	Order index	Destatis 2020
Prices	Fuel prices (coal, gas, electricity)	OE 2020
	Carbon emission prices	ICIS
Other	Cold and hot degree days	Eurostat 2020

Table 5.1.2.: Sources of input parameters tested in the setup phase of the German Base Metals model, author’s own work

Approach

A regression model is designed to assess how one output variable (the dependent variable) can be determined by different input variables (or independent variables). Given the nature of the Cobb-Douglas function, using inputs into production (capital, labour and raw materials), it was decided not to use any “down-stream” data wherever possible[1]. More specifically, to quantify labour input, the number of hours worked were used, rather than employment. Capital input was measured using fixed capital, i.e. assets, instead of (short-term) investment. It was assumed that assets depend on discounted investment, which will be important in the forecasting part.

Starting from the analysis of the Base Metals sector as described in section 5.1.1, different setups using different raw materials were tested. Beginning with a set consisting of all potential raw materials, input variables were reduced step by step if they were either statistically insignificant, or the interpretation of their coefficient was not in line with expectation and could not be explained after a more in-depth analysis.

[1] i.e. energy consumption should not be a function of factors such as production or demand, but of real inputs

Model results

It was found that the model setup using scrap consumption as a raw material, assets for capital, and hours worked for labour provides highly significant results and a very good model fit, as figure 5.1.2 shows. Further, a time dummy was included, and the intercept excluded for statistical insignificance.

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                el_cons   R-squared (uncentered):                   1.000
Model:                            OLS   Adj. R-squared (uncentered):              1.000
Method:                 Least Squares   F-statistic:                          1.777e+04
Date:                Thu, 02 Apr 2020   Prob (F-statistic):                    2.99e-38
Time:                        15:57:49   Log-Likelihood:                          61.812
No. Observations:                  26   AIC:                                     -115.6
Df Residuals:                      22   BIC:                                     -110.6
Df Model:                           4
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
scrap_consumption     0.1037      0.049      2.110      0.046       0.002       0.206
hours_worked          0.6849      0.103      6.636      0.000       0.471       0.899
assets               -0.9392      0.100     -9.410      0.000      -1.146      -0.732
time                  0.0624      0.010      6.320      0.000       0.042       0.083
==============================================================================
Omnibus:                        4.640   Durbin-Watson:                   1.555
Prob(Omnibus):                  0.098   Jarque-Bera (JB):                2.989
Skew:                           0.786   Prob(JB):                        0.224
Kurtosis:                       3.539   Cond. No.                         294.
==============================================================================
```

Figure 5.1.2.: Modelling results for German Base Metals sector, author's own work

Note here that R^2 and adjusted R^2 are not representative when no intercept is included in the model. It should therefore be mentioned that including the constant yields an adjusted R^2 of 0.818, while the constant is statistically insignificant (p-value of 0.479).

These results are interesting for several reasons. First, the statistical assessment of the model (p-values, F-statistic, LLV) suggests that, to a very large extend, variance in the consumption of power can be explained by the variance in the independent variables used in the model. Or, in other words, the model performance is remarkable.

Second, as one would expect, working hours and the consumption of the electricity-consuming raw material scrap have a positive coefficient, meaning that an increase in the use of either one yields an increase in electricity consumption.

Third, the negative coefficient for assets suggests (maybe unexpectedly) a decrease of electricity consumption associated with an increase in the use of capital. However, scientific literature provides an explanation: Schumacher and Sands 2007 in their analysis on the German steel sector found that steel production in EAFs is about 70% less capital-intensive than conventional BOFs (US-$ 11.92 vs US-$ 38.75 per tonne of crude steel). Therefore, a ceteris paribus decrease in the use of capital (i.e. decreased assets) suggests a replacement of BOFs by EAFs. As EAFs are more electricity-intensive (+129% according to Schumacher and Sands 2007), this replacement yields increased electricity consumption, hence the negative coefficient for assets. We will see that this pattern is stable for countries with relatively high shares of EAF production. Germany has increased its share of EAF production in total crude steel production from 20.3% in 1991 to 30.0% in 2017 (Worldsteel 2018). At the same time, steel production increased slightly from 42.2 Mt to 43.3 Mt. It is therefore fair to say that Germany, independently from its total steel production, is shifting its production from carbon-intensive OBFs to electricity-intensive EAF production.

Fourth, there seems to be a significant underlying electrification pattern in the German metals industry, indicated by the positive coefficient of the time dummy. It suggests linearly increasing electricity demand over time that is not otherwise reflected in the model (e.g. not by the consumption of steel scrap).

Finally, we note that the Cobb-Douglas production function seems to provide a very good approach when modelling electricity consumption. In the following sections and chapters, it will be applied to further countries and sectors. However, future analysis might focus on using this modelling approach not only for electricity, but for other energy sources as well.

5.1.3. Other country models

In order to avoid repeated explanations, in the following the country models as well as forecasting results for the other four countries will be jointly presented and interpreted. The p-values of model coefficients for the Base Metals and other sectors are presented in section A.2 of the appendix.

France

France has historically been relying on the use of EAFs more than Germany did. According to figures from Worldsteel 2020, French steel production in EAFs was 28.4% of total French steel production, peaking during the 2000's in more than 40% of production and then slowly declining back to 31.2% in 2017.

However, French use of scrap steel is somewhat decoupled from steel production: The ratio of scrap consumption to total steel production between 1991 and 2017 has fluctuated between 0.46 in 2017 and 0.7 in 2009. To put this into context, in the same period the ratio in Germany remained in the range of 0.44 to 0.5.

This is reflected in the statistical parameters of the model: While there are model setups that assign statistical significance to scrap consumption (e.g. combining with assets and no constant and time dummy), best model performance (as measured by the LLV) is reached when, instead of steel scrap, iron ore consumption is included in the model. An overview of model results and parameters can be taken from table 5.1.3.

Independent variable	**Germany**	**France**	**Belgium**	**Netherlands**	**Austria**
Assets	-0.94	-0.56	-0.32	0.89	-
Hours worked	0.69	0.35	-	-	-0.74
Scrap	0.10	-	0.31	-	-
Iron ore	-	0.22	-	-	-
Non-ferrous ores	-	-	-	0.60	-
Bauxite	-	0.26	-	-	0.16
Lead	-	-	-	-	0.14
Time dummy	0.06	-	-0.09	-	0.16
Intercept	-	-	-	-11.89	-
LLV-value	**61.81**	**34.89**	**39.00**	**17.07**	**29.25**
Adjusted R^2	**n.a.**	**n.a.**	**n.a.**	**0.80**	**n.a.**

Table 5.1.3.: Overview of model coefficients for Base Metals sector by country, author's own work

To add further detail to the overall picture, the consumption of bauxite has been added as another raw material indicator. Bauxite, an aluminium ore, is the most important raw material used in the production of aluminium (Rathe and Torgersen 2020). Primary aluminium is produced in an electrolytic reduction process. Europe's largest aluminium plant in Dunkerque, France, consumes as much as 4 TWh of electricity per year, with a total production of 284,000 tonnes of aluminium in 2017, accounting for 45% of electricity consumption for non-ferrous metals in France[2]. Note that the production of secondary aluminium from scrap material is significantly less electricity-intense, consuming approximately 5% of the electricity used for primary aluminium, according to ibid.

The interpretation of model results persists when compared to the results of the German model: An increase in assets has an adverse impact on electricity consumption. For all other input variables, an increase in inputs yields higher power demand, as explained for the case of the German metals sector. Additionally, the consumption of bauxite is driving electricity demand as well.

It remains interesting to observe that iron ore, in this case, seems to be the better indicator. This is surprising, given that steel scrap was assumed to be the more "direct" indicator of EAF production. Given the decoupling of scrap consumption and steel production as explained above, and the fact that iron ore is used in EAF production as well, the interpretation of results however remains unchanged.

[2] This compares to 66% of primary aluminium production in France by this plant, according to production data by BGS 2020

Belgium

For Belgium, the model coefficients suggest a similar impact of changes on electricity consumption for assets and scrap consumption, as was expected after analysis of the German metals sector. The time dummy in this case has a negative sign, suggesting that efficiency gains outweigh electrification.

Netherlands

Electricity consumption in the Dutch Base Metals sector is decoupled from scrap consumption. In fact, the share of EAF production in total steel production in the Netherlands has decreased from a low contribution (4.3%) in 1990 to zero in 2017. Therefore, once again non-ferrous ores will serve as indication for raw material input.

Note that working hours are statistically not significant. Further, a constant is used in the model, and the time dummy excluded, both in order to ensure significance of input variables and improve model performance[3].

Again, the consumption of raw materials drives electricity consumption as anticipated. Differing from countries in which EAF production was historically significant, increasing capital input leads to an increase in electricity consumption as well. Consequently, the Netherlands consumed only 0.4 Mtoe of electricity in the Base Metals sector in 2017 - only Austria consumed less energy from electricity (0.3 Mtoe) (Enerdata 2020), while producing negligible shares of steel from EAFs.

Austria

The Austrian metals industry differs from the German one, as crude steel is mostly produced in OBFs, with the share of EAF production fluctuating around 9% since the 1990's and reaching a mere 10% in 2017. The focus of this analysis is therefore turned to the non-ferrous metals sector. Eurostat 2020 provides detailed data on the consumption of ores in Austria (ferrous as well as non-ferrous ores, the latter being at the focus of this analysis of the Austrian case). In terms of material consumption, lead and bauxite (i.e. aluminium ores) were historically the two most used materials, which is why they were included in the model.

Note that the p-value of aluminium consumption suggests statistical insignificance, as the 0.05-threshold is not met. However, after consideration, it was decided to include the consumption of bauxite in the model setup, as its consumption has increased lately. On the other hand, lead consumption has dropped by 94% since 1990. Excluding aluminium from the model would therefore effectively result in no raw material being part of the forecasting model. Given the closeness of the p-value to the claimed threshold, it was therefore decided to keep the consumption of bauxite in the model[4].

3 Unlike in the Base Metals models for other countries, thanks to the inclusion of an intercept, measuring model performance in this case is facilitated by the fact that the R^2 and adjusted R^2 values can be used as indicators.

4 One might find that regression modelling is indeed an art, as Hauer 2015 suggests in his book "The Art of Regression Modelling in Road Safety". Indeed, setting up a regression model sometimes requires more than pure statistical significance, as this analysis is aiming to explain.

Once again, for both raw materials a positive coefficient is found by the model, indicating that increased consumption yields increased electricity demand. Different from the German model, a change in hours worked has an adverse effect on power consumption. One explanation for this could be automation of work, with workers being replaced by electricity-powered machines.

5.1.4. Conclusions on the Base Metals sector

The modelling suggests several major conclusions:

1. Especially for the more important countries in terms of electricity consumption, power demand from EAFs largely determines overall demand. The consumption of steel scrap is therefore the most important indication of power demand.

2. Assets play an ambivalent role: For countries with a high share of EAF production, a decrease in assets yields increased electricity consumption, as EAFs are less capital-intensive than OBFs. For other countries, this effect is reversed, and assets drive electricity demand.

3. The inverse effect is true for hours worked, which have a positive coefficient for EAF-intense countries (Germany, France), and a negative one for Austria.

It also becomes evident that the interpretation of some variables is not straight forward. The time dummy for some models in-, and for others decreases electricity demand, all the while being statistically significant. Further, it should be noted that all forecasts are subject to uncertainty given the fact that they are based on assumptions on the development of input variables. Finally, disruptive changes in the industrial production remain difficult to model, e.g. the introduction of new technologies impacting electricity demand, such as hydrogen steel[5]. The trend towards electrification is another element that is difficult to predict, and chapter 7 will therefore introduce different pathways for future production from EAFs.

[5] Thyssenkrupp tested a new technology using hydrogen to replace coal in OBFs in 2019 (Wettengel 2019). The technology is supposed to decrease carbon emissions. However, production of hydrogen is highly electricity-intensive, as the chapter on the Chemicals sector will show. It will therefore be crucial to see how renewable energy is integrated into the energy landscape of the future: One option could be using excess renewable generation to produce hydrogen, which would favour a switch towards hydrogen steel making.

5.2. Chemicals

5.2.1. Sector introduction

The chemicals sector from the energy point of view is the single most important electricity consumer in all five countries analysed in this study. Summing over all countries, the Chemicals sector accounts for 23.9% of total industrial electricity consumption from 1991 to 2017 (the Base Metals sector follows with 19.2%). According to Moulijn, Makkee, and Diepen 2013, p.14, the Chemicals industry is mainly based on 10 different raw materials, 10 different types of fuels, producing 20 base chemicals, 300 intermediate products and a total of about 30,000 final products. When going further into detail, one may observe that, out of the 20 base chemicals, one emerges as the main driver for electricity consumption, namely chlorine.

Chlorine production

Chlorine is produced in an electrolysis process which, as the name suggests, uses electricity to produce chlorine (Cl), caustic soda (NaOH) and hydrogen (H) from salt brine (aqueous solution of NaCl) according to the chemical reaction described in formula 5.1.

$$2NaCl + 2H_2O \longrightarrow 2NaOH + Cl_2 + H_2 \tag{5.1}$$

This chemical reaction produces outputs at a fixed ratio of 1.1 tonnes of caustic soda and 0.03 tonnes of hydrogen per tonne of chlorine produced. This output is called one Electro-Chemical Unit (ECU). On average, the production of one ECU consumes 3.3 MWh of electricity. (Eurochlor 2010)

In 2017, the chlor-alkali electrolysis process in Germany consumed as much as 9.6 TWh of electricity, which equals 18.7% of total electricity consumption in the Chemicals sector (VCI 2020). Further, as chlorine is a base chemical, used for 55% of chemicals production in Europe (Eurochlor 2010), production of chlorine drives overall industrial activity in the Chemicals sector.

Unfortunately, unlike the Base Metals industry, it is more difficult, and sometimes impossible to find data on the consumption of raw materials (e.g. NaCl, also known as "kitchen salt") in the industry. Eurostat provides statistics on the consumption of NaCl, but these are biased by different uses of NaCl, in the food industry, but also on streets to prevent icing in the winter – effects which are difficult to quantify.

However, given the fixed in- to output ratio of the above process (approximately 1.6 tonnes of pure NaCl per ECU), the input of raw materials can be deduced from the amount of output produced. Or, in other words, chlorine production can be used as a direct measure of raw material consumption, and therefore raw material (NaCl) consumption is equivalent to chlorine production.

The following analysis will therefore focus on the production of chlorine as main indicator for electricity consumption. For Germany, these production figures (for chlorine and a multitude of other chemicals) are made available by the Verband der Chemischen Industrie (VCI), the German national chemical industry association. On the international level, the European association of chlor-alkali plant operators, Eurochlor, publishes figures on the production of chlorine. Given international economic competition regulation, the figures are very often published on an aggregate base for several countries. It will therefore be crucial to make valid assumptions on the split of chlorine production between the different countries, which will be explained in more detail in the country-specific sections.

Hydrogen production

As shown in the previous section, hydrogen is a by-product of chlorine production. However, hydrogen is not only produced in the chlor-alkali electrolysis, but also in different other processes, all of which are highly energy-intensive, and some of which use electricity to produce hydrogen (e.g. water electrolysis and potentially methane pyrolysis).

The production of hydrogen will keep on gaining importance in the future, as a part of future energy systems with high renewable energy generation. In times of excess generation, electricity could be used to produce hydrogen. Hydrogen, in turn, can be used to produce methane, chemicals, or other fuels, or can directly be used to produce energy in fuel cells. These processes can be summarised as “Power-to-X” (VCI 2020).

Finally, hydrogen is used to produce more chemicals along the chemical value chain, not the least of which is ammonia, which is used in agriculture to grow food and is one of the most important chemicals in terms of production quantities.

Given the current significance of hydrogen as direct power consumer, indicator for overall industrial activity, and the fact that hydrogen production is expected to further increase its significance in the future, it will be included in the model setup if possible. Due to the different production processes of hydrogen, deduction of the consumption of raw materials is not as evident as for chlorine. While water electrolysis requires water as an input, methane pyrolysis requires methane, the main constituent of natural gas. Therefore, including the production of hydrogen in the model differs from the approach chosen in the Base Metals model. However, it will be shown that this does not change the general conclusions that can be drawn from the results.

5.2.2. Country models

Germany

Using the equivalent indicators as before – assets for capital, hours worked for labour, hydrogen and chlorine as “raw material equivalents” – a model was implemented. As shown in table 5.2.1, model performance for Germany is remarkable.

Independent variable	Germany	France	Belgium	Netherlands	Austria
Assets	0.67	-0.50	0.19	-	0.25
Hours worked	0.30	-	-	0.08	-0.55
Chlorine	0.15	0.24	0.19	0.58	0.51
Hydrogen	0.11	-	-	-	-
Nitrogen	-	0.11	-	-	-
Time dummy	-	-	-	-	0.07
Intercept	-11.07	-	-1.65	-	-
LLV	**67.10**	**44.00**	**42.61**	**53.55**	**42.99**
R2_adj	**0.89**	**n.a.**	**0.46**	**n.a.**	**n.a.**

Table 5.2.1.: Overview of model coefficients for Chemicals sector by country, author's own work

Note that, in this model, a constant was included, as it proved to be statistically significant. On the other hand, the time dummy was found to be statistically insignificant and therefore excluded. Including the constant yields an unbiased R^2 value, which indicates an excellent model fit, with all variables being statistically significant.

Generally, the model performance is remarkable. It seems that the variables chosen for the analysis indeed do drive electricity demand to a large extent, while at the same time giving an indication for overall industrial activity and thus electricity consumption in the following steps of the chemical value chain. For all independent variables, the positive coefficients indicate a positive sensitivity: Electricity consumption increases when either one of the variables is increased.

It is also worth noting that in the German chemical industry, both electrification and efficiency gains do not seem to play a significant role, or are offsetting each other; either way, the time dummy is statistically not significant.

Finally, as discussed before, including hydrogen changes the approach of a Cobb-Douglas function using only "inputs" in the economical sense as independent variables. Therefore, another model was set up, using only assets, hours worked and chlorine production as inputs (as explained before, chlorine production is equivalent to the use of NaCl as raw material). The modelling results are shown in figure 5.2.1.

The general results remain the same: All independent variables positively impact electricity consumption; model performance is not quite as outstanding as for the hydrogen case, but comparable on a high level.

This allows for two conclusions: Firstly, relaxing the assumption of the Cobb-Douglas function to use only economic input factors by using hydrogen as well does not change the general results. Secondly, the relaxation improves model performance (at least in this case).

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                el_cons   R-squared:                       0.875
Model:                            OLS   Adj. R-squared:                  0.858
Method:                 Least Squares   F-statistic:                     51.52
Date:                Wed, 15 Apr 2020   Prob (F-statistic):           4.10e-10
Time:                        13:12:07   Log-Likelihood:                 62.892
No. Observations:                  26   AIC:                            -117.8
Df Residuals:                      22   BIC:                            -112.8
Df Model:                           3
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
chlorine_production     0.1936      0.051      3.772      0.001       0.087       0.300
assets                  0.9856      0.173      5.698      0.000       0.627       1.344
hours_worked            0.3093      0.113      2.747      0.012       0.076       0.543
const                 -14.5461      3.019     -4.819      0.000     -20.806      -8.286
==============================================================================
Omnibus:                        1.609   Durbin-Watson:                   1.233
Prob(Omnibus):                  0.447   Jarque-Bera (JB):                1.459
Skew:                          -0.494   Prob(JB):                        0.482
Kurtosis:                       2.392   Cond. No.                     1.31e+04
==============================================================================
```

Figure 5.2.1.: Modelling results for German Chemicals sector without hydrogen production, author's own work

These observations are important with regards to the following countries. For some of them, data on certain inputs is scarce. Therefore, in some cases, approximations had to be made, which will be explained in the corresponding sections.

France

In order to improve model performance for France, nitrogen production was included in the model, for four main reasons:

1. As explained before, relaxing the strict input condition of the Cobb-Douglas model yielded improved model results and no fundamental change of results. Therefore, using production figures was assumed to be admissible.

2. There are more producers for nitrogen in France than for chlorine, which means that reporting of production data is possible despite competition rules. Therefore, production figures were complete and more reliable than for chlorine.

3. The production of nitrogen is energy-intense, as nitrogen is mostly produced in the Linde-process. In the process, air is first compressed and later liquefied, both processes requiring electricity as inputs (Maytal 2006).

4. Nitrogen, like chlorine, is an important basic chemical in the chemical value chain. Applications of nitrogen are e.g. ammonia fertilizers, which are used to grow food. Therefore, nitrogen can indicate overall activity in the chemical sector.

As was the case for Germany, chlorine production is clearly driving electricity demand in France. It is interesting to note that, despite the evident significance of electrolysis processes such as chlorine production, the main share of electric energy in France was used to power electric motors (e.g. compressors, pumps, mixers, etc.). According to INSEE data, in 2018 approximately 58% of electric energy used in the chemical industry was used for these purposes. This compares to about 18% of overall electric energy used for electrolysis.

Therefore, the negative coefficient of assets is interesting: It seems that France has managed to translate investment in assets into efficiency gains, i.e. reduced electricity demand, as opposed to Germany, where assets tend to drive electricity demand. (Note that more specific data on the use of electricity for different uses within the chemicals sector was not available for Germany or other countries.)

Like chlorine, nitrogen production appears to drive electricity demand as well, confirming the significance of nitrogen in overall electricity demand from the chemicals industry. The effect of working hours was statistically insignificant and therefore excluded from the model.

Belgium

As mentioned above, Eurochlor publishes European chlorine production figures. However, from 2002 to 2013, production data from the Netherlands and Belgium has been published on an aggregate basis, to ensure no conclusions on the production of single production sites could be drawn from country data (EU competition rules).

Eurochlor also publishes detailed data on installed production capacities. Therefore, aggregate production data for both countries was weighted by installed capacities for both countries, assuming similar utilisation rates.

From 2014, Eurochlor publishes even more aggregate data, with no given split on different European countries or country groups. For these years, the utilisation rate (published by Eurostat as aggregate figure for all European countries) was multiplied with installed capacities (as published by Eurochlor, see above), to approximate chlorine production levels.

For Belgium, chlorine production and assets were the most important and statistically significant factors. Model performance as measured by the R^2 value is not outstanding, but this may be due to a relatively unsteady development of the electricity demand curve, see figure 5.2.2. The model was unable to explain the spikes, positive and negative, of electricity consumption. It was however able to follow the general development. The difficulty to model spikes could also be due to the calculation methodology of chlorine production, as discussed above.

It should be noted that Belgium is a net importer of chlorine, according to UN Comtrade data. Therefore, reliable data on the import of chlorine (and potentially other basic chemicals) could

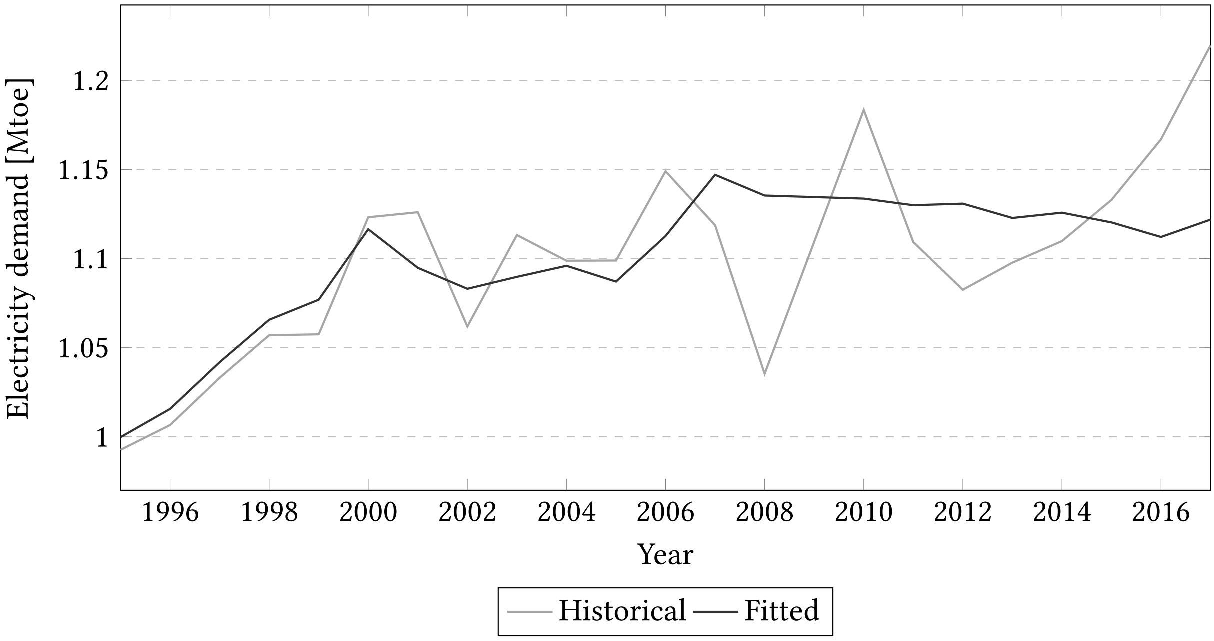

Figure 5.2.2.: Model fit for Belgian Chemicals sector, author's own work, historical data based on Odyssee Database

further improve the model. Unfortunately, UN Comtrade data for Belgium is only available after 1999. Including chlorine production in the model and training only for the period after 1999 showed that chlorine imports did drive demand, but due to fewer observations decreased overall model performance. It was therefore decided to stick to chlorine production and assets as indicators. The time dummy was excluded for statistical insignificance.

As for France and Germany, chlorine production in Belgium is driving electricity demand. Unlike France, but similar to Germany, assets have a positive coefficient as well, even though the output elasticity is lower than for Germany. This suggests that efficiency gains through investment in new and potentially more expensive equipment in Belgium do not outweigh the increased use of electric motors in machines.

Hours worked were statistically insignificant, suggesting that automation effects and increased production with increasing labour input offset in the Belgian chemicals sector.

Netherlands

For the Dutch case, chlorine production proved to be an outstanding indicator, and in combination with the number of hours worked in the industry yielded strong model performance, as indicated by the LLV value. Please note, however, that chlorine production figures were not readily available and therefore estimated using the methodology described in the section on Belgium. Both constant and time dummy were not included in the model due to statistical insignificance.

As in all other countries, chlorine production in the Netherlands clearly drives electricity demand. Unlike Belgium, the Netherlands changed from being a net chlorine importer to a net exporter several times in the past, while on average tending to export. This apparently improves model performance, such that chlorine production is a strong indicator. Like in Germany, hours worked have a positive impact on power demand, thus being a positive production indicator. Assets were statistically insignificant and therefore excluded from the model.

It is noteworthy that, comparing the Netherlands with Belgium, chlorine production is a stronger driver in the Netherlands than in Belgium. One possible explanation for this effect is the historical chlorine trade balance of both countries: With Belgium traditionally being a net importer of chlorine, chlorine production alone might be less well suited to indicate overall production activity along the chemical value chain. On the other hand, the Netherlands have either exported, or imported very little chlorine, suggesting that almost all the chlorine produced in the Netherlands is used there. Consequently, production of products made from chlorine (and electricity consumption that goes with it), is more strongly correlated with the production of chlorine.

Austria

The model setup for Austria once again includes all three inputs: labour (hours worked), capital (assets) and raw material input (indirectly through chlorine production). Chlorine production data for Austria was even more scarce than for Belgium and the Netherlands. Therefore, the approach used for those countries after 2014 (multiplying installed capacity with EU-wide utilisation rate) was used to estimate chlorine production levels in Austria for all years.

Note that Austria only has one chlorine production plant, which has expanded its production capacity from 55 k tonnes per year in 2000 to 57 k tonnes per year in 2019. An estimation such as the above is therefore prone to bias, e.g. in the case of long-term outages of the single production site. In that case, however, it can be assumed that demand for chlorine along the value chain would be covered by imports, more specifically imports from Europe. Therefore, even given the above bias, utilisation rates in Europe could be indicative for Austrian power demand along the chemical value chain.

Despite the bias as described above, the model performs very well, and all input variables are highly significant from the statistical point of view. The LLV value indicates strong model performance.

Chlorine production once again is the most important driver of power demand. Assets are a strong positive indicator as well, suggesting that the increased power consumption Austria experienced (+123% from 1991 to 2017) was at least partly due to an increase in fixed capital, such as machines and production plants. Still, the negative coefficient of hours worked suggests that automation of production processes does play a role in the Austrian chemicals sector.

Finally, the time dummy suggests an underlying increase of power demand, potentially through electrification of processes. The constant was insignificant and therefore excluded from the model.

5.2.3. Conclusions on the Chemicals sector

The major conclusions to be drawn from the above are the following:

1. The chlor-alkali process is the single most important driver of electricity demand in all five countries. This is due to the significance of direct power consumption in the process on one hand. On the other hand, chlorine, which is a product from this process, is the base chemical for a multitude of chemical products, and therefore the production of chlorine is an indicator of overall industrial activity in the sector.

2. Production of major products in an industry can be an important indicator where data on the consumption of raw materials is unavailable or biased by different applications of the material. This is the case for chlorine (even though production in this case allows for direct deduction of material use), hydrogen and nitrogen in the countries analysed above.

However, the same limits to the analysis as for the Metals sector apply here as well. It remains difficult to predict disruptive changes taking place in a sector. Further, it should be noted that the expected increased importance of hydrogen as a means to store energy has not been analysed in this paper, as this has no connection with the Chemicals sector as such.

5.3. Pulp & Paper

5.3.1. Sector introduction

The Pulp & Paper industry in Europe is another of the most electricity-intensive industries in Europe. In the five countries at the focus of this work, the industry has contributed 10% to overall electricity consumption since 1991 (Enerdata 2020).

The countries however differ quite significantly in terms of the relative significance of the industry, as the following figure shows. While the Pulp & Paper industry in Austria has contributed more than 20% to overall electricity consumption, in Belgium the share is just 7%, as displayed in figure 5.3.1.

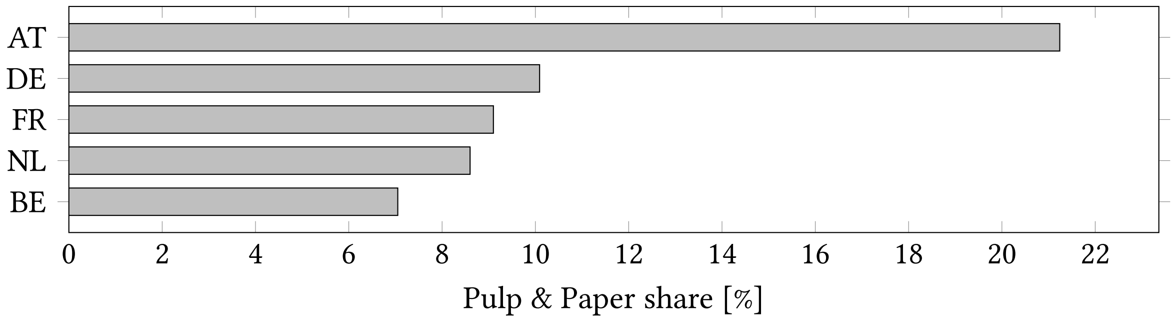

Figure 5.3.1.: Contribution of Pulp & Paper to overall industrial electricity consumption by country, 1991 - 2017, based on Enerdata 2020

The explanation for this can be found in the very different availability of raw materials and the subsequent historical development of the industry in the specific countries. While Austria has quite significant natural resources (i.e. wood) for Pulp & Paper production, the other countries have historically focused on different industries. The consequences can still be observed very clearly: While Austria in 2017 produced only 47% (Austropapier 2019) of its total paper and cardboard output from recycled material (recycling paper), this figure amounted to 85% in the Netherlands (VNP Netherlands 2018). Note that the EU target for recycling paper use is 74% in 2020.. A recycling share of 100% is rather unlikely, as the used fibres lose their characteristics, the more often they are recycled.

In this context, another interesting observation is that, the higher the share of recycled paper, the lower the contribution of biomass to overall energy consumption within the Pulp & Paper industry in a country, as the following figure shows (Enerdata 2020, national Pulp & Paper producer associations).

This effect is due to the availability of biomass to provide heat for the production process. While electricity is needed especially in the process of preparing primary materials (e.g. decortication, shredding of wood), heat is needed in particular for drying paper in the end of the production process. The more primary materials are used in the production, the more waste products

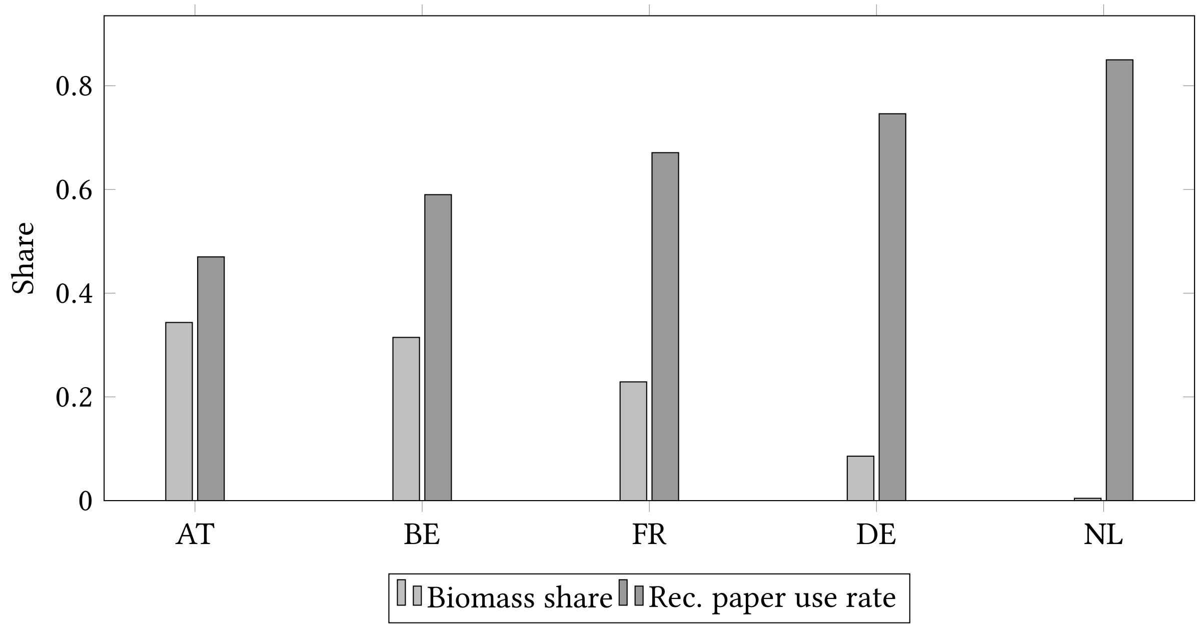

Figure 5.3.2.: Share of Biomass in overall energy consumption, 1991 - 2017 and share of recycling paper in overall paper & board production, 2017 by country, author's own work, based on Enerdata 2020 and national paper producer associations

accumulate during the production process, which, in this case, can be used to generate heat from biomass (Schaffrath 2020).

While pulp (primary fibres) and recycling paper (secondary fibres) serve as the main components to produce paper from, non-fibrous materials are used to give the final product its specific characteristics (e.g. photographic papers have other characteristics than cardboard) (ibid.). The analysis will therefore focus on the two main raw materials pulp and recycling paper and include raw materials wherever their contribution to electricity consumption was statistically relevant, as for their p-value.

Data availability

CEPI, the European association of paper producers, provided detailed data on the consumption of raw materials in the five countries. Due to competition regulation however, not all data could be provided to a full extent. The following table gives an overview of data availability based on CEPI data (CEPI 2020).

For the Netherlands, the national association of paper producers VNP publishes historical annual consumption data. For Belgium, missing data for recycling paper was provided by the national association COBELPA. However, data on the consumption of wood pulp was still unavailable. The approach to mitigate this gap will be discussed in the country model.

Consumption of...	Germany	France	Belgium	Netherlands	Austria
Paper for Recycling	CEPI	CEPI	Nat. ass.	CEPI	CEPI
Wood Pulp	CEPI	CEPI	-	Nat. ass.	CEPI
Non-fibrous Materials	CEPI	CEPI	CEPI	CEPI	CEPI

Table 5.3.1.: Overview of data sources (CEPI or national association) for Pulp & Paper sector, author's own work

5.3.2. Country models

Germany

While hours worked were statistically insignificant, two other input variables (assets, consumption of paper for recycling and non-fibrous materials) were statistically significant and had positive correlation.

Note that, in this model, a constant was included, as it proved to be statistically significant. On the other hand, the time dummy was found to be statistically insignificant and therefore excluded. Including the constant yields an unbiased R^2 value, which indicates an excellent model fit, with all variables being statistically significant (s. table 5.3.2).

Independent variable	**Germany**	**France**	**Belgium**	**Netherlands**	**Austria**
Assets	0.69	-	0.64	1.42	-
Hours worked	-	-	-0.36	-	-0.43
Recycling Paper	0.39	0.54	-	0.80	-
Wood pulp	-	0.42	-	-	0.22
Non-fibrous materials	0.50	0.50	0.19	-	0.65
Time dummy	-	-0.10	-	-	-0.08
Intercept	-9.46	-11.39	-	-11.26	-2.22
LLV-value	**44.37**	**46.11**	**39.82**	**31.60**	**57.29**
Adjusted R^2	**0.93**	**0.94**	**n.a.**	**0.89**	**0.89**

Table 5.3.2.: Overview of model coefficients for Pulp & Paper sector by country, author's own work

As stated above, Germany has a rather high share of recycling paper usage in overall paper production (74.6% in 2017, 75.9% in 2018). Therefore, the consumption of recycling paper is a stronger indicator than the consumption of the wood pulp made from primary fibres. The use of non-fibrous materials is assumed to be independent from the use of one or the other source of fibre, as the kind of paper produced does not depend on input materials. However, it is possible that the rather large coefficient for non-fibrous materials is related to the missing wood pulp consumption, as non-fibrous materials are used with both fibre sources.

France
The model for France includes, apart from the time dummy and the intercept, only raw materials (recycling paper, pulp and non-fibrous materials input). There are model setups in which assets and hours worked are statistically significant; however, it was found that best model performance, as measured by the LLV-value, is reached in this setup, in which all raw materials enter with a positive coefficient.

In terms of its recovered paper utilisation rate (68.6% in 2018, COPACEL 2018), France is moving at the critical point between relying on primary vs secondary fibres. As explained above, production from primary fibres is more electricity-intensive, therefore even with two thirds of its paper production based on secondary fibres, wood pulp is still a statistically significant indicator for France.

Hours worked and assets did not improve model results in the final setup. However, the inclusion of an intercept and the time dummy yields a strong model performance, indicated by both, the LLV-value (46.11, see table 5.3.2) and adjusted R^2 (0.941).

Belgium
As discussed above, data availability for Belgium was not as good as for the other countries in this analysis. However, given a good model performance using only hours worked, assets and non-fibrous materials, it was decided to limit the model to these input factors.

In this context, it is important to point out that a large part of the Belgian paper production is aimed at graphical papers (70% of total production in 2017, according to COBELPA, 2018), which are more intensive in the consumption of non-fibrous materials than e.g. packaging material (24% of total production). When comparing consumption of non-fibrous materials to overall paper production, these materials make up for 18% of the weight of the paper production in Belgium, surpassed only by Austria (20%).

It is therefore concluded that the use of non-fibrous materials in Belgium is important and indicative for overall paper production and, eventually, electricity consumption. This conclusion is supported by the modelling results, which suggest statistical significance of the consumption of non-fibrous materials, in combination with assets and hours worked, as table 5.3.2 shows.

Netherlands
For the Netherlands, a rudimentary setup with assets, consumption of recovered paper and an intercept proved to deliver good model results (adjusted R^2 of 0.892). As shown in figure 5.3.2, the Netherlands have the highest recycling paper utilisation rate among the five countries. This explains the strong model performance even without including other raw materials.

Austria
As mentioned above, Austria, in relation to its overall paper production, consumes most non-fibrous materials among the five countries. Further, as shown in 5.3.2, Austria has the lowest

recycling paper utilisation rate among the five countries. It comes therefore as no surprise that for the Austrian model, a setup that includes the consumption of non-fibrous materials and pulp delivers best performance. Including hours worked, an intercept and a time dummy, the adjusted R^2-value is 0.888, indicating strong model performance, which is confirmed by the LLV-value (57.29).

5.3.3. Conclusions on the Pulp & Paper sector

As table 5.3.2 shows, the results for all countries are similar: For three countries, assets have a positive coefficient. Hours worked are insignificant for all countries but two (Belgium, Austria), where their correlation is negative.

In the countries with highest recycling rates, recycling paper consumption was significant, and has a positive coefficient. For Austria, producing around half of its paper from primary fibre, consumption of pulp (i.e. primary fibres) is statistically significant (while recycling paper is not). When the intercept was significant, it was negative (all countries except for Belgium). The Austrian model was further improved by a time dummy (negative).

This allows for several conclusions: Given the positive impact of assets, and negative coefficients of hours worked, it seems that workers have been replaced by machines in all countries, thus using more electricity for those machines.

Further, it seems that the higher the recycling share of countries, the more likely is recycling paper to drive demand. Note that the break point is not at 50%: As primary fibres are more electricity-intensive to turn into pulp and paper, even if more than half of the paper was produced from recycled paper, wood pulp is still a significant driver (e.g. France).

The main conclusions to be drawn from the above analysis of the Pulp & Paper sectors in the five countries are as follows:

1. Depending on the specific conditions in a country, its paper production landscape differs. Countries such as Austria, having rich natural resources for the production of pulp and paper, still rely strongly on the production from primary fibres. On the other hand, countries like the Netherlands produce mainly from recovered paper. The modelling results show that this is reflected in the statistical significance of certain input parameters.

2. There is strong evidence that labour is replaced by machines, as for all countries in which hours worked were significant, the coefficient is negative. For assets, the opposite effect is true.

5.4. Non-metallic Minerals

5.4.1. Sector introduction

Sector structure

The Non-metallic Minerals industry can be divided into different sub-sectors according to the products manufactured, as table 5.4.1 shows.

PRODCOM classification	Product group
23.1	Glass & glass products
23.2	Refractory products
23.3	Clay building materials
23.4	Other porcelain & ceramic products
23.5	Cement, lime & plaster
23.6	Articles of concrete, cement & plaster
23.7	Cut, shaped & finished stone
23.9	Other non-metallic mineral products

Table 5.4.1.: Classification of non-metallic minerals products according to PRODCOM classification (Eurostat 2019)

The different sub-sectors are not equally important in the different countries: As table 5.4.2 shows, the Netherlands produce almost exclusively articles made of cement, lime & plaster (PRODCOM 23.6), which is the focus of most of the countries. The German landscape on the other hand is the most diversified, with glass (23.1), cement, lime & plaster (23.5), articles thereof (23.6) and other non-metallic minerals products (23.9) all contributing significantly to overall production quantities. Note that quantities here refer to weight (i.e. tonnes), not contribution to GDP or power consumption.

Country	23.1	23.2	23.3	23.4	23.5	23.6	23.7	23.9
Austria	0.01%	0.72%	0.11%	0.00%	11.48%	75.69%	0.51%	11.49%
Belgium	0.40%	0.07%	0.00%	0.01%	18.70%	73.71%	0.27%	6.84%
France	6.99%	0.15%	0.45%	0.02%	11.76%	62.25%	0.26%	18.12%
Germany	15.88%	0.66%	0.63%	0.20%	39.83%	18.78%	1.23%	22.78%
Netherlands	0.21%	0.16%	0.00%	0.00%	0.00%	99.35%	0.27%	0.00%

Table 5.4.2.: Overview of relative product share in overall production weights by country, non-metallic minerals products, 2018 data, author's own work, based on Eurostat 2020

While the production of cement, lime & plaster and articles thereof is more significant in terms of production quantities in most countries, glass production is more electricity-intensive than the production of cement: On average, producing a tonne of glass consumed 2.1 GJ (583 kWh) of electricity per tonne of glass produced (differing by the type of glass produced - lowest for hollow glass, highest for special glass, according to Fleiter, Schlomann, and Eichhammer 2013). At the same time, producing cement from clinker consumes approximately 0.4 GJ (110 kWh) of electricity per tonne. This specific power consumption has increased since falling to a low of 99.0 kWh in 2008, mainly due to increased electrification of processes and more demanding specifications for product quality (VDZ 2019). The electricity demand of the subsequent production of concrete and similar products is more difficult to specify. MPA 2018 indicates that the total electricity consumption in the production process ranges between 120 and 180 kWh per tonne of concrete, depending on product characteristics.

Unfortunately, there is no reliable historic data on the split of electricity consumption between the different sub-sectors, and thus no split by products. However, given the information about electricity-intensity above, a focus for the specific countries can be defined: For Germany, the analysis will focus on both the production of glass (PRODCOM 23.1) and cement, lime & plaster (23.5). The models for France, Austria and Belgium focus on the production of cement, lime & plaster and articles thereof. In the Netherlands, despite the relatively low electricity-intensity of the production of articles from cement & lime, the focus will be on these products, as no other products were produced with a significant market share.[6]

Raw materials

As discussed above, the analysis will focus on three different sub-sectors: Manufacture of glass (23.1), cement, lime & plaster (23.5) and articles thereof (23.6). Even though the sectors differ quite significantly in their electricity-intensity and outputs, they do share some raw materials, as figure 5.4.1 shows.

Both the production of glass and cement use limestone as important raw material. In 2018, the German cement industry consumed a total of 38.6 mio tonnes of limestone, and 7.7 mio tonnes of granulated blast furnace slag, a byproduct of iron production - the two most important inputs in the production of 24.5 mio tonnes of clinker and 33.7 mio tonnes of cement. Eurostat only reports direct figures for limestone consumption. Slag consumption is included in the circular economy reporting of non-metallic minerals (MF3), as is glass waste and most mineral waste from construction and demolition (Eurostat 2018).

In 2018, 38% of total glass products manufactured in Germany were flat glass products, followed by hollow glass (19%) and container glass (18%) (BV Glas 2019). According to Leisin 2019, the production of flat glass is the second most electricity-intensive type of glass, requiring 3.3 GJ (917 kWh) of electricity per tonne of glass produced. Only the production of special glass has higher specific electricity needs (5.0 GJ / 1,390 kWh per tonne). Given a market share of only 5.8%, this type of glass is not a main driver of electricity consumption.

[6] Other non-metallic mineral products combined in 23.9 are too diverse to be specifically analysed in this work. The category contains, among others, abrasive products, millstones and articles made from asphalt.

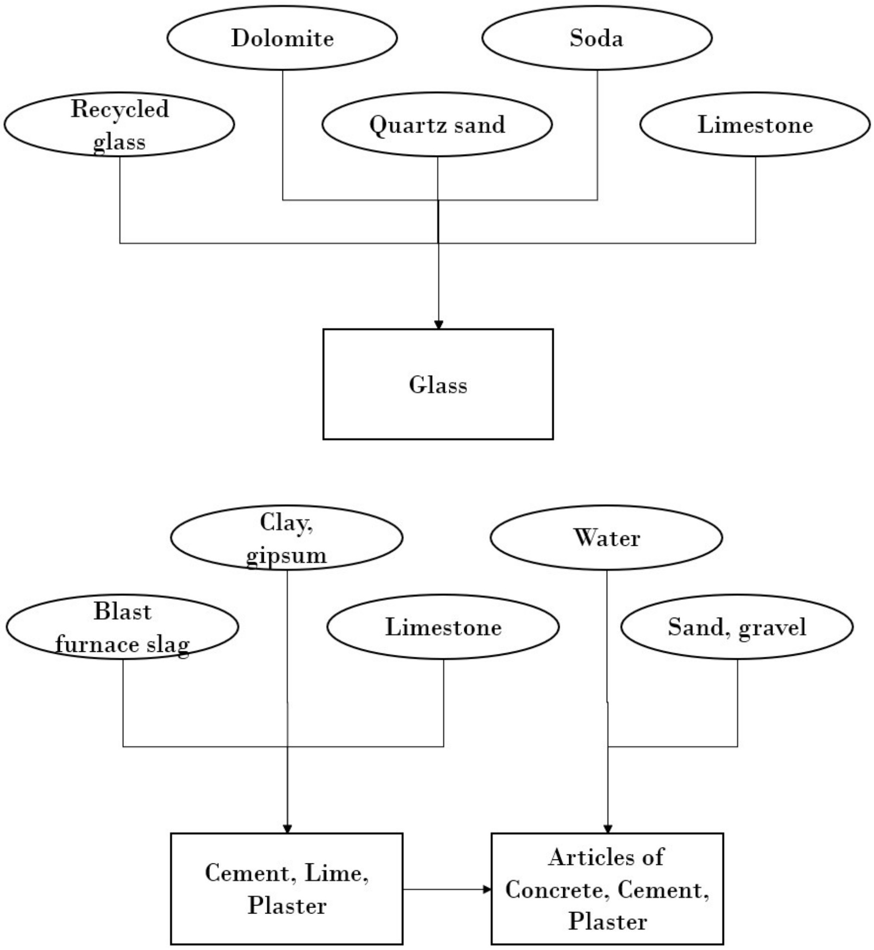

Figure 5.4.1.: Overview of material inputs for selected sub-sectors of the Non-metallic Minerals sector, simplified, author's own work, based on Schaeffer and Langfeld 2014, Fleiter, Schlomann, and Eichhammer 2013

With regards to raw materials, the different glass products differ notably in their share of recycling glass. The potential of recycling shares depends mainly on the requirement of pure raw materials. While container glass in Germany uses between 65 and 90% of recycled glass (cullet), green glass reaches recycling shares of 95% of the weight and white glass ranges between 50 and 70%. Flat glass uses only around 20% cullet, which is driving its energy consumption: Using recycled glass reduces the energy consumption by approximately 3% per 10% of production weight from recycled glass. (Leisin 2019)

5.4.2. Country models

As per table 5.4.3, the individual countries' results correspond very well with the countries' industrial focus in the Non-metallic Minerals sector.

Limestone is used in both the production of glass and cement, as figure 5.4.1 shows. Given the industrial structure in Germany (see 5.4.1), it seems therefore intuitive that limestone consumption plays an important role in overall electricity consumption. Likewise, it was shown that using recycled glass instead of primary materials decreases electricity consumption, which is reflected in the model results as well. Note that the figure for recycling of glass here refers to packaging glass waste, not the entirety of recycled glass in Germany. It unfortunately is the only figure that is officially reported.

As Table 5.4.2 shows, the focus in all other countries is on the production of articles from concrete, cement & plaster. As per figure 5.4.1, sand & gravel are among the most important inputs in this sub-sector. Unfortunately, Eurostat reporting on production data for cement is insufficient, probably due to competition rules. Therefore, sand & gravel in this case are the more reliable indicator, which is reflected in the model results. Consumption of sand & gravel is statistically significant for France, Belgium and the Netherlands.[7]

For Austria, the case is a little different: The country is the world leader in the use of alternative raw materials in the cement and concrete industry, having used 14% of alternative resources in cement production in 2018, which compares to just 3.6% for the EU-28 countries (VOZ 2019). Further, the database for Austria is more extensive than for the other countries. Therefore, data from Global Cement and Concrete Association 2020 (GCCA) were included in the model setup, to better reflect the use of alternative materials in cement and concrete production. As the results show, consumption of limestone, gypsum (used in cement production) and substitutes (for cement in the production of concrete were statistically significant and therefore included in the model results. Note that given an insignificant share of glass production in Austria, limestone consumption as an independent variable remained unbiased.

5.4.3. Conclusions on the Non-metallic Minerals sector

According to the individual structure of the Non-metallic Minerals industries in the five countries, different drivers for electricity demand were identified. In Germany, glass production is an important driver of electricity consumption, with recycling glass that is used in the production reducing overall demand. In the other countries, the focus was on the production of cement and articles from cement, lime & plaster, with sand & gravel serving as the most important indicators. Austria, leading consumer of alternative raw materials in cement production, can be modelled using data on these substitutes. The model results thus reflect the relative importance of the different products manufactured in the industry.

7 Limestone consumption was not conclusive, as especially France produces non-negligible amounts of glass, using limestone and thus biasing the factor.

8 Note here that Eurostat reports only the combined consumption of limestone and gypsum (of which limestone is the by far more important one). For all countries except Austria, the limestone figure therefore includes both, limestone and gypsum. For Austria, Global Cement and Concrete Association (GCCA) reports data for the consumption of limestone and gypsum seperately, which is reflected in the gypsum consumption below.

Independent variable	Germany	France	Belgium	Netherlands	Austria
Assets	-	-0.86	0.29	0.57	1.59
Hours worked	0.29	-	-0.58	-	-
Limestone[8]	0.58	-	-	-	0.43
Recycled glass	-0.56	-	-	-	-
Sand & gravel	-	0.56	0.30	0.29	-
Gypsum	-	-	-	-	0.10
Substitutes	-	-	-	-	0.04
Time dummy	-	0.08	-	-	-
Intercept	-	-	-4.47	-9.91	-20.78
LLV-value	**48.26**	**34.51**	**41.91**	**35.89**	**34.99**
Adjusted R^2	**n.a.**	**n.a.**	**0.78**	**0.81**	**0.74**

Table 5.4.3.: Overview of model coefficients for Non-metallic Minerals sector by country, author's own work

5.5. Summarised results

The sensitivities provided by the model allow for a detailed assessment of the influence of individual variables on overall electricity consumption. As explained in section 4.1.1, the coefficients of the model indicate by what percentage electricity consumption changes for a 1% in- or decrease of the input variable. Consequently, the absolute change in electricity consumption can be evaluated by multiplication of the coefficient with total electricity consumption in a specific sector and country.[9]

When performing this calculation for all sectors and countries, and summing up the effects by variable, one can evaluate which of the factors used has the highest impact. Figure 5.5.1 displays the summed up absolute effect for all input variables. As the figure shows, assets in the Primary Metals sector have, by far, the highest influence. In general, hours worked and assets seem to be the most influential factors, followed by chlorine production in the Chemicals sector.

When summing up the absolute impact of the individual variables by sector, one can understand how strongly a specific sector could be driving electricity demand. Figure 5.5.2 shows the impact of a hypothetical 100% change in all input variables within a sector[10]. It becomes

[9] For example, assets in the German Primary Metals sector have a coefficient of -0.939. Multiplying this with the electricity demand in the German Primary Metals sector of 3.68 Mtoe in 2017, the theoretical effect of a 100% increase in assets ceteris paribus would be a decrease of -3.46 Mtoe in electricity consumption. Of course, this is a hypothetical calculation, but it still allows for an assessment of the relative importance of individual variables.

[10] Note that the *absolute* effect, which is used here, refers to a 100% change in the "demand-driving" direction, i.e. for variables with a negative coefficient a -100% *decrease* instead of an *increase*. E.g., in order for this effect to materialise, the Primary Metals sector would have to decrease its assets by -100%, which again shows that the calculation is a hypothetical one.

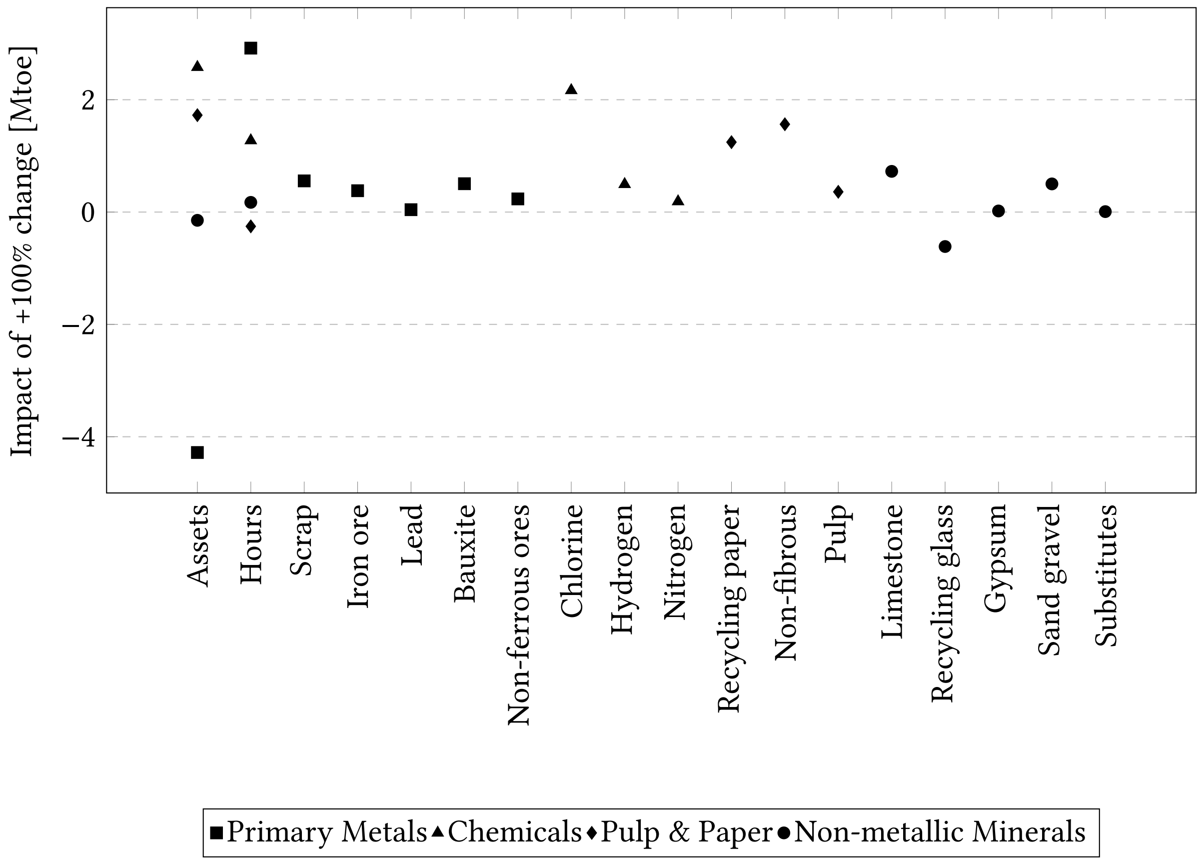

Figure 5.5.1.: Effect on total electricity consumption for +100% change of input variable for all countries, author's own work

apparent that, despite the Chemicals sector being the largest electricity consumer among the four industries, the Primary Metals industry is indeed the one with the potentially stronger levy.

The above analysis will serve as the basis for the scenarios introduced in chapter 7. The scenario modelling will focus on the input factors with the highest impact on overall electricity consumption. Nonetheless, to ensure consistency within the scenarios, all factors will be varied, according to the methodology presented.

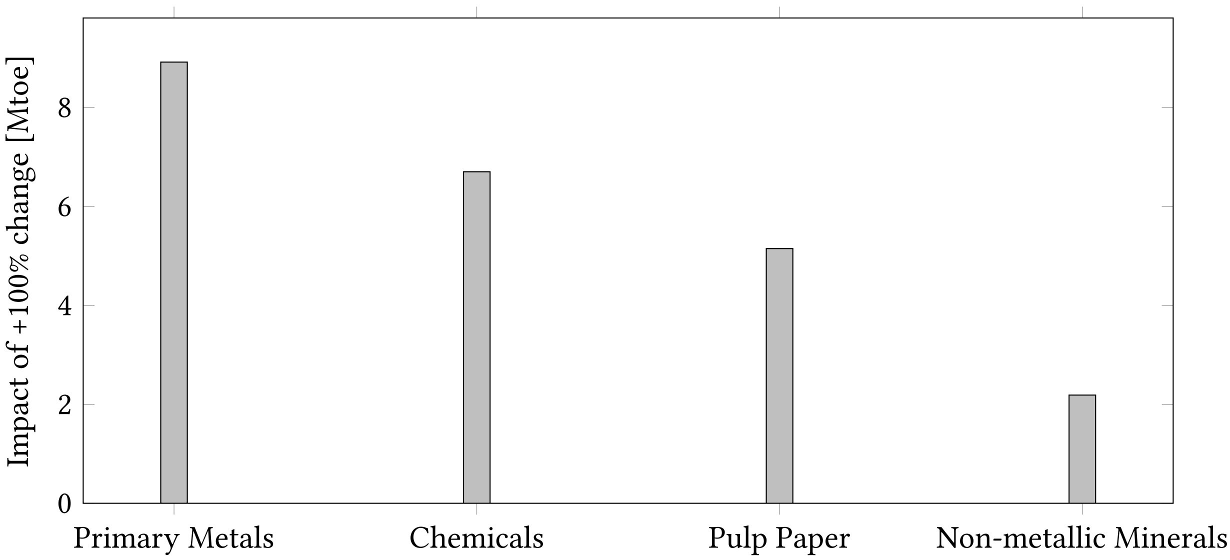

Figure 5.5.2.: Effect on total electricity consumption for +100% change of all input variables for all countries by sector, author's own work

6. Forecasting

6.1. Base Metals

6.1.1. Assumptions

Forecasts are implemented using the model coefficients found above, making assumptions on the development of the independent variables included in the model. For all developments, external sources were used if reliable sources were available. The following assumptions were made in order to achieve a consistent demand forecast:

- **Assets**: Assets are assumed to be the discounted invest over the total life time of assets: Oxford Economics data on investment in the industry is discounted over an assumed depreciation period of 10 years (typical for the steel and other industries, s. BMF 2020), using a discount rate of 10% (as used e.g. by Keys, Van Hout, and Daniëls 2019). The yearly in- or decrease in assets calculated this way is scaled and applied to the assets data used in the modelling part.

- **Hours worked**: Using data on population (Eurostat 2020), employees and hours worked (both Destatis 2020), two figures are calculated: The share of total population working in the Base Metals industry, and the number of hours worked per employee (both country-specific). Both figures are assumed to develop with a logarithmic trend over time. These developments are then used as the base to calculate future working hours: The number of employees as the result of multiplying the (assumed) share of total population working in the industry with the population forecast (Eurostat 2020 base case), and the number of hours worked as the result of multiplying the assumed hours per employee and the number of employees.

- **Scrap consumption**: According to Wortler et al. 2013, EU steel scrap consumption can be assumed to grow by 0.9% annually through 2050. This value is assumed to apply for all countries equally.

- **Consumption of metal ores**: It was assumed that the consumption of non-ferrous ores will develop according to the logarithmic trend of the historically observed trend. There unfortunately is no reliable forecast available with regards to future consumption of metal ores. Fitting the historical data to a logarithmic curve produces R^2 values of between 0.84 and 0.94, indicating a very good fit, which is why the assumption appears valid in the absence of disruptive events.

Figure 6.1.1 displays assumed developments of the input variables at the example of the German Base Metals model. Table A.3.1 in the Appendix gives an overview of assumptions on the development of input variables for all sectors.

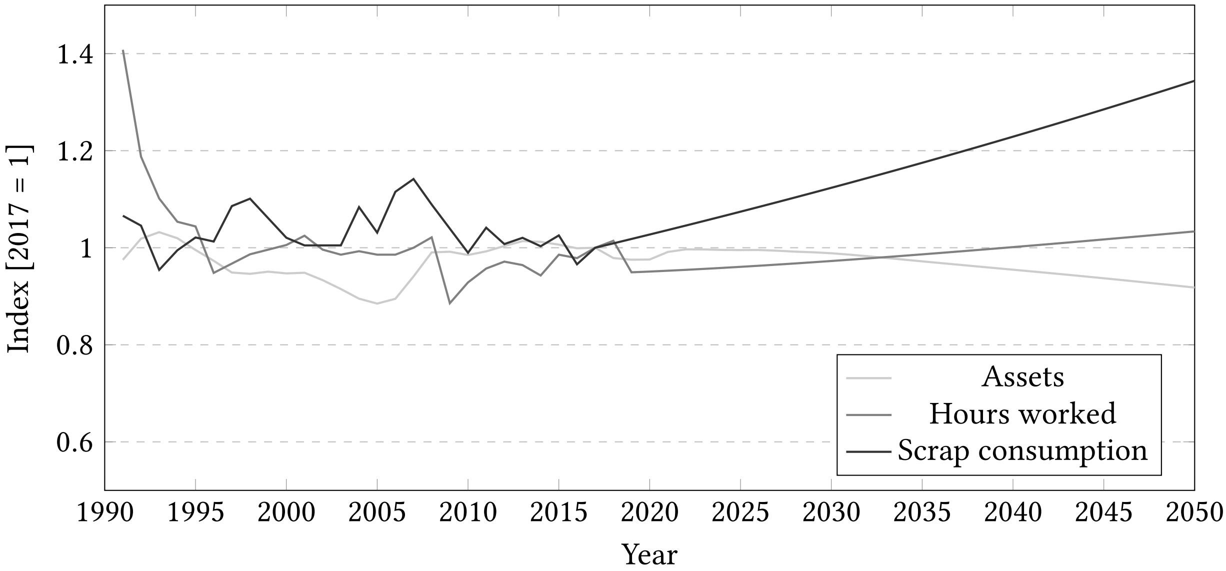

Figure 6.1.1.: Development of independent variables: Historical development and assumed evolution after 2017, German Base Metals sector, author's own work

6.1.2. Results

Applying the coefficients determined by the regression model, as well as the time dummy yields an increased electricity demand by the German Base Metals sector of +19% (+0.7 Mtoe/a or +8.1 TWh/a). This is the equivalent of a moderate increase of 0.5% per year. This increase is mainly driven by a decrease in assets, suggesting that German steel production switches from OBF to EAF production in the assessed time frame. Figure 6.1.2 displays the forecast development of electricity consumption.

Note that the drop of electricity consumption in 2019 is caused by the inclusion of reported values for working hours in 2019, which dropped by 4%, according to official figures.

Combining the effects of all five countries in this analysis, the modelling suggests a moderate decrease of -4% in electricity consumption by the Base Metals sector by 2050. This is the equivalent of a decrease of -0.24 Mtoe. The CAGR equals -0.1%. As suggested by figure 6.1.3, the decrease is realised mostly before 2030, with electricity demand forecast to increase again after 2040.

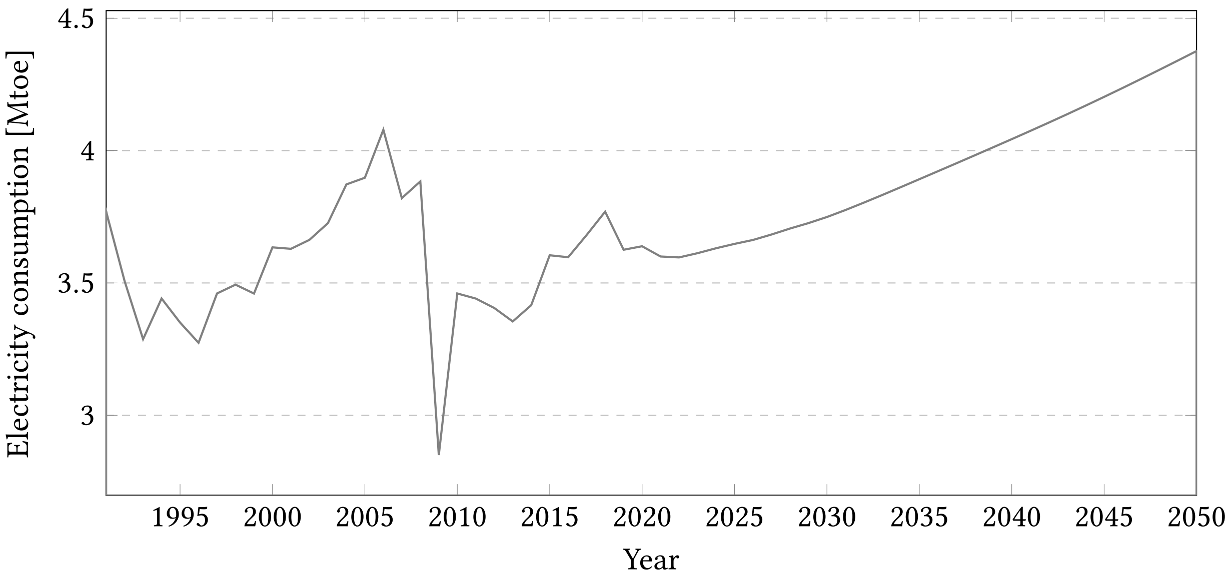

Figure 6.1.2.: Forecasting results for electricity consumption, German Base Metals sector through 2050, author's own work

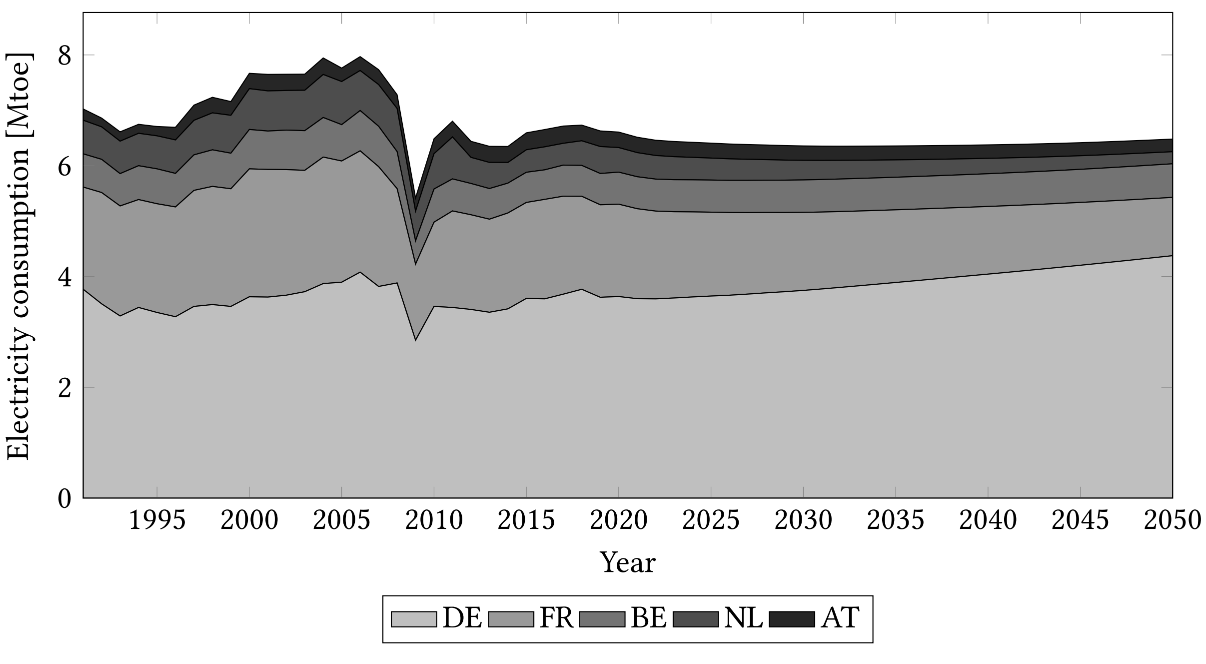

Figure 6.1.3.: Forecasting results for electricity consumption Base Metals sectors through 2050 in the five countries and total, author's own work

Figure 6.1.4 depicts annual electricity demand by the Base Metals sector for the milestones 1991, 2017 (last year of historical data), 2030, 2040 and 2050. What the results also suggest is that Germany not only increases its consumption; it also manifests its position as the biggest power consumer among the five countries. While Germany accounted for 55% of demand in 2017, this share increases to 68% in 2050. France experiences the opposite trend. With a share of 26%

on the second rank, the share drops to 16%. Belgium, placed third with 8% in 2017, slightly increases its share to 9%. Austria (5% in 2017, 4% in 2050) and the Netherlands (dropping from 6% to 3%) are the only countries to switch positions.

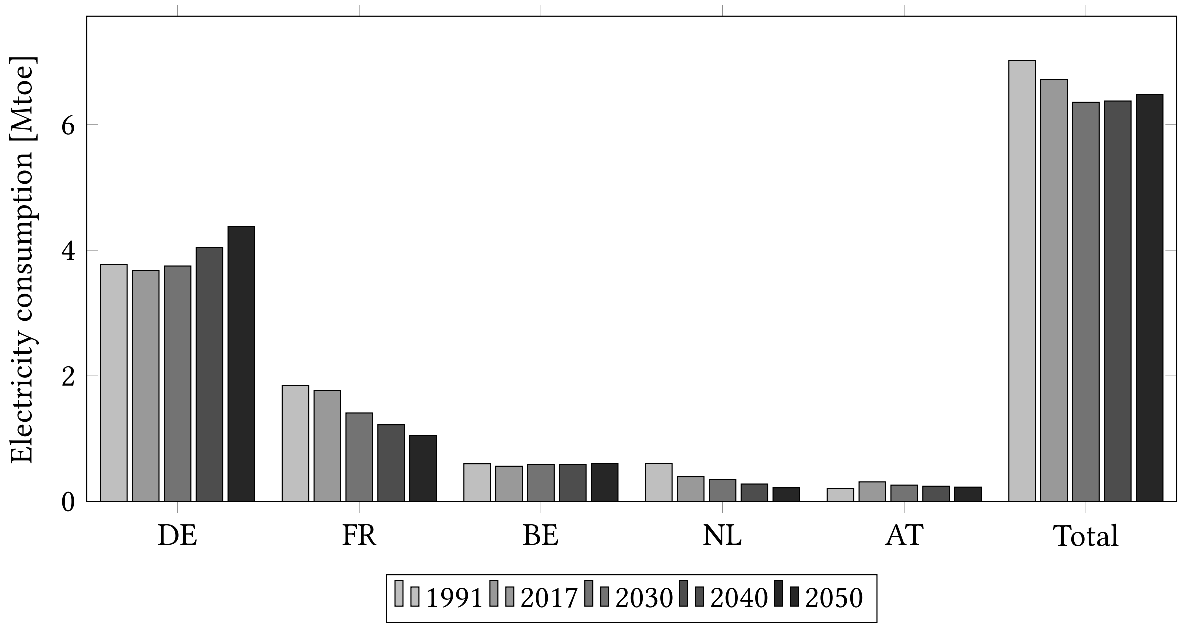

Figure 6.1.4.: Forecasting results for electricity consumption Base Metals sectors through 2050 in the five countries and total for milestone years, author's own work

Table 6.1.1 displays the absolute impact by the different input variables on overall electricity demand through 2050. What becomes apparent with this figure is that, even though scrap consumption has a positive impact on electricity demand, in the sum of all countries, assets are dominating the mix: As assets tend to decrease, and are negatively correlated with electricity demand, as shown before, electricity consumption is driven by this trend. Hours worked on the other hand have a strong negative effect.

Indicator	**Change 2017 - 2050 [Mtoe]**
Assets	0.40
Scrap consumption	0.17
Time dummy	0.05
Consumption of non-ferrous ores[1]	-0.27
Consumption of iron ore	-0.33
Hours worked	-0.36
Total	**-0.24**

Table 6.1.1.: Absolute impact of changes in input variables on total electricity consumption in the Base Metals sector, 2017 vs. 2050, deviations from total are due to rounding errors, author's own work

6.2. Chemicals

6.2.1. Assumptions

Applying the same methodology as before, demand forecasts were implemented. The only change in assumptions was made for raw materials. The European Chemical Industry Council (CEFIC) in 2013 published a study on expected developments in the European chemical industry until 2050 (CEFIC 2013). In four scenarios, it developed different pathways towards a future chemical landscape in Europe. The scenarios differ from each other primarily in the ambition of Europe and its international partners with regards to climate change.

For this analysis, the "Isolated Europe" scenario was chosen to represent the future pathway, as it currently appears that the EU in its climate ambitions is going to aim for climate neutrality by 2050. Other industrialised countries, especially the US, are more hesitant to implement measures to reach net-zero emissions. The scenario suggests a CAGR of 0.7% to 2030, and 0.1% thereafter, which was implemented for all countries.

Assumptions for all other inputs (i.e. assets, hours worked and hydrogen production) do not deviate from the assumptions made for the Base Metals sector. In particular, the production of hydrogen is assumed to develop with a logarithmic trend, rather than according to different studies describing the potential development paths for hydrogen in Europe (e.g. Fraunhofer, 2019). The studies forecasting significant increases in hydrogen production expect hydrogen to play a vital role as energy storage medium in future energy systems. This, however, has no relation with the Chemicals sector (hydrogen is not produced in the chemical industry, but rather by storage operators). Details on the assumptions made can be found in table A.3.1 in the annex.

6.2.2. Results

The model results suggest an overall increase of electricity consumption in the chemicals sector of 0.24% per year, driven primarily by the increase in Germany, as displayed by figure 6.2.1. This compares to an average annual increase of 0.35% since 1991. Absolute demand increases by 8% from 9.08 to 9.84 Mtoe in 2050.

The larger part of the increase is realised by 2030 already, once again due to a slower increase in Germany (s. figure 6.2.2).

The German chemicals sector increases its electricity consumption from 4.66 Mtoe per year by 22% to 5.59 Mtoe annually, an increase of 0.55% year on year. This increase is mostly driven by an increase in fixed capital, as calculated based on investment data from Oxford Economics.

[1] Includes consumption of bauxite and lead

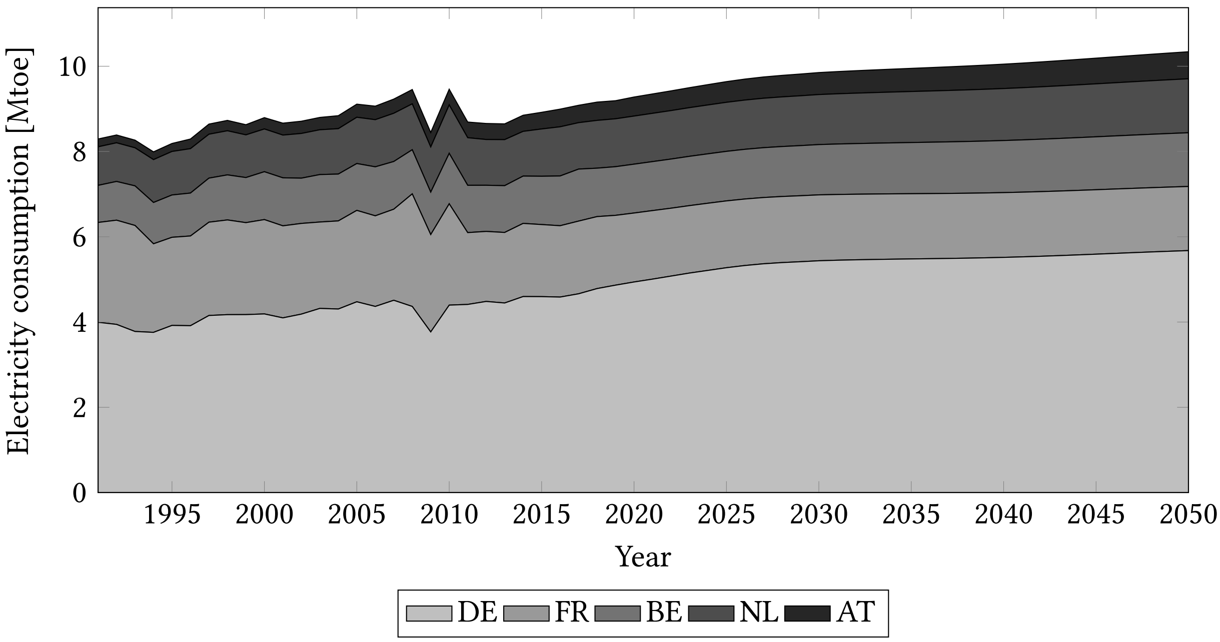

Figure 6.2.1.: Forecasting results for electricity consumption Chemicals sectors through 2050 in the five countries and total, author's own work

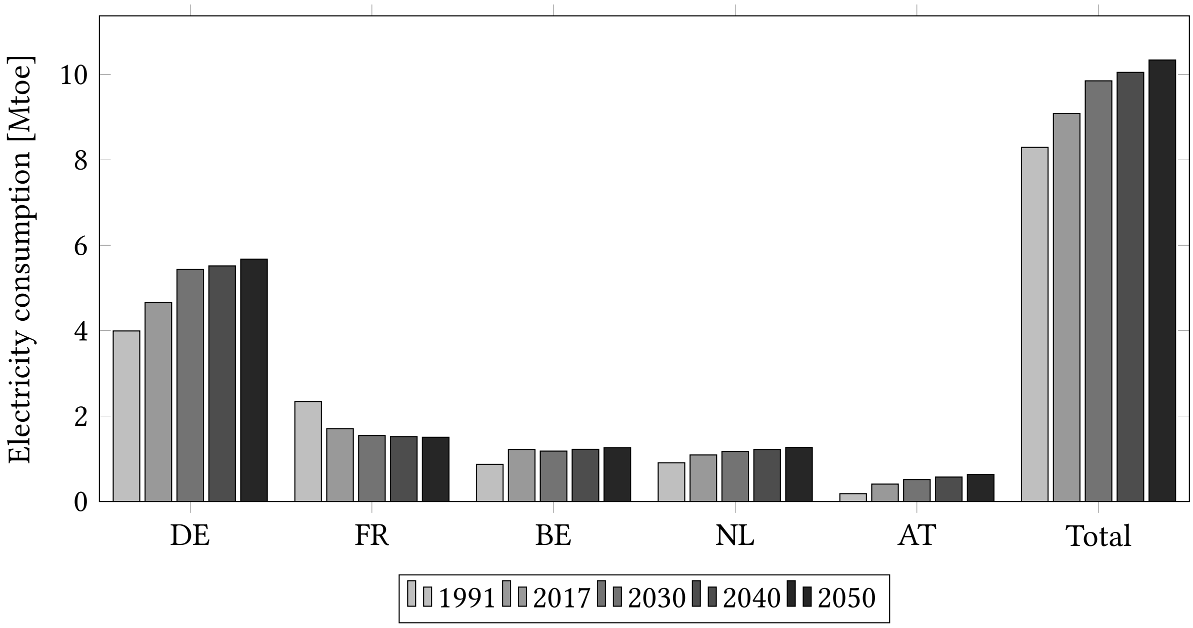

Figure 6.2.2.: Forecasting results for electricity consumption Chemicals sectors through 2050 in the five countries and total for milestone years, author's own work

The number of hours worked is expected to decrease, consequently slowing down the increase in electricity demand.

Electricity consumption in the French chemicals sector is expected to decrease by -14% until 2050, according to model results, equalling a drop of -0.45% per year. This compares to an average annual decrease of -1.2% realised in the period from 1991 to 2017. The change is mainly driven by the assumed increased efficiency, indicated by the negative output elasticity of assets. Increased production of chlorine and nitrogen soften the overall effect.

Belgium is expected to experience hardly any significant change in electricity consumption. Both, increased chlorine production and an increase in fixed capital tend to drive electricity demand, while hours worked decrease demand. The overall effect is yields a -4% decrease by 2050, or -0.14% per year.

The Netherlands are expected to decrease their electricity demand in the chemicals sector by -2%, as Belgium is expecting a -4% decrease. Whilst Belgium has experienced stronger growth in the past (+40% from 1991 to 2017, NL +20%), Dutch demand is expected to be more stable in the period from 2017 to 2050.

Austria is expected to continue the development observed in the last 25 years, increasing electricity consumption. By 2050, demand in the chemicals sector increases by 35% (0.91% annually), which compares to an increase of about 3.13% from 1991 to 2017. The strongest driver of demand increase, yet again, is increased production of chlorine. However, in the Austrian case, all input factors (assets, hours worked, chlorine production, time dummy) have an increasing effect on electricity consumption in the chemicals sector.

Indicator	**Change 2017 - 2050 [Mtoe]**
Assets	0.73
Hydrogen production	0.39
Chlorine production	0.00
Nitrogen production	0.01
Time dummy	0.00
Hours worked	-0.32
Total	**0.83**

Table 6.2.1.: Absolute impact of changes in input variables on total electricity consumption in the Chemicals sector, 2017 vs. 2050, differences in total are due to rounding errors, author's own work

The ranking of the countries by consumption remains unchanged, as Germany and France remain in first and second position, respectively. It is noteworthy that France is decreasing its share of overall consumption from 19% to 15%, its share eaten up by Germany (increase from 51% to 57% in 2050). All other countries have similar shares in the comparison of 2017 to 2050.

When breaking down overall developments on the different indicators, it becomes evident that assets once again are the main driver of electricity consumption: Of the total increase of approximately 1.3 Mtoe, 0.7 Mtoe are driven by the development of assets. This compares to

0.5 Mtoe for chlorine production. Hours worked are decreasing overall electricity demand. For details see table 6.2.1.

Note that this analysis is based on the interaction of different indicators in the different models. In- and exclusion of certain indicators can impact results by taking importance (i.e. decreasing the coefficient) from another input, and vice versa. Therefore, the split of effects on indicators should be considered indicative rather than a direct contribution of certain effects to overall consumption.

6.3. Pulp & Paper

6.3.1. Assumptions

As described in 6.1, assets are expected to develop according to the investment forecast by Oxford Economics, and hours worked according to the trend of population forecast and hours worked per employee.

With regards to the input of raw material, the approach is based on the theoretical limits of paper recycling. According to EPRC 2017, the "current theoretical limit" of recovered paper utilisation is 78%. However, this figure has to be considered within the context of European paper production, with a focus on two important aspects: Availability of resources and reusability of recovered paper.

Some countries (especially in Scandinavia) possess extensive wood resources and produce virtually all of their paper from primary fibres. In 2017, the utilisation rate for recovered paper in Finland was just 5% (Finnish Forest Industries 2020 and FAO 2019). However, Finland exports more than 95% of its production (2016, Finnish Forest Industries 2020). Therefore, the used paper cannot be recycled in Finland. In other countries (such as e.g. the Netherlands), paper can be produced from recovered paper that is being recycled in the country, or even imported (in 2019, the Netherlands imported almost 6 Million tonnes of pulp and waste paper, according to Eurostat 2020). This enables a recycling rate of more than 78%.

Further, depending on the type of paper, reusability differs. On average, fibres can be reused between four and six times, before losing their properties (Schaffrath 2020). Some papers, such as hygiene papers, cannot be recycled at all (Blanco, Miranda, and Monte 2013). This is the reason for the overall theoretical utilisation limit of 78%.

Given these facts, the following assumptions were made:

1. Countries that currently exceed the theoretical maximum will maintain their utilisation rate, due to imports of recovered paper from other countries (Netherlands).

2. Countries that according to the trend of their utilisation rates would exceed an extended theoretical limit of 80% before 2050 reach 80% utilisation rates and then maintain this share (Germany by 2021, France by 2041). Note that the *current* theoretical limit can be extended through different measures, such as enhanced recycling, sorting and improvements in production technologies (ibid.).

3. Countries that according to their trend do not reach the theoretical limit will produce paper from recovered paper according to this trend (Austria, Belgium).

This utilisation rate will be applied to overall paper consumption, as per the per-capita consumption forecast by Tissari 2012 and the population forecast by Eurostat 2020, assuming a constant relation of supply from in-country production and imports, providing the usage of recovered paper.

The same calculation was done to forecast future usage of primary fibres, applying a rate of 100% minus the recovered paper utilisation rate calculated above.

Finally, it was assumed that the input of non-fibrous materials develops independently from the use of fibres, according to the overall paper consumption trend.

6.3.2. Results

Figure 6.3.1 displays the development of electricity demand by the Pulp & Paper sectors in the five countries and in total. The model suggests that electricity consumption in the Pulp & Paper sectors of the five countries will decrease by -6% through 2050, or -0.20% annually. In the period through 2025, consumption is forecast to increase slightly by 0.15 Mtoe, but decreases by more than 0.35 Mtoe between 2025 and 2050, as figure 6.3.2 shows.

The decrease is driven by Germany, with a decrease of -0.2 Mtoe by 2050. Austria is the strongest winner, with an increase of 0.08 Mtoe.

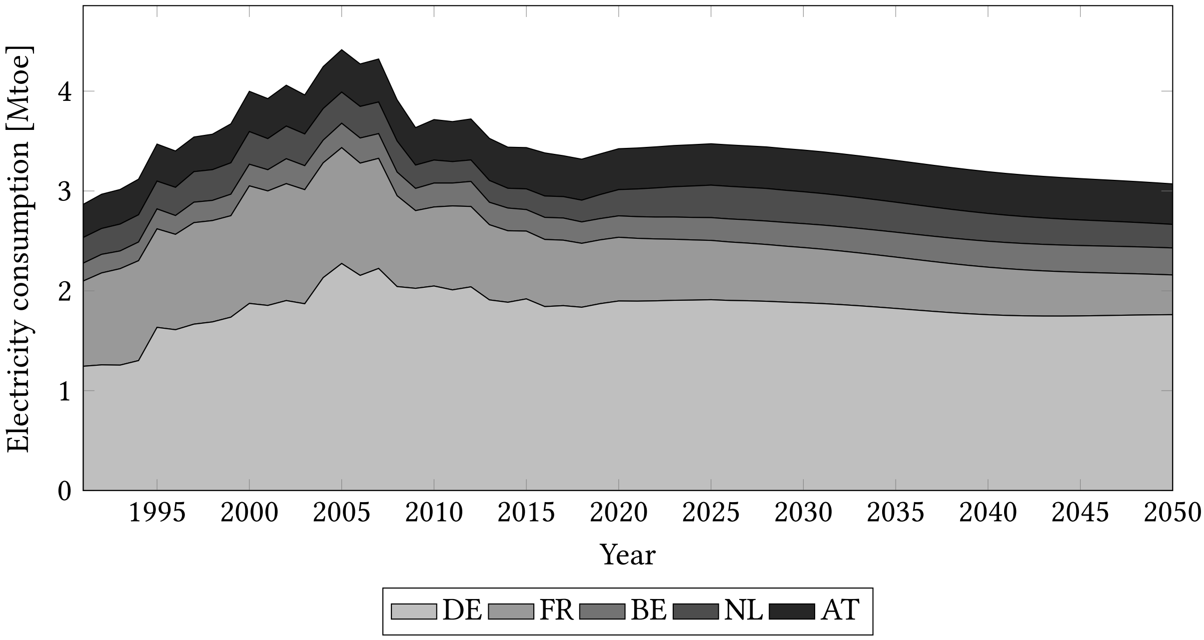

Figure 6.3.1.: Forecasting results for electricity consumption Pulp & Paper sectors through 2050 in the five countries and total, author's own work

The German Pulp & Paper sector is forecast to decrease its electricity consumption by -11% (-0.21 Mtoe) between 2017 and 2050, or an average annual -0.36%. Between 2017 and 2020, consumption increases slightly, as figure 6.3.1 suggests. This increase is however consumed shortly thereafter. Assets are the most important driver for the overall decrease, with recycling

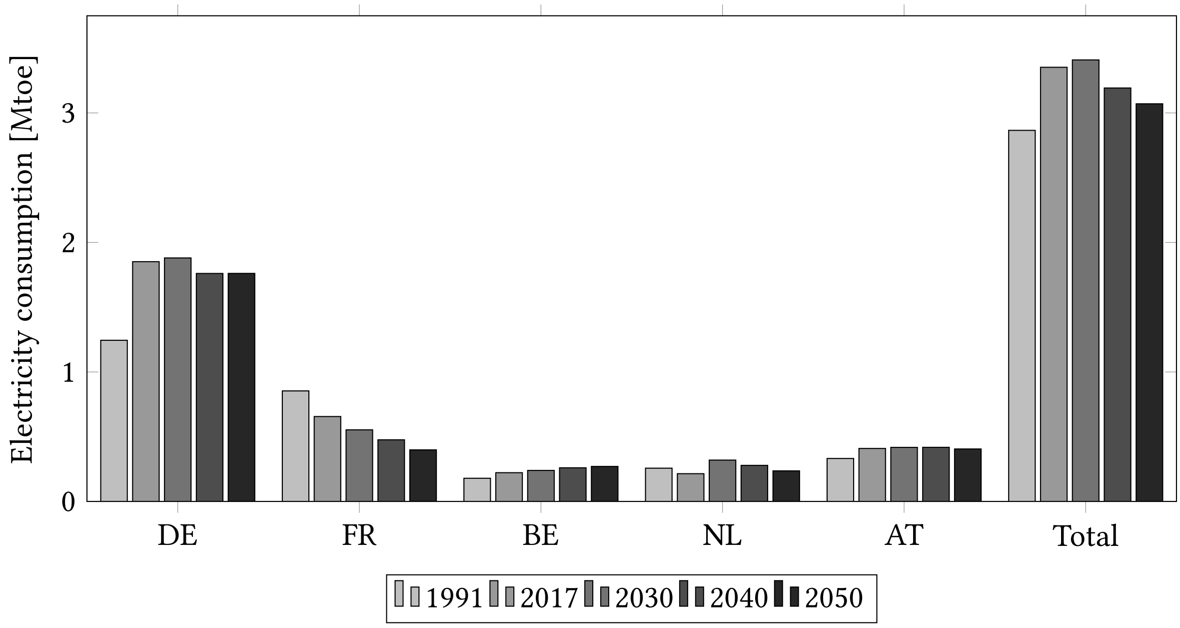

Figure 6.3.2.: Forecasting results for electricity consumption Pulp & Paper sectors through 2050 in the five countries and total for milestone years, author's own work

paper consumption, first going against the trend, from 2023 decreases as well, along with an overall decrease in forecast paper consumption.

France's Pulp & Paper sector will decrease its electricity consumption by -18% (-0.12 Mtoe) between 2017 and 2050, an average annual -0.58%. As France is forecast to decrease its overall paper consumption, input of all raw materials drives the decrease, with decreased consumption of primary fibres causing the main share.

The modelling suggests that Belgium increases its electricity consumption by 22% by 2050, an average increase of 0.6%. This effect is mainly due to a decrease in working hours, suggesting that more workers are replaced by machines, thus increasing electricity demand. Towards the end of the time horizon however, the increase is virtually zero, as figure 6.3.1 shows.

Unlike Belgium, the Netherlands are forecast to decrease their Pulp & Paper sector's electricity consumption, by -8% until 2050 (the equivalent of -0.02 Mtoe, -0.26% annually). Consumption rises until 2025, before decreasing until 2050. This unsteady development is carried by the development of assets, as per the Oxford Economics investment forecast. It results in assets rising through 2025, and decreasing thereafter.

The Austrian forecast suggests an increase of electricity consumption in the Pulp & Paper sector of 20% (0.08 Mtoe) by 2050, an annual increase of 0.56%. As figure 6.3.1 suggests, this increase is relatively steady over the whole time horizon. Overall, the main driver for this increase are decreasing hours worked, even though until 2020 this effect is outweighed by increased consumption of non-fibrous materials and pulp.

As per table 6.3.1, the strongest driver for an increase in electricity is hours worked, which suggests that the trend of replacing manpower with electricity-fuelled machines will continue through 2050. On the other hand, the negative effect of a decrease in assets outweighs this effect. Note that this is not necessarily contradictory: It is possible that human labour is replaced in one place, when in another a company closes its doors, leading to an overall decrease in assets despite machines replacing human workers.

Indicator	**Change 2017 - 2050 [Mtoe]**
Hours worked	0.18
Recycling paper	0.05
Time	-0.02
Non-fibrous materials	-0.06
Pulp	-0.12
Assets	-0.20
Total	**-0.24**

Table 6.3.1.: Absolute impact of changes in input variables on total electricity consumption, 2017 vs. 2050, author's own work

Again, there are certain sector-specific limits to this analysis. Notably, the assumption that paper production is going to move in parallel to paper consumption is a strong one, and especially for smaller, net importing countries subject to uncertainty. Further, it should be noted that the shares of different paper products might change more significantly than can be reflected in this work. It is possible that graphical and hygiene papers become more important in the future, both of which are relatively intensive in terms of additional materials, and thus more difficult to recycle (if not entirely impossible). This might lead to recycling rates below the rates assumed in this forecast, and potentially more complex (and thus electricity-intensive) re-pulping processes.

6.4. Non-metallic Minerals

6.4.1. Assumptions

The assumptions for future development of the independent variables can be split in the two product categories, glass (for Germany) and cementitious products. For the glass sector, assumptions on the development of future use of recycled glass as most important indicator had to be made. Glass For Europe 2020 suggest that the share of recycled glass in total glass production can be increased by 40% by 2050. It was therefore assumed, that total glass production in Germany would develop according to the logarithmic trend of historical production. The increase of 40% was applied to the historically observed ratio of recycled glass consumption divided by total glass production. Multiplying the assumed development of total glass production with this share, consumption of recycled glass was forecast.

For the products 23.5 and 23.6 of the PRODCOM classification, the following assumptions were made:

- Both CEMBUREAU 2013 and MPA 2013 assume a flat development of overall cement production through 2050.
- According to ibid., up to 30% of conventional raw materials for clinker production, such as limestone and clay, could be replaced by alternative materials, such as fly ash or slag ("cementitious substitution"). This decrease was applied to the conventional inputs limestone and gypsum.
- To compensate for this decrease, an increase in the use of substitutes of the same size (weight) was estimated, while keeping 2017 shares of single materials in overall substitute weight steady (e.g. in 2017, the share of fly ash in overall substitutes in the Austrian cement production was 9%, to be kept constant, while overall use of substitutes is forecast to increase by 19.5%).
- Sand & gravel will remain essential to the production of concrete from cement. It is therefore assumed that their share is going to move in parallel to overall production of cement.

There are several limitations to these assumptions, which are discussed here and will be reflected in the scenario-building section. First, in Germany, the share of recycled glass has decreased over the last years, rather than increased. A potential explanation is that Germany is already quite developed in the use of recycling material in glass production. In the scenario section, a scenario with a lower share of recycled glass will therefore be introduced.

Second, the assumption that cement production remains constant is a strong one, and the actual development could deviate into both directions: On the one hand, the European Non-metallic Minerals industry, and especially the energy-intensive production of cement is subject to strong international competition, given that cement is a standardised product and can therefore easily be produced in countries outside of the EU. On the other hand, worldwide demand for concrete has increased strongly over the last decades, and might increase another 12 to 23% by 2050, according to IEA 2018a, with Europe potentially contributing to this increase. The scenario section will therefore reflect these potential development paths.

6.4.2. Results

As displayed in figure 6.4.1, overall electricity consumption in the Non-metallic Minerals sector is forecast to decrease, by -10% (-0.23 Mtoe) through 2050. Germany is bound to decrease its consumption by -0.5 Mtoe by 2050, due to increased levels of recycled glass used. France is taking the lead in terms of electricity consumption, despite decreasing its electricity demand by -0.1 Mtoe (-14%). Austria, driven by increased electrification (i.e. investment in assets), increases its electricity consumption by 0.25 Mtoe (+145%). Belgium and the Netherlands increase their electricity consumption by 43% (0.1 Mtoe) and 15% (0.02 Mtoe), respectively.

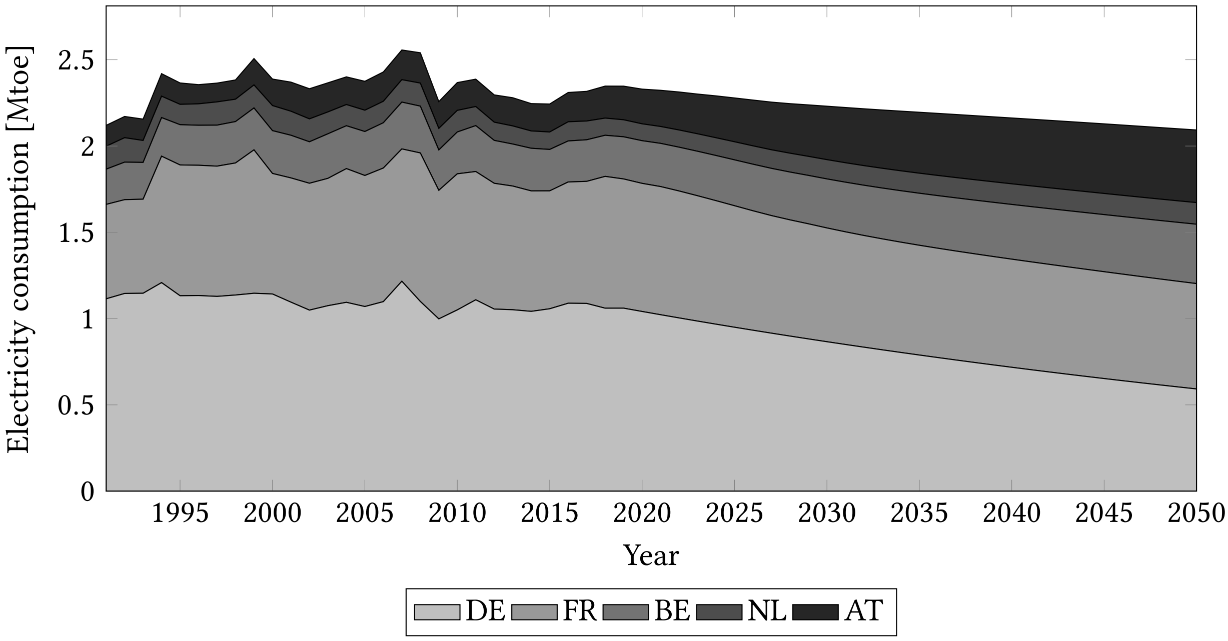

Figure 6.4.1.: Forecasting results for electricity consumption Non-metallic Minerals sectors through 2050 in the five countries and total, author's own work

For all countries, the trend is relatively stables, as figure 6.4.2 shows. Towards mid-century, the decrease in France tends to dissolve. At the same time, the steep increase in Austria flattens out towards 2050.

The strongest driver for decreased electricity demand is a decrease in use of the energy-intensive raw material limestone, potentially to be replaced by less intensive substitutes. The increased usage of recycled glass, reducing electricity consumption, plays an important role as well.

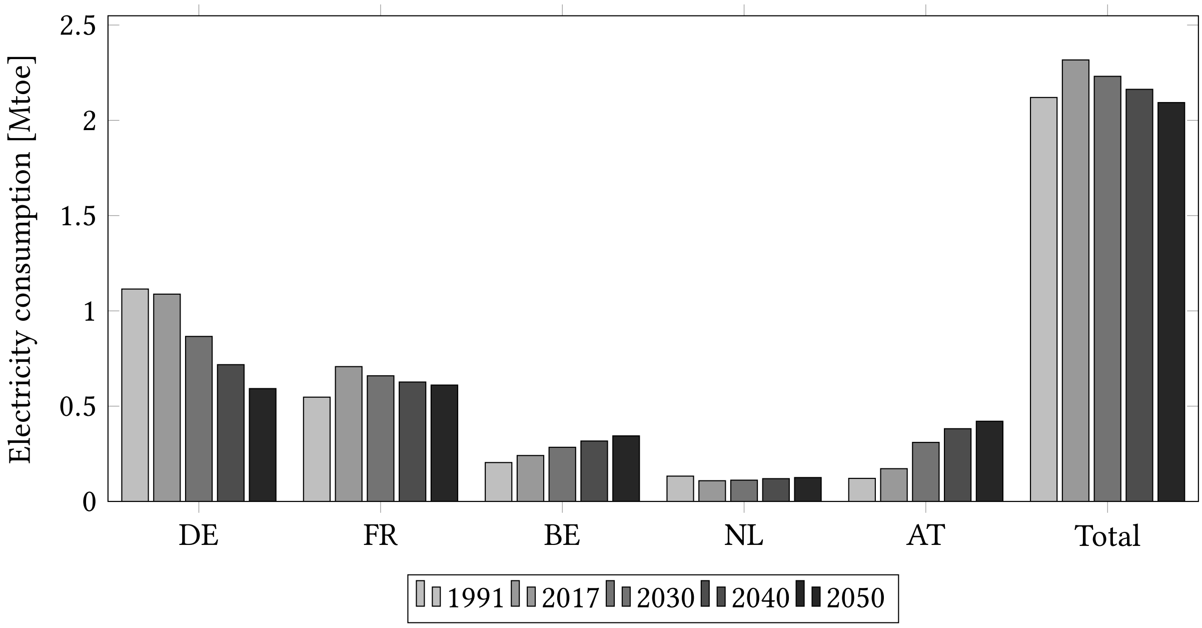

Figure 6.4.2.: Forecasting results for electricity consumption Non-metallic Minerals sectors through 2050 in the five countries and total for milestone years, author's own work

Investment into machines and electrification are driving the opposing effect, particularly in Austria, that is leading the technological change in the Non-metallic Minerals sector in Europe.

Indicator	**Change 2017 - 2050 [Mtoe]**
Assets	0.17
Sand & gravel	0.03
Time	0.01
Gypsum	-0.01
Substitutes	0.00
Hours worked	-0.08
Recycled glass	-0.18
Limestone	-0.19
Total	**-0.22**

Table 6.4.1.: Absolute impact of changes in input variables on total electricity consumption, 2017 vs. 2050, author's own work

Note that the assumptions made on the development of input variables are strong. New technologies such as completely electrified cement production, alongside lower increases of recycled glass consumption can potentially increase electricity consumption significantly. While generally an electrification trend of existing installations can be observed, the macroeconomic pressure and use of less electricity-intensive raw materials decrease overall industrial activity and thus - directly and indirectly - electricity consumption.

6.5. Summarised results

Total electricity demand in the five countries and four sectors analysed in this thesis is forecast to increase slightly by 0.4% (0.1 Mtoe) through 2050. The development for specific countries and sectors looks however very different from this, as this section shows.

6.5.1. Results by country

While Austria is expected to experience an increase of 30% (0.4 Mtoe) in electricity consumption, France is forecast to decrease its demand by -24% (-1.2 Mtoe). The model results further suggest that Germany will experience the strongest absolute increase (0.9 Mtoe, +8%), Belgium will increase its consumption by 0.1 Mtoe (+6%) and the Dutch demand will decrease (-0.2 Mtoe, -11%). Figure 6.5.1 shows the absolute development of electricity consumption by country as predicted by the model.

The significantly different development in the specific countries could be due to their current structure. In 2018, the manufacturing sector in France contributed only 11% to total gross value added, according to data from Eurostat 2020. This is the lowest share among the five countries, while Germany, with a contribution of 23%, is clearly more reliant on the industrial sector. Potentially, this enables France to switch away from industrial production, especially for products that can easily be standardised, so production can be externalised, and the finished products imported. Note that France is expected to experience the most significant decrease in electricity consumption in the Base Metals sector.

The development described above is not linear, as figure 6.5.2 shows. Total demand, driven by Germany, increases from 2017 to 2030, then falls slightly (while German demand stagnates) until 2040, and increases again through 2050.

6.5.2. Results by industry

The strongest gainer among the industrial sub-sectors is the Chemicals sector, increasing its electricity demand by 8% (0.8 Mtoe). On the other hand, the Non-metallic Minerals sector is forecast to decrease its demand by -10% through 2050 (-0.2 Mtoe). Base Metals (-0.2 Mtoe, -4%) and Pulp & Paper (-0.2 Mtoe, -6%) are forecast to decrease their energy consumption as well, as figure 6.5.3 shows.

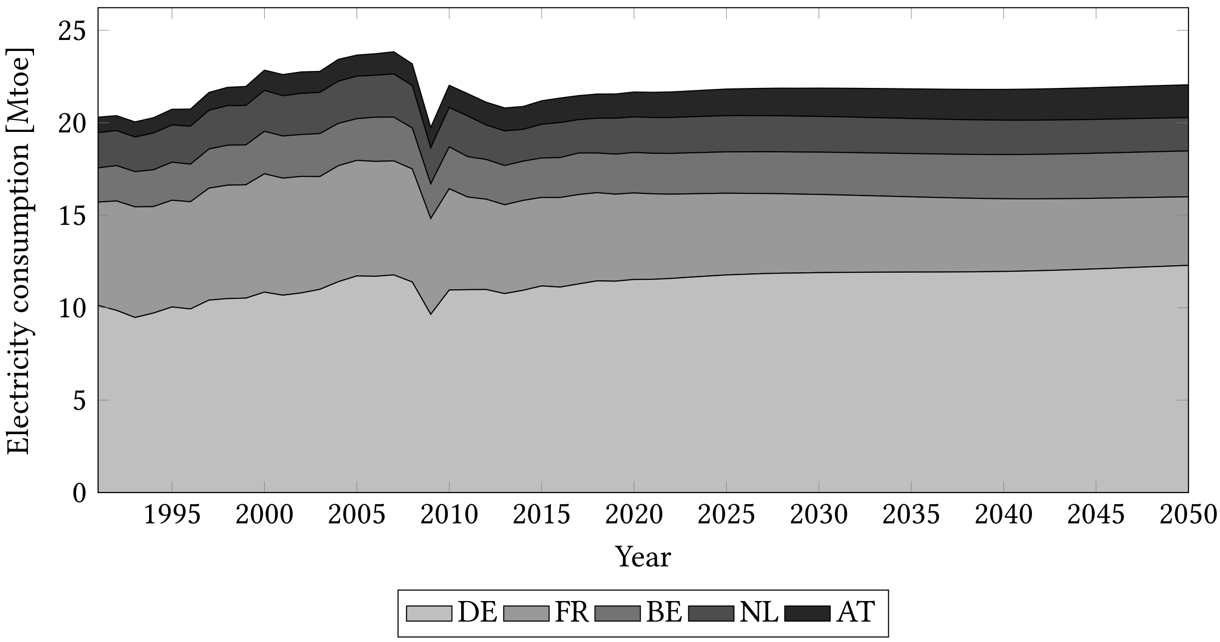

Figure 6.5.1.: Forecasting results for electricity consumption for the industrial sectors by country through 2050, author's own work

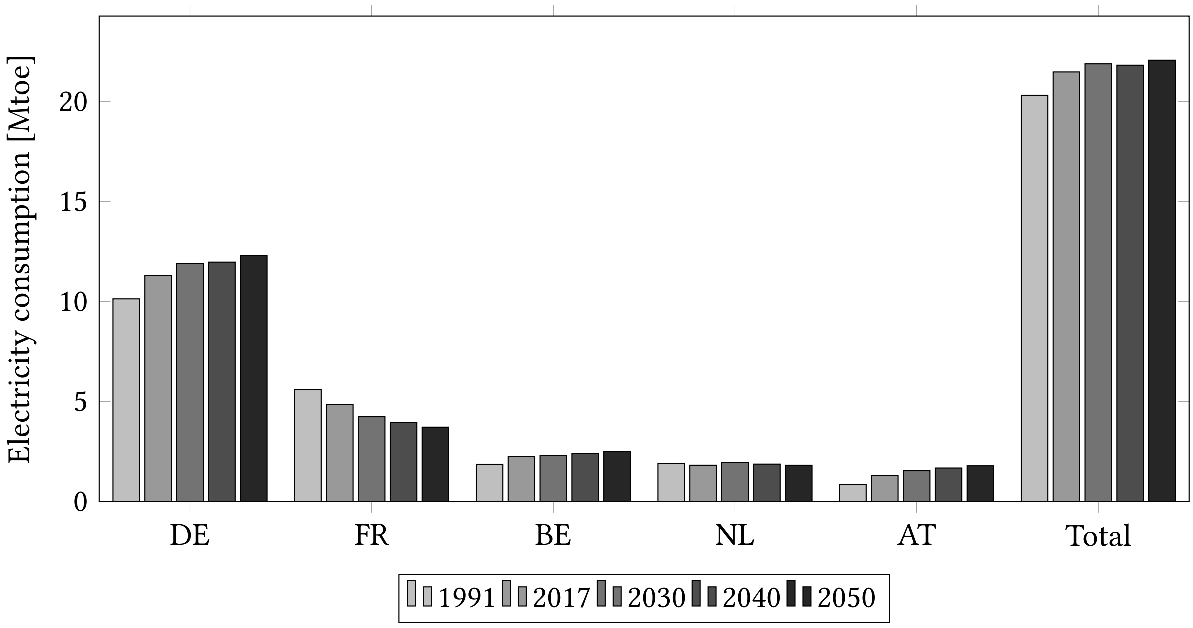

Figure 6.5.2.: Forecasting results for electricity consumption for the industrial sectors by country through 2050 for milestone years, author's own work

Interestingly, the Chemicals sector is the one with the most diverse value chain, and also the one that, between 2018 and 2050, is going to be the subject of more than 55% (€ 816bn, 2015 prices) of the total investment (€ 1,494bn) into any of the four sectors, according to data from OE 2020. One possible explanation for this is the commitment of the countries, to keep high-quality (and thus high-profit) industries within the EU, whereas the production of other products, such as steel or cement, could be shifted to less economically developed regions of the world.

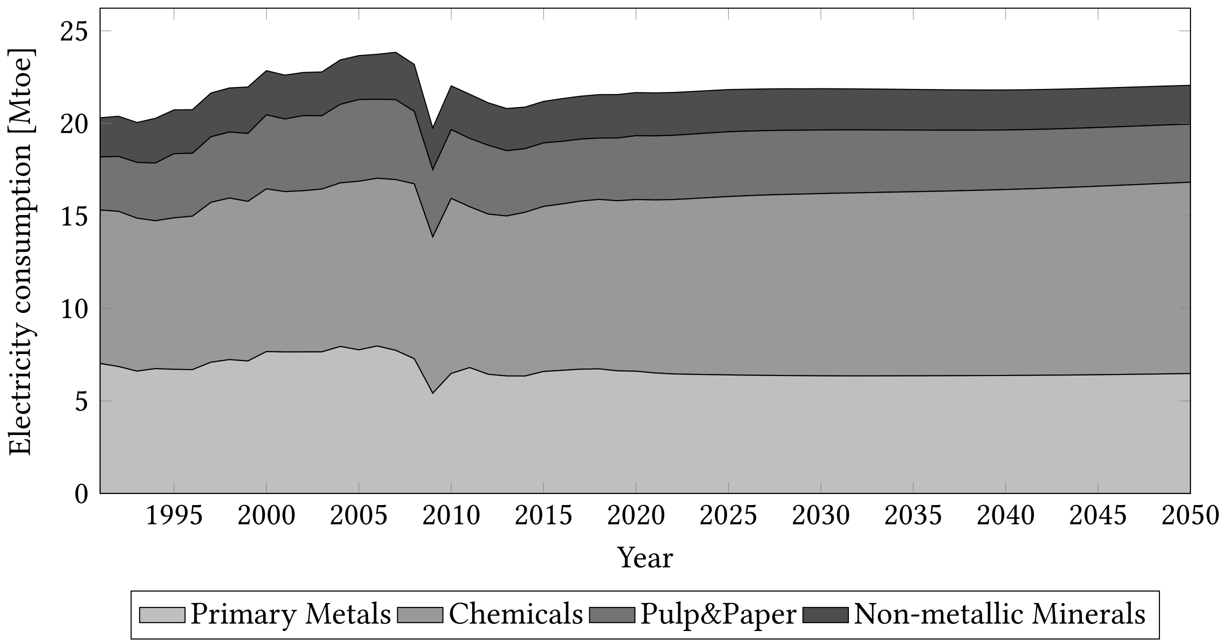

Figure 6.5.3.: Forecasting results for electricity consumption for all countries by industrial sector through 2050, author's own work

Again, the development is not steady for all sectors. While the Base Metals sector first decreases its consumption to 2030, demand slightly increases afterwards. The Chemicals sector is the only sector to experience relatively steady growth through 2050, as per figure 6.5.4.

With regards to the main drivers, one central message for sure is that labour input will keep on being substituted by automated processes, driving electricity demand, as suggested by table 6.5.1. Raw materials on the other hand have, in total, a negligible effect on demand. Note that this is true for the total figure only, and depends to a large extent on the sector and specific material included in the model setup.

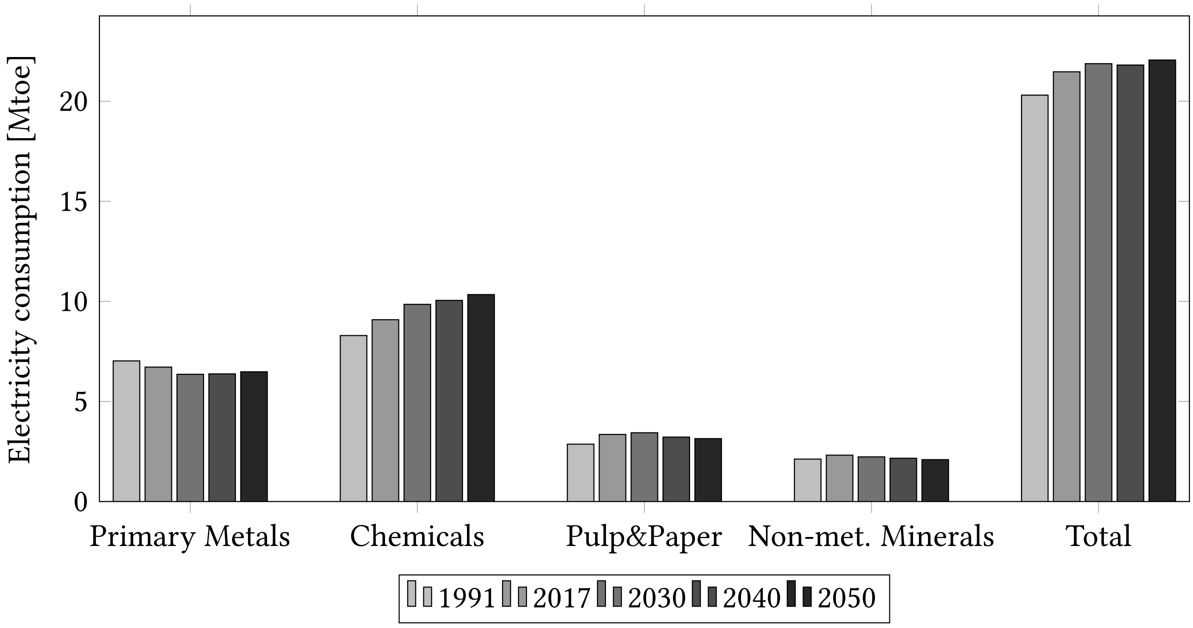

Figure 6.5.4.: Forecasting results for electricity consumption for all countries by sector through 2050 for milestone years, author's own work

Indicator	**Change 2017 - 2050 [Mtoe]**
Assets	1.10
Hours worked	-0.59
Total raw materials	-0.01
Time	0.05
Total	**0.55**

Table 6.5.1.: Absolute impact of changes in input variables on total electricity consumption, all countries and industries, 2017 vs. 2050, author's own work

7. Scenarios

The assumptions fed into the forecast of course are not a given, and depending on macroeconomic factors, political measures and technology development, the results of the forecast are subject to uncertainty. Therefore, apart from the *Base case (base)*, four scenarios were implemented, describing potential pathways based on a variable set of assumptions.

7.1. Scenario description

The four scenarios are based on assumptions on political measures and electrification:

- The *Electrification (elec)* scenario describes a pathway aiming to increase the share of electricity in total energy demand, while improving energy efficiency and supporting the development of renewable energy sources.
- The *Low Ambition (low)* scenario reflects the Business as Usual pathway, with no increased ambition towards climate neutrality and stagnating investment into less carbon-intensive technologies.
- The *Max (max)* scenario combines all effects driving electricity demand from the Base case, and the Electrification and Low Ambition scenarios described above. For instance, the use of scrap glass in the Non-metallic Minerals industry decreases electricity demand, but is expected to increase in the Electrification scenario, thus decreasing expected electricity consumption. In the Max scenario, the share of recycling glass in total glass production is therefore assumed to decrease.
- The *Min (min)* scenario reflects the combination of all potential pathways decreasing electricity demand, equivalent to the Max scenario.

Table A.4.1 in the annex provides an overview of the changes to the base case assumptions made in order to model the scenarios. It includes both reasoning for the assumption, and quantification of the assumed variation. This approach is based on the methodology presented by Gausemeier and Plass 2014.

7.2. Scenario results

7.2.1. Overview of results for all sectors and countries

As per figure 7.2.1, the Base case is showing the most stable development, with a Compund Annual Growth Rate (CAGR) of +0.05%. The Low Ambition scenario moves very close to the base case, with a CAGR of ±0.0%. The electrification scenario shows a moderate growth of +0.47% annually. In the Max scenario, the CAGR is (naturally) the highest (+0.90%). Finally, the Min scenario shows negative growth of -0.41% per year.

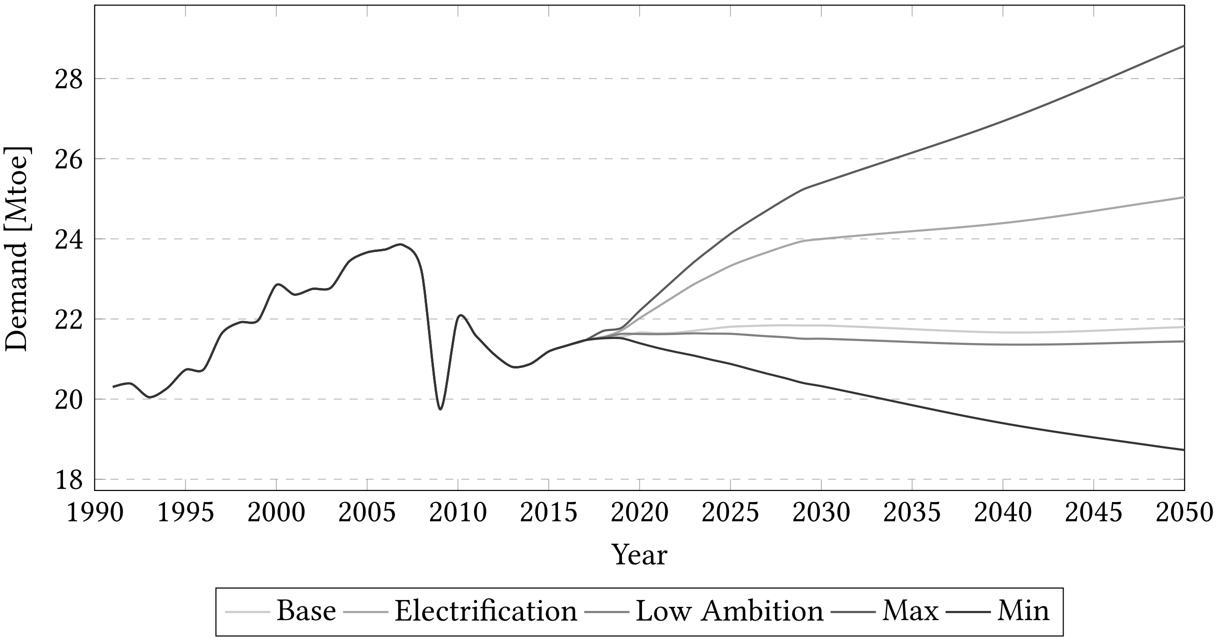

Figure 7.2.1.: Electricity consumption by scenario, total of all countries and sectors, author's own work

It becomes evident that the two-sided effects in the Low Ambition scenario, as compared to the Base case, yield a very similar development in overall electricity consumption. For some sectors, such as the Chemicals sector, the decrease in investment assumed for the Low Ambition scenario is balanced by an increase in working hours, while raw materials have a negligible effect. As a consequence, the CAGR in both scenarios for the overall Chemicals sector is almost the same, as figure 7.2.2 shows. The Non-metallic Minerals industry, on the other hand, shows a stronger CAGR in the Low Ambition scenario, due to increased material consumption. Finally, the Pulp & Paper sector shows a stronger decrease in electricity consumption in the Low scenario.

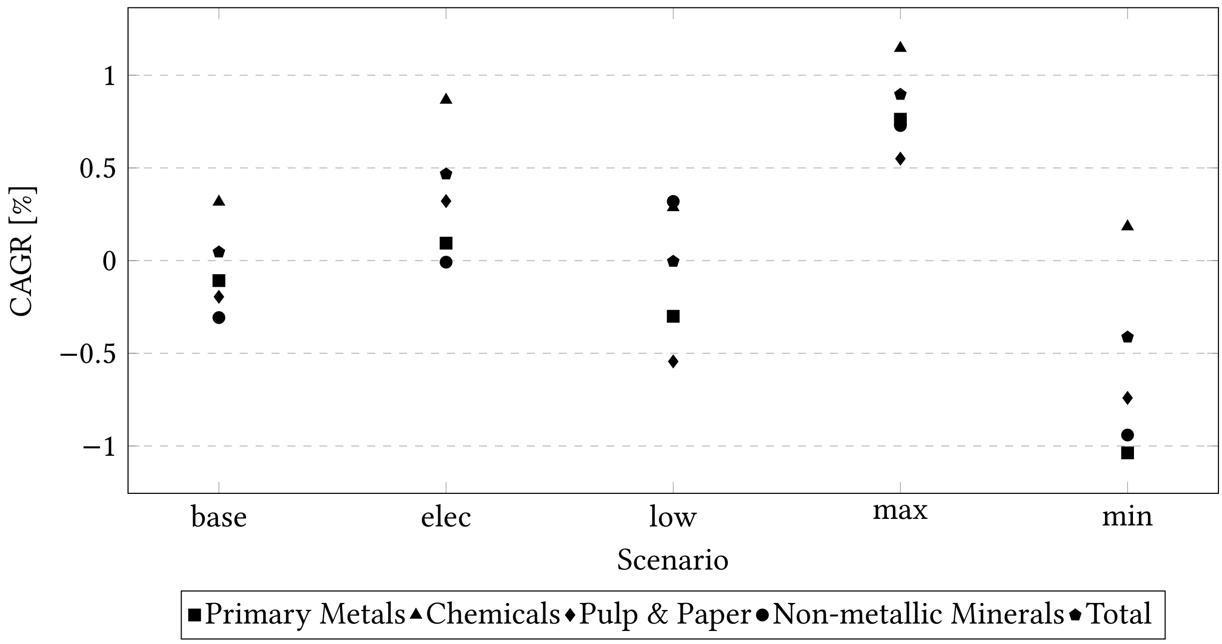

Figure 7.2.2.: CAGR by sector and and scenario, all countries, author's own work

7.2.2. Exemplary results

While the overall results can be used to reach a deeper understanding for the development pathways in the different sectors, they differ quite significantly in terms of both direction and interpretation for the individual countries. This will be illustrated at the example of different models and scenarios in the following.

Primary Metals - DE vs. NL

The assumptions in the scenarios are based on the absolute effect of a variable on total electricity consumption. E.g., in the Primary Metals sector, assets have an overall strongly negative effect on electricity consumption, as shown in figure 5.5.1. For the individual countries, however, this is not necessarily true. The German model on the one hand suggests a negative influence, but in the Netherlands, the coefficient is positive, suggesting that electricity demand increases when assets are increased. This, of course, is due to the nature of the model, as it takes into account historical data to fit the model. Countries for which no steel is produced in EAFs, no negative impact could be observed - so the coefficient is positive.

In the scenario building, this leads to difficulties in building of the scenarios. Of course, the Netherlands could switch their steel production from OBFs to EAFs. Supposedly, as is the case for Germany, the EAFs would be significantly less capital-intensive than OBFs, and thus assets would decrease. Given the positive coefficient of assets, this would lead to a *decrease* rather than an *increase* in electricity consumption.

This effect can be observed in the results of the scenarios. Given that assets are assumed to decrease from the Low Ambition to the Base to the Electrification scenario, electricity demand increases by 0.58 Mtoe from the low to the base, and by 0.92 Mtoe from the base to the elec scenario because of the decrease in assets in Germany, as figure 7.2.3 shows.

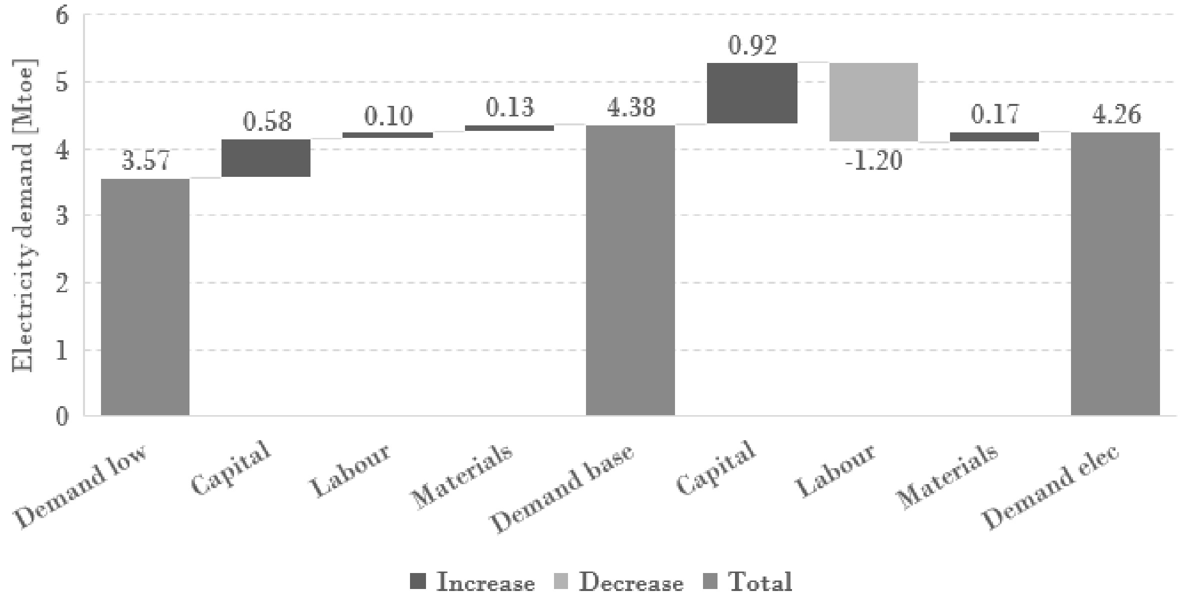

Figure 7.2.3.: Electricity demand by German Base Metals sector in 2050 by scenario, and breakdown of effects by input, author's own work

Given the positive coefficient of assets in the Netherlands however, the effect is reversed, as figure 7.2.4 shows - electricity demand decreases from the low to the base to the elec scenario, driven by the decrease in assets. This is a weakness of the approach chosen in this thesis; naturally, the Netherlands could switch their production to EAFs just like Germany, only that, in their case, the model would calculate a decrease in electricity consumption, which would not be the case. On the overall level, due to the higher relative weight of the countries such as Germany, the effect of this weakness is negligible.

Nonetheless, this effect was mitigated in the setup of the min and max scenarios, to allow for a more realistic picture of future pathways in the Netherlands, but in other countries as well. As the min and max scenarios include all effects decreasing (min) or increasing (max) electricity demand, demand is the lowest in the min scenario, and the highest in the max scenario. In the Dutch case this means that for the max scenario, the pathway leading towards maximum assets in 2050 (i.e. the "low" pathway) was chosen.

As figure 7.2.5 shows, this results in electricity demand in the max scenario equalling demand in the low scenario (likewise min scenario equals elec scenario). In future research, an alternative option could be the introduction of a new sensitivity to future changes, e.g. by assuming a similar sensitivity in the Netherlands as in other countries.

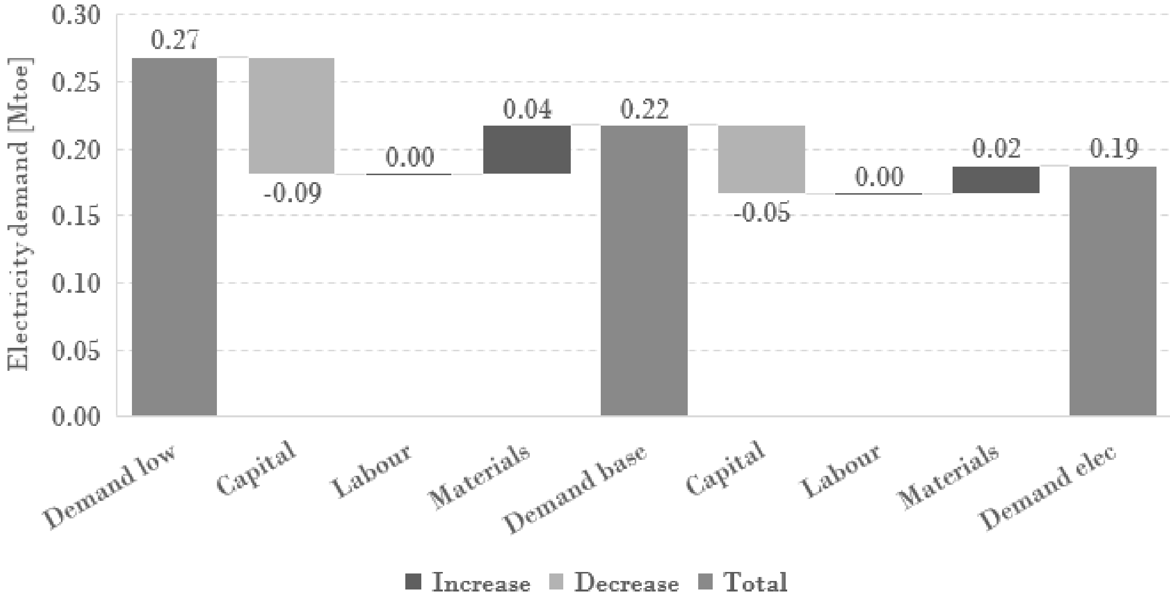

Figure 7.2.4.: Electricity demand by Dutch Base Metals sector in 2050 by scenario, and breakdown of effects by input, author's own work

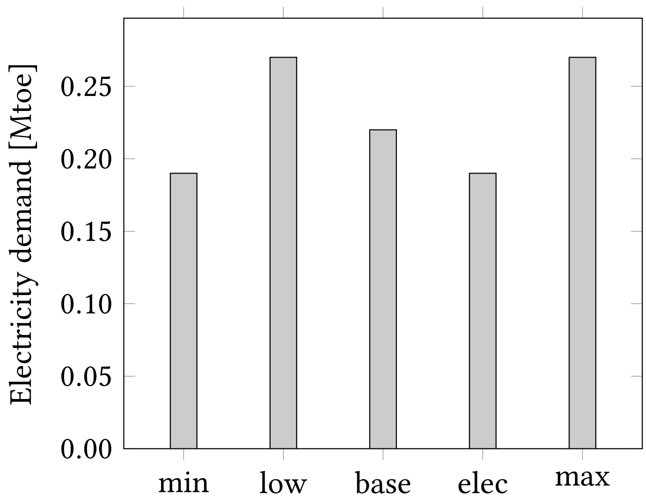

Figure 7.2.5.: Dutch Base Metals electricity consumption in 2050 by scenario, author's own work

Pulp & Paper Austria

The Electrification scenario is not necessarily the scenario forecasting highest electricity demand among the low, base and elec scenarios, as the example of the Austrian Pulp & Paper sector shows. As per figure 7.2.6, electricity demand is actually the highest in the Base scenario. But due to a decrease in hours worked in the comparison of the two scenarios (-24% in 2050 in the elec scenario compared to the base scenario), electricity demand decreases by 0.03 Mtoe in 2050 - despite an increase in assets and raw materials.

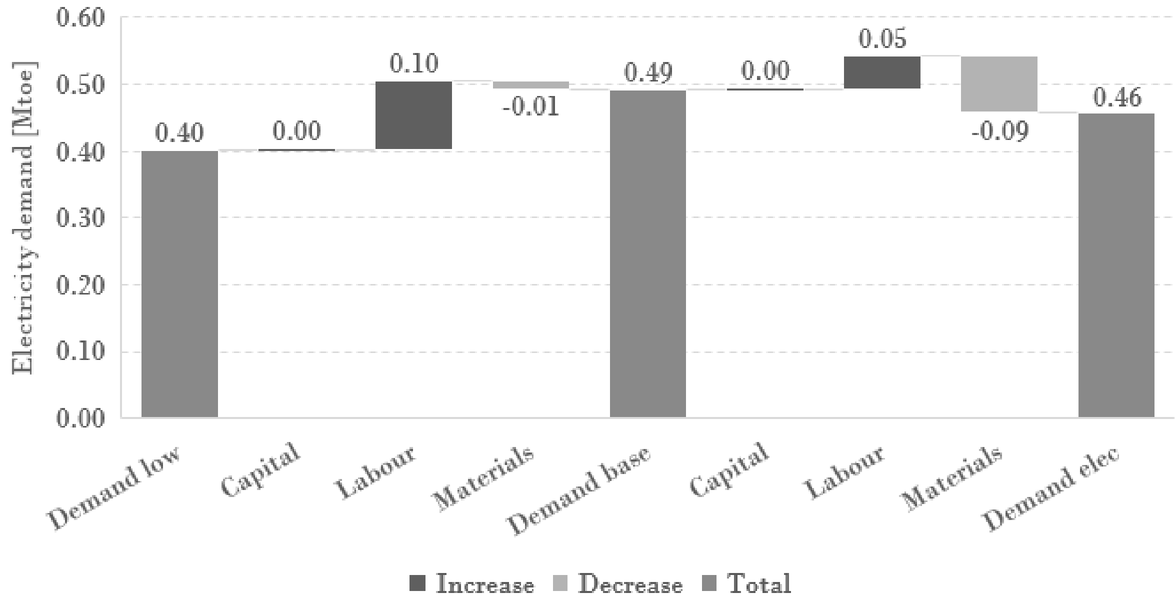

Figure 7.2.6.: Electricity demand by Austrian Pulp & Paper sector in 2050 by scenario, and breakdown of effects by input, author's own work

This is due to the approach chosen for the calculation of hours worked in the Electrification scenario. The base forecast (based on Eurostat population data) was taken as a starting point, and the overall CAGR was applied to the individual countries. In this case, the *overall* decrease of -2.53% for all five countries assumed in the base forecast was applied to the countries *individually*. In the case of Austria, this resulted in a -24% lower figure for hours worked in 2050 compared to the base case.

Once again, this effect is taken into account in the max scenario, in which electricity demand reaches 0.57 Mtoe in 2050, using the low scenario forecast for hours worked, as figure 7.2.7 shows. Alternatively, future analysis could investigate the effect of country-specific CAGRs, to be applied to the country data.

France

Out of the five countries, France - forecast to decrease its electricity consumption by -24% between 2017 and 2050 in the Base scenario - sticks out due to this significant decrease. Breaking down the decrease by factor, it becomes apparent that all inputs, capital, labour and raw materials, contribute to the overall decrease (capital -0.36 Mtoe, labour -0.46 Mtoe, raw materials -0.35 Mtoe). Labour, being the strongest driver for the trend, is assumed with very different pathways in the different scenarios, which has implications for the results in the scenarios, as shown in figure 7.2.8.

The basic methodology applied to forecast hours worked implies decreases in the range of -58% to -62% for all four sectors in France - by far the largest overall decreases assumed for all

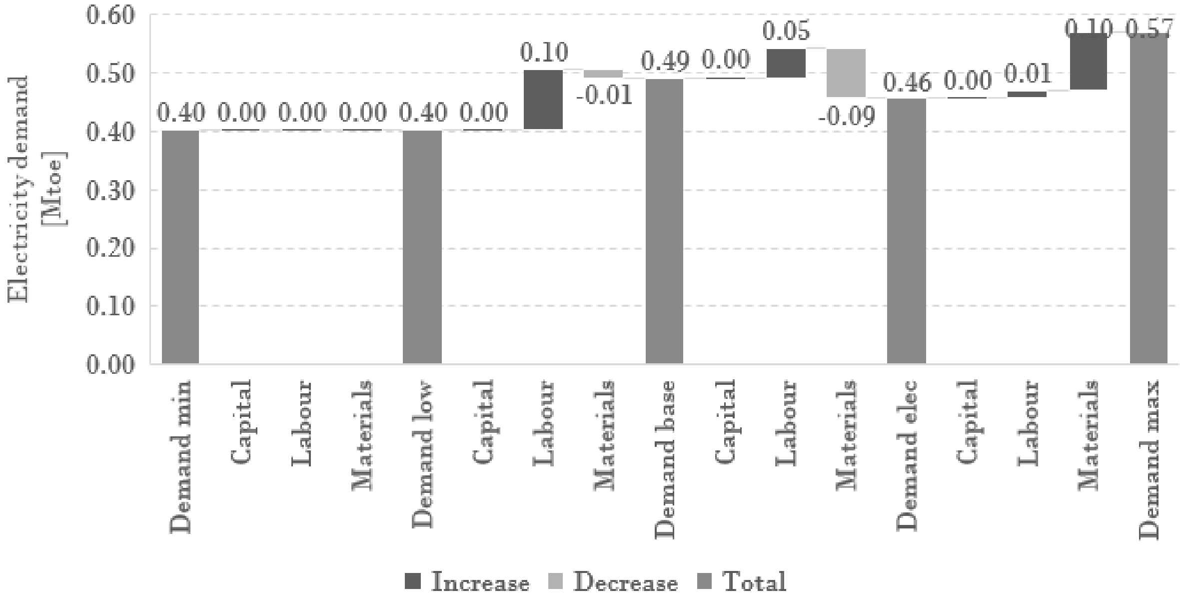

Figure 7.2.7.: Electricity demand by Austrian Pulp & Paper sector in 2050 by scenario, including max and min scenario, and breakdown of effects by input, author's own work

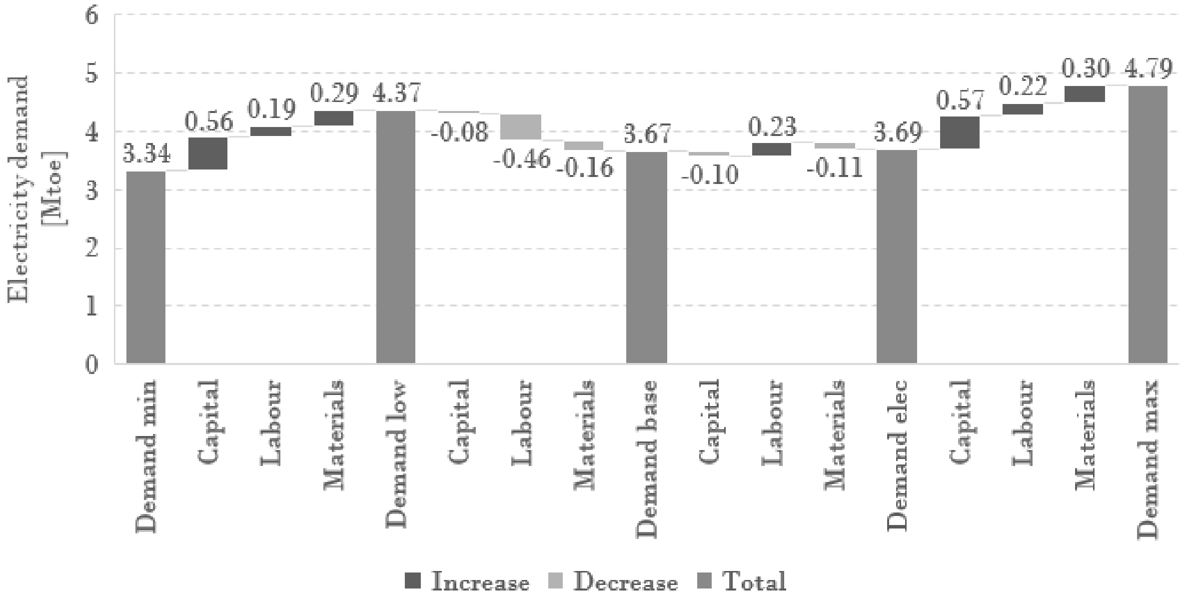

Figure 7.2.8.: French industrial electricity demand in 2050 by scenario, and breakdown of effects by input, all sectors, author's own work

countries. Consequently, the assumption of a stagnation of working hours, as applied in the Low Ambition scenario, has a significant effect on overall results. Therefore, in the case of France, the Low Ambition scenario implies the second-to-largest electricity demand by 2050, behind the Max scenario. Note however that even in the Max scenario, France is forecast to decrease its electricity consumption by -0.05 Mtoe in 2050 compared to 2017 (-1%).

The example shows that a single input can be a strong driver of electricity consumption, if significant changes are assumed, as is the case for labour in France. This could be mitigated by implementing an sector and country-specific approach to forecast future working hours, which would have exceeded the scope of this thesis. Nonetheless, given the results found in the different scenarios, it appears that the French industrial sector will decrease its electricity consumption in any case.

Summary

The examples above show that the methodology which was applied in this thesis allows for a very detailed analysis of the individual effect of specific inputs. The effects of varied assumptions in the different scenarios can be quantified. The potentials for improvement discussed above can be used to apply a different approach in the scenario building by changing the methodology the assumptions on future developments of inputs is based on. But even given the present set of scenarios, a wide range of potential pathways was identified and quantified, enabling a sound understanding of the impact of changes in assumptions.

8. Conclusion

This chapter provides a summary of the findings of the present thesis in section 8.1. In section 8.2, the present results will be compared to the EU Reference Scenario to assess the differences in results and approach. Section 8.3 explores the limits of the study, and section 8.4 presents potential for further research based on this thesis.

8.1. Key findings

This thesis suggests two major types of findings: First with regards to electricity consumption, the overall industrial electricity consumption forecast for the countries and sectors in this analysis, summarised in 8.1.1. And second, the contribution to scientific work on both, the analysis of the industrial landscape, and the use of a Cobb-Douglas function to model industrial electricity demand, as presented in 8.1.2.

8.1.1. Industrial electricity demand

The present work presents an in-depth analysis of the dynamics in various European countries and industrial sectors with regards to their electricity consumption. In the Primary Metals industry, the usage of scrap for steel production and the switch from OBFs to EAFs will be a key driver of electricity demand. The Chemicals industry is to a large extent driven by the chloralkali electrolysis, which consumes significant amounts of electricity directly, but also indicates overall industrial acitivity in the Chemicals sector. The Pulp & Paper industry will depend on the use of recycling paper or alternative raw materials. And finally, the Non-metallic Minerals sector is subject to electrification that opposes pressure to externalise production.

As discussed in section 5.5, electricity demand in the four industrial sectors and five countries analysed here is forecast to increase by a total of 3% by 2050. While the Chemicals sector is bound to increase its consumption, all other sectors will experience a more or less significant decrease. This is mainly due to automation and electrification, but, depending on the sector and country, raw materials play an important role as well.

Some countries, such as Austria, are forecast to experience a significant increase in electricity consumption, whereas especially France is set to decrease its industrial electricity consumption by one quarter through 2050. As a main driver, decreased industrial activity was identified, indicated by decreased investment and decreased use of raw materials.

However, particularly the highly profitable Chemicals sector is expected to increase its demand, driven by strong invest and electrification. On the other hand, sectors such as Primary Metals and Non-metallic Minerals will decrease their consumption, partly through efficiency measures, partly through decreased activity and invest.

8.1.2. Scientific contribution

Historically, the Cobb-Douglas function was the tool of choice for economists to model industrial output. This work shows that, if adapted accordingly, the model can serve as a basis to model electricity demand as well, delivering both highly significant results and meaningful insights into industrial dynamics.

A necessary prerequisite for the application of the function is an understanding for the processes in the industries, and the main drivers for electricity demand. This yields outstanding model performances and a quantification of the implications of changes in one of the independent variables for overall electricity consumption. The quantification of the basic dynamics allows to build a forecast for industrial electricity demand in the five European countries at the core of this analysis, which can be extended to additional countries and industries.

8.2. Benchmarking with the EU Reference Scenario

In 2018, the EC published its long-term vision, including eight scenarios for pathways towards climate neutrality in 2050, ranging from −80% to −100% CO2 emission reductions (EC 2018). The scenarios indicate a range of +12% to +59% increased electricity consumption in the industrial sector. This compares to a range of −13% to +34% suggested by the present model results. Note however, that there are significant differences in both methodology and scope of the studies.

First and foremost, the EU Reference Scenario includes all 28 countries, thus a wider range of different economies. Second, its methodology is based on the implementation of political measures and quantification of their effects. And finally, the Reference Scenario includes effects of emerging technologies, such as hydrogen, which have a non-negligible effect on the industrial electricity demand.

While the EU provides an accompanying document with more detailed information on the split between different countries, this date does not reveal the split of electricity consumption between different sectors or fuels, i.e. only overall electricity consumption by country, and total energy consumption by the industrial sector of a country.

The Base case proposed in the present work suggests a CAGR of +0.1% between 2020 and 2030, and −0.0% thereafter. This compares to a CAGR of overall electricity consumption of +0.5% from both 2020 to 2030, and 2030 to 2050 for all sectors in the Reference Scenario. However, for the industrial sector, the Reference Scenario suggests a CAGR of −0.9% from 2020 to 2030 and −0.3% thereafter. Assuming that a fuel switch from conventional fuels such as coal and oil is going to materialise between today and 2050, the results are in line with the base case of this work. Depending on the scale of the fuel switch, the range can expected to be covered by the proposed scenarios.

8.3. Limits of the work

While the results of this work provide a deep insight into the European industrial landscape, there are non-negligible limits to this work, exceeding the geographical and sectoral limitations discussed in chapter 2.

8.3.1. Disruptive innovation

Due to the very nature of the model used in this work, it remains difficult to evaluate the implications of disruptive innovation, caused by the introduction of a new technology in a specific sector.

Base Metals
An example for such innovation that might materialise at some point between now and 2050 is hydrogen steel, which was mentioned in section 5.1.4. The introduction of hydrogen steel could potentially replace EAFs, thus reducing direct electricity consumption in the steel sector (while on the other hand increasing the demand for electricity to produce hydrogen). For the production of aluminium, the introduction of inert anodes has the potential to further increase electricity consumption. (EC 2018)

Chemicals
An important limit of the analysis in the Chemicals sector is the production of hydrogen. This thesis explicitly does not include an outlook on future production of hydrogen as a means to store energy, as this was considered to be part of the energy supply rather than the demand side. Hebling et al. 2019 in their study forecast a potential bandwidth of 800 - 2,250 TWh of hydrogen demand in Europe in 2050, which compares to 325 TWh in 2015 (FCH 2019).

Pulp & Paper
One trend that in part has been observed in the past already is the electrification of production

in the Pulp & Paper industry. However, technical innovations such as electrode boilers could replace conventional thermal heating in the industry, but are not yet economical and waiting to exceed the prototype stage (Schaffrath 2020).

Non-metallic Minerals

There are two possible downside risks that might significantly change the results of this thesis: Replacing concrete by renewable materials, such as wood (Hildebrandt, Hagemann, and Thrän 2017); and potential production shift to non-EU countries, especially in the case that no carbon border tax should be introduced in Europe (CEMBUREAU 2020). Both, replacing concrete as a construction material and shifting cement production away from Europe could potentially significantly decrease industrial activity in the Non-metallic Minerals sector and thus decrease electricity demand.

On the other hand, the Swedish utility Vattenfall and Cementa AB, a Swedish subsidiary of Heidelberg Cement, in 2017 launched a project to investigate the feasibility of producing electrified cement, using electricity as only source of energy in the production process, thus reducing the use of carbon-intensive fossil fuels. The project is yet in the pilot phase, but could see a first fully electrified cement production plant before 2030. (Bioenergy International 2019, Cementa AB 2020)

8.3.2. Macroeconomic events

Situations such as the COVID-19 pandemic in 2020 show very clearly that all forecasts are prone to macroeconomic events such as an economic crisis. According to BDEW 2020, electricity demand in Germany decreased by -13% in April 2020 compared to March. In France, the decrease was even stronger (-24%). Industrial production in ETS-covered installations decreased by -27.6% in April 2020, compared to April 2019 as per the Eurostat industrial production index (Eurostat 2020).

The model proposed in this thesis is not designed to forecast peaks in electricity consumption - which is the reason why the year of the financial crisis 2009 was excluded from the training data set. On the contrary, the model tends to flatten peaks in consumption by including data that is not subject to high fluctuation, such as fixed capital (assets) and the number of workers (for the forecast). This on the other hand enables the model to reflect more general trends in electricity consumption and their long-term effects.

8.3.3. Choice of independent variables

The selection of the independent variables to be included in the model, especially with regards to raw materials, is not always straight forward. In order to reduce the number of inputs and thus model complexity, some variables were left out of the model despite being statistically significant, if their overall contribution was marginal. Further, variables that were statistically insignificant despite being important from a theoretical perspective were excluded. As the case of the Austrian Base Metals sector shows (s. 5.1.3), a balance between significance, logic and model performance had to be found. Given that especially for smaller countries the database is insufficient to set up long-term regression models, including all variables for all countries would have been neither possible nor sensible.

8.3.4. Countries and sectors exceeding the scope of the work

For the sectors exceeding the scope of this work, it seems reasonable to assume that the present results, representing almost two thirds of industrial electricity demand in the five countries, can be scaled to the whole economy, as almost all sectors out of the scope are either up- or down-stream along the industrial value chain from one of the sectors within the scope of this work (e.g. Wood industry is up-stream for Pulp & Paper production).

However, with regards to other European countries, this analysis cannot be used to scale overall electricity demand. The industrial sectors in the other European countries differ (partially significantly) from the countries analysed here.

8.4. Perspectives

Most notably, the scope of this study can be extended to further countries and industries. In this regards, it is important to note that a reliable database is a prerequisite for building a meaningful forecast. This, for some industries and countries, could cause a necessity to change input parameters (e.g. use of production output instead of raw materials). Further, sectors that are very diverse, such as the Metals Products sector, sometimes prove difficult to split into their constituents. This has implications for the ability to build meaningful models. Future research could therefore focus on how to model these very diverse sectors.

As stated above, the model used here is not able to forecast the implications of disruptive technological changes. Therefore, the emergence of new technologies, such as hydrogen steel or electrified cement production, are not quantified in the results. Future research could therefore quantify these trends, and combine the results of this analysis with the present work, to build a more resilient forecast. In this context, it should once again be pointed out that hydrogen as a means to store energy was not part of this analysis, as it was judged to belong to the energy supply rather than the demand side. As discussed above, the production of hydrogen could potentially significantly increase electricity demand and should therefore not be neglected in a comprehensive forecast of electricity demand.

From the macro perspective, electricity is only one part - even though one with increasing importance - of the overall industrial energy demand side. Future research could therefore use the approach proposed in this study, and apply the Cobb-Douglas function to model either total energy demand, or, better, the demand for specific fuels, such as coal, gas or biomass.

Finally, the probably most coherent way of modelling industrial energy or electricity demand is modelling the specific industrial installations, as this would allow to implement the effects of new technologies, investments in efficiency, or even plant closures more directly. This however brings with it not only the problem of a high invest of time and effort, but also of the scarcity of data on specific production sites and will therefore remain difficult to achieve in the scientific context in the foreseeable future. The approach chosen in the present work is therefore considered the most comprehensive and feasible one.

Bibliography

Adams, F. Gerard and Yochanan Shachmurove (May 2008). "Modeling and forecasting energy consumption in China: Implications for Chinese energy demand and imports in 2020". In: *Energy Economics* 30.3, pp. 1263–1278. ISSN: 01409883. DOI: 10.1016/j.eneco.2007.02.010.

Adeyemi, Olutomi I. and Lester C. Hunt (July 2007). "Modelling OECD industrial energy demand: Asymmetric price responses and energy-saving technical change". In: *Energy Economics* 29.4, pp. 693–709. ISSN: 01409883. DOI: 10.1016/j.eneco.2007.01.007.

Austropapier (2019). *Statistiken 2018 - Austropapier*. URL: https://www.austropapier.at/daten-fakten/statistiken-2018/.

Bazzanella, Alexis and Florian Ausfelder (June 2017). *Low carbon energy and feedstock for the European chemical industry*. Tech. rep. Frankfurt/Main: DECHEMA.

BDEW (June 2020). *Corona und die Energiewirtschaft: Was jetzt passiert*. URL: https://www.bdew.de/energie/corona-und-die-energiewirtschaft-fakten-und-argumente/.

Beneki, Christina and Emmanuel Sirimal Silva (2013). "Analysing and Forecasting European Union Energy Data". In: *International Journal of Energy and Statistics* 01.02. ISSN: 2335-6804. DOI: 10.1142/s2335680413500099.

BGS (2020). *World Mineral Production*. Tech. rep. British Geological Society.

Bioenergy International (Jan. 2019). "Vattenfall and Cementa proceed towards climate neutral cement with CemZero | Bioenergy International". In: URL: https://bioenergyinternational.com/heat-power/vattenfall-and-cementa-take-the-next-step-towards-a-climate-neutral-cement.

Blanco, A., R. Miranda, and M.C. Monte (Nov. 2013). "Extending the limits of paper recycling - improvements along the paper value chain". In: *Forest Systems* 22.3, p. 471. ISSN: 2171-9845. DOI: 10.5424/fs/2013223-03677. URL: http://revistas.inia.es/index.php/fs/article/view/3677.

BMF (2020). *Bundesfinanzministerium - AfA-Tabellen*. URL: https://www.bundesfinanzministerium.de/Web/DE/Themen/Steuern/Steuerverwaltungu-Steuerrecht/Betriebspruefung/AfA_Tabellen/afa_tabellen.html.

BV Glas (2019). *Annual Report 2018*. Tech. rep. BV Glas.

Cattant, François, Didier Crusset, and Damien Féron (Oct. 2008). "Corrosion issues in nuclear industry today". In: *Materials Today* 11.10, pp. 32–37. ISSN: 13697021. DOI: 10.1016/S1369-7021(08)70205-0.

CEFIC (2013). *European chemistry for growth Unlocking a competitive, low carbon and energy efficient future*. Tech. rep.

CEMBUREAU (Sept. 2013). *The role of Cement in the 2050 Low Carbon Economy*. Tech. rep. Brussels: The European Cement Association.

– (Apr. 2020). *Position Paper: Carbon Boarder Mechanisms*. Tech. rep. Brussels: European Cement Association. URL: www.cembureau.eu.

Cementa AB (2020). *CemZero*. URL: https://www.cementa.se/sv/cemzero.

CEPI (2017). *Investing in Europe for Industry Transformation - 2050 Roadmap to a low-carbon bioeconomy*. Tech. rep. Brussels: CEPI.

– (2020). *Raw Materials consumption Pulp & Paper Europe*. Tech. rep.

Ceylan, Halim and Harun Kemal Ozturk (Sept. 2004). "Estimating energy demand of Turkey based on economic indicators using genetic algorithm approach". In: *Energy Conversion and Management* 45.15-16, pp. 2525–2537. ISSN: 01968904. DOI: 10.1016/j.enconman.2003.11.010.

Chui, F. et al. (2009). "Long-term electricity demand forecasting for power system planning using economic, demographic and climatic variables". In: *European Journal of Industrial Engineering* 3.3, pp. 277–304. ISSN: 17515254. DOI: 10.1504/EJIE.2009.025049.

Cobb, Charles W. and Paul H. Douglas (1928). "A Theory of Production". In: *The American Economic Review* 18, pp. 139–165. DOI: 10.2307/1811556. URL: https://www.jstor.org/stable/1811556.

COPACEL (2018). *Rapport annuel 2017*. Tech. rep. COPACEL.

Cui, Ryna Yiyun et al. (Dec. 2019). "Quantifying operational lifetimes for coal power plants under the Paris goals". In: *Nature Communications* 10.1, pp. 1–9. ISSN: 20411723. DOI: 10.1038/s41467-019-12618-3.

Destatis (2020). *Statistisches Bundesamt Deutschland - GENESIS-Online*.

EC (2012). *Energy roadmap 2050 Energy*. Tech. rep. Brussels: European Commission. DOI: 10.2833/10759. URL: http://europa.eu.

– (July 2016). *EU Reference Scenario 2016 Energy, transport and GHG emissions Trends to 2050*. Tech. rep. European Commission.

– (Nov. 2018). *A Clean Planet for all: A European long-term strategic vision for a prosperous, modern, competitive and climate neutral economy*. Tech. rep. Brussels: European Commission.

– (Dec. 2019). *The European Green Deal*. Tech. rep. Brussels: European Commission. URL: https://sustainabledevelopment.un.org/post2015/transformingourworld.

Echevarria, Cristina (1998). "A three-factor agricultural production function: The case of Canada". In: *International Economic Journal* 12.3, pp. 63–75. ISSN: 1743517X. DOI: 10.1080/10168739800000029.

Enerdata (2020). *Odyssee MURE database*. URL: https://odyssee.enerdata.net/database/.

EPRC (May 2017). *European Declaration on Paper Recycling*. Tech. rep. Brussels: EPRC. URL: www.paperforrecycling.eu.

Eurochlor (2010). *The European Chlor-Alkali industry: an electricity intensive sector exposed to carbon leakage*. Tech. rep. URL: http://www.eurochlor.org.

Eurostat (2018). *Circular material use rate - calculation method*. Tech. rep. Eurostat. DOI: 10.2785/132630. URL: https://ec.europa.eu/eurostat/about/policies/copyright.

– (2019). *RAMON - Classification Detail List*. URL: https://ec.europa.eu/eurostat/ramon/nomenclatures/index.cfm?TargetUrl=LST_NOM_DTL&StrNom=PRD_2019&StrLanguageCode=EN&IntPcKey=&StrLayoutCode=HIERARCHIC.

– (2020). *Database*. URL: https://ec.europa.eu/eurostat/data/database.

FAO (2019). *Recoverd Paper Data 2017*. Tech. rep. Rome: FAO. URL: http://www.wipo.int/amc/en/mediation/rules.

FCH (2019). *Hydrogen Roadmap Europe*. Tech. rep. Brussels: Fuel Cells and Hydrogen - Joint Undertaking. DOI: 10.2843/249013.

Finnish Forest Industries (2020). *Pulp and Paper industry*. URL: https://www.forestindustries.fi/statistics/pulp-and-paper-industry/.

Fleiter, Tobias, Barbara Schlomann, and Wolfgang Eichhammer (2013). *Energieverbrauch und CO2-Emissionen industrieller Prozesstechnologien – Einsparpotenziale, Hemmnisse und Instrumente*. Stuttgart: Fraunhofer Verlag.

Gausemeier, Jürgen and Christoph Plass (2014). *Zukunftsorientierte Unternehmensgestaltung*. DOI: 10.3139/9783446438422.

Glass For Europe (2020). *Flat Glass in a Climate-Neutral Europe*. Tech. rep. URL: www.glassforeurope.com.

Global Cement and Concrete Association (2020). *GNR - GCCA in Numbers*. URL: https://gccassociation.org/sustainability-innovation/gnr-gcca-in-numbers/.

Griffin, James M. and Craig T. Schulman (2005). "Price asymmetry in energy demand models: A proxy for energy-saving technical change?" In: *Energy Journal* 26.2, pp. 1–21. ISSN: 01956574. DOI: 10.5547/ISSN0195-6574-EJ-Vol26-No2-1.

Hauer, Ezra (2015). *The Art of Regression Modeling in Road Safety*. DOI: 10.1007/978-3-319-12529-9.

Hebling, C et al. (Oct. 2019). *Eine Wasserstoff-Roadmap für Deutschland*. Tech. rep. Karlsruhe, Freiburg: Fraunhofer.

Hildebrandt, Jakob, Nina Hagemann, and Daniela Thrän (Oct. 2017). "The contribution of wood-based construction materials for leveraging a low carbon building sector in europe". In: *Sustainable Cities and Society* 34, pp. 405–418. ISSN: 22106707. DOI: 10.1016/j.scs.2017.06.013.

IEA (2018a). *Technology Roadmap - Low-Carbon Transition in the Cement Industry*. Tech. rep. International Energy Agency.

– (Nov. 2018b). *World Energy Outlook 2018*. Tech. rep. International Energy Agency. URL: https://www.iea.org/reports/world-energy-outlook-2018.

Keys, A, M Van Hout, and B Daniëls (2019). *Decarbonisation options for the dutch steel industry*. Tech. rep. URL: www.pbl.nl/en..

Kohlenstatistik (2019). *Statistik der Kohlenwirtschaft e.V.* URL: https://kohlenstatistik.de/downloads/deutschland/.

Kvalseth, Tarald O and Tarald Kvalseth (2018). "Cautionary Note about R^2". In: *The American Statistician* 39.4.

Leisin, Matthias (Aug. 2019). *Energiewende in der Industrie - Potenziale und Wechselwirkungen mit dem Energiesektor - Branchensteckbrief der Glasindustrie*. Tech. rep. Navigant Energy Germany GmbH.

Maytal, B. Z. (Jan. 2006). "Maximizing production rates of the Linde-Hampson machine". In: *Cryogenics* 46.1, pp. 49–54. ISSN: 00112275. DOI: 10.1016/j.cryogenics.2005.11.004.

Moulijn, Jacob A., Michiel Makkee, and Annelies E. van Diepen (2013). *Chemical Process Technology*, pp. 14–14. ISBN: 9781444320251.

MPA (Feb. 2013). *Cement 2050 Strategy*. Tech. rep. London: Mineral Products Association. URL: http://cement.mineralproducts.org.

– (July 2018). *Summary of performance indicators*. Tech. rep. Mineral Products Association Ltd. URL: sustainableconcrete.org.uk/reports.

OE (2020). *Oxford Economics Database*. URL: https://www.oxfordeconomics.com/.

OECD (2020). *OECD Data*. URL: https://data.oecd.org/.

Pilli-Sihvola, Karoliina et al. (2010). "Climate change and electricity consumption-Witnessing increasing or decreasing use and costs?" In: *Energy Policy* 38.5. ISSN: 03014215. DOI: 10.1016/j.enpol.2009.12.033.

Rathe, Liv and Lasse Torgersen (Apr. 2020). *Interview with NorskHydro*.

Saunders, Harry D. (June 2000). "A view from the macro side: Rebound, backfire, and Khazzoom-Brookes". In: *Energy Policy* 28.6-7, pp. 439–449. ISSN: 03014215. DOI: 10.1016/S0301-4215(00)00024-0.

Schaeffer, Helmut A. and Roland Langfeld (2014). *Werkstoff Glas*. Technik im Fokus. Berlin, Heidelberg: Springer Berlin Heidelberg. ISBN: 978-3-642-37230-8. DOI: 10.1007/978-3-642-37231-5. URL: http://link.springer.com/10.1007/978-3-642-37231-5.

Schaffrath, Jan (2020). *Interview with VDP*.

Schumacher, Katja and Ronald D. Sands (July 2007). "Where are the industrial technologies in energy-economy models? An innovative CGE approach for steel production in Germany". In: *Energy Economics* 29.4, pp. 799–825. ISSN: 01409883. DOI: 10.1016/j.eneco.2006.12.007.

Seabold, Skipper and Josef Perktold (2010). "statsmodels: Econometric and statistical modeling with python". In: *9th Python in Science Conference*.

Suganthi, L. and Anand A. Samuel (Feb. 2012). *Energy models for demand forecasting - A review*. DOI: 10.1016/j.rser.2011.08.014.

Sun, J. W. (June 2001). "Energy demand in the fifteen European Union countries by 2010 - A forecasting model based on the decomposition approach". In: *Energy* 26.6, pp. 549–560. ISSN: 03605442. DOI: 10.1016/S0360-5442(01)00021-4.

Tissari, Jukka (2012). *FAO Outlook Study on Sustainable Forest Industries: Opening Pathways to Low-Carbon Economy*. Tech. rep. Rome.

VCI (2020). *Daten und Fakten Energiewende*. Tech. rep.

VDZ (2019). *Umweltdaten der deutschen Zementindustrie Environmental Data of the German Cement Industry (2018)*. Tech. rep. VDZ.

VNP Netherlands (2018). *Papier en Karton - Klaar voor de Toekomst*. Tech. rep. VNP Netherlands. URL: www.vnp.nl.

Von Hirschhausen, Christian and Michael Andres (Apr. 2000). "Long-term electricity demand in China - from quantitative to qualitative growth?" In: *Energy Policy* 28.4, pp. 231–241. ISSN: 03014215. DOI: 10.1016/S0301-4215(00)00014-8.

VOZ (Nov. 2019). *Nachhaltigkeitsbericht 2018/19*. Tech. rep. Wien: Vereinigung der Österreichischen Zementindustrie. URL: www.zement.at.

Wei, Taoyuan (Apr. 2007). "Impact of energy efficiency gains on output and energy use with Cobb-Douglas production function". In: *Energy Policy* 35.4, pp. 2023–2030. ISSN: 03014215. DOI: 10.1016/j.enpol.2006.08.009.

Wettengel, Julian (Nov. 2019). *Thyssenkrupp tests use of hydrogen in steel production to bring down emissions*. URL: https://www.cleanenergywire.org/news/thyssenkrupp-tests-use-hydrogen-steel-production-bring-down-emissions.

Worldsteel (2018). *Steel statistical yearbook 2018*. Tech. rep. Worldsteel. URL: https://www.worldsteel.org/en/dam/jcr:e5a8eda5-4b46-4892-856b-00908b5ab492/SSY_2018.pdf.

– (2020). *Annual statistical reports*. Tech. rep. Worldsteel. URL: https://www.worldsteel.org/steel-by-topic/statistics/steel-statistical-yearbook.html.

Wortler, Martin et al. (2013). *Steel's Contribution to a Low-Carbon Europe 2050: Technical and Economic Analysis of the Sector's CO2 Abatement Potential*. Tech. rep. URL: www.stahl-online.de.

WTO (2020). *World Trade Organization Data*. URL: https://timeseries.wto.org/.

Yuan, Chaoqing, Sifeng Liu, and Junlong Wu (Aug. 2009). "Research on energy-saving effect of technological progress based on Cobb-Douglas production function". In: *Energy Policy* 37.8, pp. 2842–2846. ISSN: 03014215. DOI: 10.1016/j.enpol.2009.04.025.

A. Appendix

A.1. Data sources

Sector	Country	Type	Factor	Source	Preprocessing
Primary Metals	Germany	Capital	Assets	DeStatis	Discounted using OxEcon Eurozone deflator
		Labour	Hours worked	DeStatis	
		Raw materials	Scrap	Worldsteel	
	France	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator, split between Primary Metals and Metals Processing according to relative value added using OECD value added data
		Labour	Hours worked	INSEE, Eurostat	Result of multiplying numbers worked per employee in Primary Metals industry (INSEE data) and number of employees in industry (Eurostat)
		Raw materials	Iron ore	Eurostat	
	Belgium	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator, split between Primary Metals and Metals Processing according to relative value added using OECD value added data
		Raw materials	Scrap	Worldsteel	

Sector	Country	Type	Factor	Source	Preprocessing
	Austria	Labour	Hours worked	Eurostat	
		Raw materials	Lead	Eurostat	
			Bauxite	Eurostat	
	Netherlands	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator, split between Primary Metals and Metals Processing according to relative value added using OECD value added data
		Raw materials	Non-ferrous ores	Eurostat	
Chemicals	Germany	Capital	Assets	DeStatis	
		Labour	Hours worked	DeStatis	
		Raw materials/ basic products	Chlorine	VCI	
			Hydrogen	VCI	
	France	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator, split between Primary Metals and Metals Processing according to relative value added using OECD value added data
		Labour	Hours worked	INSEE, Eurostat	Result of multiplying numbers worked per employee in Primary Metals industry (INSEE data) and number of employees in industry (Eurostat)
		Raw materials	Iron ore	Eurostat	
	Belgium	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator, split between Primary Metals and Metals Processing according to relative value added using OECD value added data
		Raw materials	Scrap	Worldsteel	
	Austria	Labour	Hours worked	Eurostat	
		Raw materials	Lead	Eurostat	

Sector	Country	Type	Factor	Source	Preprocessing
			Bauxite	Eurostat	
	Netherlands	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator, split between Primary Metals and Metals Processing according to relative value added using OECD value added data
		Raw materials	Non-ferrous ores	Eurostat	
Pulp & Paper	Germany	Capital	Assets	DeStatis	
		Labour	Hours worked	Eurostat	
		Raw materials	Recovered paper	CEPI	
			Pulp	CEPI	
			Non-fibrous materials	CEPI	
	France	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator
		Labour	Hours worked	Eurostat	
		Raw materials	Recovered paper	CEPI	
			Pulp	CEPI	
			Non-fibrous materials	CEPI	
	Belgium	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator
		Labour	Hours worked	Eurostat	
		Raw materials	Recovered paper	COBELPA	
			Pulp		
			Non-fibrous materials	CEPI	
	Netherlands	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator
		Labour	Hours worked	Eurostat	

Sector	Country	Type	Factor	Source	Preprocessing
		Raw materials	Recovered paper	CEPI	
			Pulp	VNP Netherlands	
			Non-fibrous materials	CEPI	
	Austria	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator
		Labour	Hours worked	Eurostat	
		Raw materials	Recovered paper	CEPI	
			Pulp	CEPI	
			Non-fibrous Materials	CEPI	
Non-metallic Minerals	Germany	Capital	Assets	DeStatis	
		Labour	Hours worked	Eurostat	
		Raw materials	Limestone	Eurostat	
			Reovered glass	Eurostat	
			Sand & gravel	Eurostat	
	France	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator
		Labour	Hours worked	Eurostat	
		Raw materials	Limestone	Eurostat	
			Reovered glass	Eurostat	
			Sand & gravel	Eurostat	
	Belgium	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator
		Labour	Hours worked	Eurostat	
		Raw materials	Limestone	Eurostat	
			Reovered glass	Eurostat	
			Sand & gravel	Eurostat	
	Netherlands	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator

Sector	Country	Type	Factor	Source	Preprocessing
		Labour	Hours worked	Eurostat	
		Raw materials	Limestone	Eurostat	
			Reovered glass	Eurostat	
			Sand & gravel	Eurostat	
	Austria	Capital	Assets	OECD	Disounted using OxEcon Eurozone deflator
		Labour	Hours worked	Eurostat	
		Raw materials	Limestone	GCCA	
			Gypsum	GCCA	
			Substitutes	GCCA	
			Reovered glass	Eurostat	
			Sand & gravel	GCCA	

Table A.1.1.: Data sources by country and sector, author's own work

A.2. P-values of models by sector

Independent variable	Germany	France	Belgium	Netherlands	Austria
Assets	0.00	0.00	0.00	0.00	-
Hours worked	0.00	0.00	-	-	0.00
Scrap	0.05	-	0.00	-	-
Iron ore	-	0.05	-	-	-
Non-ferrous ores	-	-	-	0.00	-
Bauxite	-	0.02	-	-	0.06
Lead	-	-	-	-	0.00
Time dummy	0.00		0.00	-	0.00
Intercept	-	-	-	0.00	-

Table A.2.1.: Overview of model p-values for Base Metals sector by country, author's own work

Independent variable	Germany	France	Belgium	Netherlands	Austria
Assets	0.00	0.00	0.03	-	0.00
Hours worked	0.01	-	-	0.00	0.01
Chlorine	0.01	0.00	0.04	0.00	0.01
Hydrogen	0.01	-	-	-	-
Nitrogen	-	0.02	-	-	-
Time dummy	-	-	-	-	0.00
Intercept	0.00	-	0.04	-	-

Table A.2.2.: Overview of model p-values for Chemicals sector by country, author's own work

Independent variable	Germany	France	Belgium	Netherlands	Austria
Assets	0.01	-	0.00	0.00	-
Hours worked	-	-	0.00	-	0.00
Non-fibrous	0.03	0.00	0.00	-	0.00
Pulp	-	0.04	-	-	0.03
Recovered paper	0.02	0.00	-	0.01	-
Time dummy	-	0.01	-	-	0.01
Intercept	0.00	0.00	-	0.00	0.00

Table A.2.3.: Overview of model p-values for Pulp & Paper sector by country, author's own work

Independent variable	**Germany**	**France**	**Belgium**	**Netherlands**	**Austria**
Assets	-	0.00	0.02	0.00	0.01
Hours worked	0.02	-	0.01	-	-
Limestone	0.00	-	-	-	0.02
Recovered glass	0.00	-	-	-	-
Sand & gravel	-	0.00	0.01	0.01	-
Gypsum	-	-	-	-	0.01
Substitutes	-	-	-	-	0.03
Time dummy	-	0.00	-	-	-
Intercept	-	-	0.00	0.00	0.00

Table A.2.4.: Overview of model p-values for Non-metallic Minerals sector by country, author's own work

A.3. Independent variables - assumptions

Sector	Type	Factor	Assumption
All	Capital	Assets	Assets are assumed to be the discounted invest over the total lifespan of assets: OE 2020 data on investment in the industry is discounted over an assumed life time of 10 years (typical for industry, s. BMF 2020), using a discount rate of 10% (as used e.g. by Keys, Van Hout, and Daniëls 2019). The yearly change of the assets calculated this way is applied to the assets data used in the modelling part.
	Labour	Hours worked	Using data on population (Eurostat), employees (Eurostat, national statistical offices) and hours worked (Eurostat, national statistical offices), two figures are calculated: The share of total population working in the specific industry, and the number of hours worked per employee (both country-specific). Both figures are assumed to develop with a logarithmic trend over time. These developments are then used as the base to calculate future working hours: The number of employees as the result of multiplying the (assumed) share of total population working in the industry with the population forecast (Eurostat base case), and the number of hours worked as the result of multiplying the assumed hours per employee and the number of employees.
Primary Metals	Raw materials	Scrap	According to a study by BCG and VDeH (Wortler et al. 2013), EU steel scrap consumption can be assumed to grow by 0.9% annually through 2050. This value is assumed to apply for all countries equally.
		Metal ores (ferrous/ non-ferrous)	Assumed to develop according to a logarithmic trend.
Chemicals	Raw materials	Chlorine	Applying a 0.7% growth rate to 2030 and 0.1% thereafter, according to CEFIC 2013 "Isolated Europe" scenario.

Sector	Type	Factor	Assumption
		Hydrogen	Assumed to develop according to a logarithmic trend, despite potentially significantly higher increase. This increase is however mostly associated with the use of hydrogen as a means to store energy, and therefore not considered part of the industrial electricity demand side.
		Nitrogen	Assumed to develop according to a logarithmic trend.
Pulp & Paper	Raw materials	Recovered paper	Countries that currently exceed the theoretical maximum on 78% will maintain their utilisation rate, due to imports of recovered paper from other countries (Netherlands). Countries that according to the trend of their utilisation rates would exceed an extended theoretical limit of 80% before 2050 reach 80% utilisation rates and then maintain this share (Germany by 2021, France by 2041). Note that the current theoretical limit can be extended through different measures, such as enhanced recycling, sorting and improvements in production technologies. Countries that according to their trend do not reach the theoretical limit will produce paper from recovered paper according to this trend (Austria, Belgium). This utilisation rate will be applied to overall paper consumption, as per the per-capita consumption forecast by Tissari 2012 and the population forecast by Eurostat 2020, assuming a constant relation of supply from in-country production and imports, providing the usage of recovered paper.
		Pulp	Applying a rate of 100% minus the recovered paper utilisation rate calculated above.
		Non-fibrous materials	It is assumed that the input of non-fibrous materials develops independently from the use of fibres, according to the overall paper consumption trend.
Non-metallic Minerals	Raw materials	Limestone & gypsum	According to MPA 2013, up to 30% of conventional raw materials for clinker production, such as limestone and clay, could be replaced by alternative materials, such as fly ash or slag ("cementitious substitution"). This decrease was applied to the conventional inputs limestone and gypsum.

Sector	Type	Factor	Assumption
		Substitutes	To compensate for this decrease, an increase in the use of substitutes of the same size (weight) was estimated, while keeping 2017 shares of single materials in overall substitute weight steady (e.g. in 2017, the share of fly ash in overall substitutes in the Austrian cement production was 9%, to be kept constant, while overall use of substitutes is forecast to increase by 19.5%).
		Sand & gravel	Sand & gravel will remain essential to the production of concrete from cement. It is therefore assumed that their share is going to move in parallel to overall production of cement.
		Recovered glass	Glass For Europe 2020 suggest that the share of recycled glass in total glass production can be increased by 40% by 2050. It was therefore assumed, that total glass production in Germany would develop according to the logarithmic trend of historical production. The increase of 40% was applied to the historically observed ratio of recycled glass consumption divided by total glass production. Multiplying the assumed development of total glass production with this share, consumption of recycled glass was forecast.

Table A.3.1.: Assumptions for development of input variables, author's own work

A.4. Scenario assumptions

Sector	Factor	Scenario	Assumption (CAGR if not specified)	Reasoning
Primary Metals	Scrap steel consumption	base	+ 0.9%	Wortler et al. 2013
		elec	+1.5%	Circular economy: increased usage of scrap and recycled material, higher EAF shares
		low	+/- 0%	No increased ambition to use scrap material
	Assets	base	-0.2%	OE 2020 investment forecast
		elec	-0.7%	Lower investment costs for EAFs comapred to OBFs (Schumacher and Sands 2007), -19.9% vs base case (-69% invest for EAF vs OBF, with 65% of assets in machines)
		low	+/-0%	High industrial activity, invest into fossil-fuelled and capital-intensive OBFs, High invest, +19.9% vs base case
	Hours worked	base	-1.15%	Projection of EU baseline
		elec	-1.15%	Projection of EU baseline
		low	+-0%	High industrial activity, but replacement of human labour by machines
	Non-ferrous ores	base	-11% to +2%, depending on the ore	Trend consumption
		elec	-11% to +2%, depending on the ore	Trend consumption
		low	-11% to +2%, depending on the ore	Trend consumption
Chemicals	Chlorine production	base	+0.7% to 2030, 0.1% later	CEFIC 2013 Isolated Europe scenario
		elec	+1.1% to 2020, 1.0% to 2030, 0.7% to 2050	Differentiated Global Action scenario

		low	+0.7% to 2030, 0.1% later	CEFIC 2013 Isolated Europe scenario
	Hydrogen production	base	+0.85%	Trend consumption
		elec	+1.9%	Bazzanella and Ausfelder 2017, maximum scenario, 220% increase by 2050, linearly realised
		low	+0.5%	ibid., intermediate scenario, 60% increase by 2050, linearly realised
	Nitrogen production	base	+0.21%	Trend consumption
		elec	+0.21%	Trend consumption
		low	+0.21%	Trend consumption
	Hours worked	base	-1%	Projection of EU baseline
		elec	-1%	Projection of EU baseline
		low	+-0%	High industrial activity, but replacement of human labour by machines
	Assets	base	+0.85%	OE 2020 investment forecast, assumed to be Bazzanella and Ausfelder 2017 ambitious scenario
		elec	+1.9%	ibid. study, maximum scenario, scale OE forecast by 39%
		low	+0.5%	ibid. study, intermediate scenario, scale OE forecast by -11.5%
Pulp & Paper	Assets	base	-0.38%	OE 2020 investment forecast
		elec	+0.64%	CEPI 2017: 40% higher investment compared to BAU scenario
		low	-0.83%	ibid.: no fuel switch, -1/3 invest in emerg. Technologies

	Hours worked	base	-2.5%	Projection of EU baseline
		elec	-2.5%	Projection of EU baseline
		low	+-0%	High industrial activity, but replacement of human labour by machines
	Recycling paper and pulp	base	Recycling rates max 80%	technical limits
		elec	Recycling rates max 85%	technical progress, improved sorting, potentially import of rec. Paper
		low	Recycling rates stagnating	low ambition to improve
	Non-fibrous materials	base	195 kg pP by 2050, down from 210 in 2020	Per-capita forecast by Tissari 2012
		elec	195 kg pP by 2050, down from 210 in 2020	Per-capita forecast by ibid.
		low	195 kg pP by 2050, down from 210 in 2020	Per-capita forecast by ibid.
Non-metallic minerals	Assets	base	+1.3%	OE 2020 investment forecast
		elec	+2.1%	IEA 2018a, 2DS scenario, 31% higher by 2050
		low	+0.6%	ibid., No Action scenario, -20% lower by 2050
	Hours worked	base	-1.9%	Projection of EU baseline
		elec	-2%	Projection of EU baseline
		low	+-0%	High industrial activity, but replacement of human labour by machines
	Limestone	base	-0.81%	Cementicious subsitution
		elec	-1%	Increased subsitution
		low	+-0%	No subsitution
	Recycled glass	base	+1.17%	Glass For Europe 2020 forecast, 5% increase of glass production

	elec	+0.55%	Increased usage of electricity-intensive materials, no increased production
	low	+0.29%	Stagnating use of recycling glass, production increased by 10%
Sand & gravel	base	+-0%	Stagnating consumption of cement
	elec	+-0%	Stagnating consumption of cement
	low	+1%	Increased cement production

Table A.4.1.: Assumptions by sector for all scenarios, Author's own work

A.5. Python script

Listing A.1: Python code for setup of models by country and sector, including forecast

```
#!/usr/bin/env python
# coding: utf-8

# # All countries analysis

# In[1]:


import pandas as pd
import numpy as np
import statistics
import statsmodels.api as sm
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler


# In[2]:


# input data file csv_in_path = 'I:\\PersonalFolders\\SRilling\\Master_Thesis\\Data\\Analysis\\EU\\
    ↪ EU_Metals_inputs.csv'
# 'I:\\PersonalFolders\\SRilling\\Master_Thesis\\Data\\Analysis\\PyCharm\\Production_function\\20200220
    ↪ _DE_Metals_ProdFunction.csv'
xlsx_in_path = 'I:\\Products - Power\\2050 extension\\2050 Demand\\Industry (SebR)\\Inputs\\
    ↪ IndustrialDemand_inputs_final.xlsx'


# In[3]:


# input data sheet
data_sheet = 'Data'


# In[4]:


# read data from input file
all_data = pd.read_excel(xlsx_in_path, sheet_name=data_sheet)


# In[5]:


# define all countries and sectors to be analysed - available:
# countries = ['DE', 'FR', 'BE', 'NL', 'AT']
# sectors = ['Primary Metals', 'Chemicals', 'Pulp&Paper', 'Non-metallic Minerals']
# scenarios = ['base', 'electrification', 'low ambition', 'max', 'min']
countries = ['DE', 'FR', 'BE', 'NL', 'AT']
sectors = ['Primary Metals', 'Chemicals', 'Pulp&Paper', 'Non-metallic Minerals']
```

```
scenarios = ['base', 'electrification', 'low␣ambition', 'max', 'min']


# In[6]:


# define csv input path for settings: which variables to use
csv_in_path = 'I:\\Products␣−␣Power\\2050␣extension\\2050␣Demand\\Industry␣(SebR)\\Inputs\\
    ↪ inputs_use_variables.csv'


# In[7]:


# read settings data from csv file
settings = pd.read_csv(csv_in_path, index_col=[0,1])


# In[8]:


# create dataframe to store results
results_columns = ['Year', 'Country', 'Sector', 'Factor', 'Value', 'Scenario']
consumption_all = pd.DataFrame(columns=results_columns)


# In[9]:


# create dataframe to store statistics
statistics_columns = ['Country', 'Sector', 'Factor', 'Coeff', 'P−Value', 'Scenario']
statistics_all = pd.DataFrame(columns=statistics_columns)


# In[10]:


# create dataframe to store effects
effects_all = pd.DataFrame()


# In[11]:


# iterate through countries and sectors
for scenario in scenarios:
    for sector in sectors:
        for country in countries:
            print(scenario, sector, country)

            # store data for sector and country in dataframe
            data = all_data.loc[(all_data['Country'] == country) & (all_data['Sector'] == sector)
                                & (all_data['Scenario'] == scenario)]
```

```
# set year as index
data = data.set_index('Year')

# store all input factor names in variable
features = data.Factor.unique()
print(features)

# store all years in variable
years = data.index.unique()

# create new dataframe with yearly values for all factors
df_variables = pd.DataFrame(columns=features)
df_variables = df_variables.assign(Year=years)
df_variables = df_variables.set_index('Year')

# itarate through dataframe and fill with values from dataframe data
for index, row in df_variables.iterrows():
    for column in df_variables.columns:
        sets = data.loc[(data['Factor'] == column)]
        value = sets.loc[index, 'Value']
        df_variables.loc[index, column] = value

# identify independent variables for this country
independent_vars = settings.loc[(country, sector), 'Variables']
independent_vars = list(independent_vars.split(", "))

# define varibales to be taken into account in regression - see above for variables available
target_var = 'el_cons'
use_var = [target_var]
use_var.extend(independent_vars)

# allow for technical progress?
progress = settings.loc[(country, sector), 'Progress']

# Regression thorugh the origin (RTO) - include constant?
constant = settings.loc[(country, sector), 'Constant']

# exclude years (outliers)
exclude_years = settings.loc[(country, sector), 'Exclude']
exclude_years = list(exclude_years.split(", "))

# define breakpoint of training vs. forecast
start_forecast = 2018

# drop variables that are not used in the analysis
for var in df_variables.columns:
        if not var in use_var:
            df_variables = df_variables.drop(var, axis=1)

print(df_variables.head())

# split data in training and forecast
min_year = min(df_variables.index)
```

```
# define forecast data
df_variables_forecast = df_variables.loc[start_forecast:2050, :]
df_variables_forecast = df_variables_forecast.drop(columns=target_var, axis=1)

# define training data
df_variables_train = df_variables.loc[min_year:(start_forecast-1), :]
df_variables_train_complete = df_variables_train

# drop data that is not available
df_variables_train = df_variables_train.dropna()
print(df_variables_train.head())

# exclude outliers
for year in exclude_years:
    year = int(year)
    print("Length before removal: ", df_variables_train.shape[0])
    df_variables_train = df_variables_train.loc[df_variables_train.index != year]
    print("Length after removal: ", df_variables_train.shape[0])

# define method to standardize data
def standardize(dataframe):
    columns = dataframe.columns
    index = dataframe.index

    dataframe = pd.DataFrame(StandardScaler().fit_transform(dataframe))
    dataframe.columns = columns
    dataframe.index = index

    return dataframe

# standardize data
#df_variables_train = standardize(df_variables_train)

# define method to calculate logs
def log_vars(exp_dataframe):
    for column in list(exp_dataframe):
        log_undefined = False
        for index in exp_dataframe.index:
            if exp_dataframe.loc[index, column] <= 0:
                log_undefined = True

        if log_undefined:
            exp_dataframe[column] = -exp_dataframe[column].min() + exp_dataframe[column
                ↪ ] + 1

    # apply log to training data
    log_dataframe = np.log(exp_dataframe.astype(np.float64))

    return log_dataframe

# calculate log of input variables
df_variables_log = log_vars(df_variables_train)

# define dependent and explanatory variables
```

```
explanatory = df_variables_log.drop(columns=target_var, axis=1)

if constant:
    explanatory_const = explanatory.assign(const=1.0)
else:
    explanatory_const = explanatory

dependent = df_variables_log[target_var]

print("Explanatory variables:")
print(explanatory_const.head())
print("")
print("Dependent variable:")
print(dependent.head())

# allow for technical progress
if progress:
    explanatory_const = explanatory_const.assign(time=lambda x: np.log(x.index-min(
        ↪ explanatory_const.index)+1))
    print(explanatory_const.head())

# set up linear regression model
model = sm.OLS(dependent, explanatory_const).fit()
print(model.summary())

# create short result overview
results_summary = pd.DataFrame(round(model.params,3))
results_summary.insert(column='p-values', value=round(model.pvalues,3), loc=1)
results_summary = results_summary.rename(columns={0: 'coeff'})

# plot results of regression on scatter plots
fig = plt.figure(figsize=(12,8))
fig = sm.graphics.plot_partregress_grid(model, fig=fig)

# define method to calculate model results
def calculate_results(dataframe, parameters):

    # multiply input variabls with parameters
    final_vars_log = dataframe.dot(parameters)

    # de-log calculated values
    final_vars_exp = np.exp(final_vars_log)

    return final_vars_log, final_vars_exp

# calculate results
params = model.params
explained_log, explained = calculate_results(explanatory_const, params)
print(explained.head())

# plot model vs real data
x_values = df_variables_train.index

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,6))
```

```
ax1.plot(x_values, df_variables_train[target_var], color="black", label="actual values")
ax1.plot(x_values, explained, color="red", label="estimated values")
ax1.set_title(target_var + " - real vs. estimation")
ax1.set_xlabel("Year")
ax1.set_ylabel("Final energy consumption")
ax1.legend()

ax2.plot(x_values, dependent, color="black", label="actual values")
ax2.plot(x_values, explained_log, color="red", label="estimated values")
ax2.set_title(target_var + " - real vs. estimation (log)")
ax2.set_xlabel("Year")
ax2.set_ylabel("Final energy consumption")
ax2.legend()

plt.show()

# define method to calculate forecast
def calculate_forecast(dataframe, parameters):

    # calculate log
    dataframe_log = log_vars(dataframe)

    # add constant to forecast
    if constant:
        dataframe_log = dataframe_log.assign(const=1.0)

    # allow for technical progress
    if progress:
        dataframe_log = dataframe_log.assign(time=lambda x: np.log(x.index-min_year+1))

    # calculate log results
    final_vars_log = dataframe_log.dot(parameters)

    # calculate de-log results
    final_vars = np.exp(final_vars_log)

    return final_vars, final_vars_log

# calculate forecast
forecast, forecast_log = calculate_forecast(df_variables_forecast, params)

# plot forecast results
x_values = df_variables_forecast.index

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20,6))

ax1.plot(x_values, forecast, color="black", label="estimated values")
ax1.set_title(target_var + " - forecast")
ax1.set_xlabel("Year")
ax1.set_ylabel("Final energy consumption")
ax1.legend()

ax2.plot(x_values, forecast_log, color="black", label="actual values")
```

```
ax2.set_title(target_var + " - forecast")
ax2.set_xlabel("Year")
ax2.set_ylabel("Final energy consumption")
ax2.legend()

plt.show()

# create dataframe containing all modelled data (past and forecast)
total = explained.append(forecast)

# plot total development vs. real data
x_values = total.index

fig, (ax1) = plt.subplots(1, 1, figsize=(20,6))

ax1.plot(x_values, total, color="red", label="modelling result")
ax1.plot(df_variables_train.index, df_variables_train[target_var], color="black", label="actual 
    ↪ values")
ax1.set_title(target_var + " - real and forecast")
ax1.set_xlabel("Year")
ax1.set_ylabel("Electricity consumption [Mtoe]")
ax1.legend()

plt.show()

# define method to calculate specific effects
def calculate_effects(dataframe, params, calc_result):

    # add constant to forecast
    if constant:
        dataframe = dataframe.assign(const=1.0)

    # allow for technical progress
    if progress:
        dataframe = dataframe.assign(time=lambda x: np.log(x.index-min_year+1))

    change = pd.DataFrame(index=df_variables_forecast.index, columns=dataframe.columns)

    for index, row in change.iterrows():

        for column in change.columns:
            change.loc[index, column] = ((dataframe.loc[index, column] - dataframe.loc[(index
                ↪ -1), column]) /
                                        dataframe.loc[(index-1), column])

    impact_rel = pd.DataFrame(index=change.index, columns=change.columns)

    for index, row in impact_rel.iterrows():
        impact_rel.loc[index, 'total'] = ((calc_result[index] - calc_result[(index-1)]) / calc_result
            ↪ [(index-1)])
        for column in impact_rel.columns:
            if column == 'total':
                continue
            else:
```

```
                impact_rel.loc[index, column] = (change.loc[index, column] * params[column])

        if constant:
            impact_rel = impact_rel.drop(columns='const', axis=1)

        impact_abs = pd.DataFrame(index=impact_rel.index, columns=impact_rel.columns)

        for index, row in impact_abs.iterrows():
            for column in impact_abs.columns:
                impact_abs.loc[index, column] = (impact_rel.loc[index, column] * calc_result[index
                    ↪ −1])

        impact_rel = impact_rel.assign(Country=country)
        impact_rel = impact_rel.assign(Effect="rel")
        impact_rel = impact_rel.assign(Sector=sector)
        impact_rel = impact_rel.assign(Scenario=scenario)
        impact_abs = impact_abs.assign(Country=country)
        impact_abs = impact_abs.assign(Effect="abs")
        impact_abs = impact_abs.assign(Sector=sector)
        impact_abs = impact_abs.assign(Scenario=scenario)

        return impact_rel, impact_abs

    # calculate impact
    impact_rel, impact_abs = calculate_effects(df_variables.drop(columns=target_var, axis=1), params,
        ↪ total)
    #print(impact_rel)
    #print(impact_abs)
    effects_all = effects_all.append(impact_rel)
    effects_all = effects_all.append(impact_abs)

    # join actual data with forecast
    past_forecast = df_variables_train_complete[target_var].append(forecast)

    # create dataframe with current results
    consumption_current = pd.DataFrame({'Year':years,
                                        'Country':country,
                                        'Sector':sector,
                                        'Factor':target_var,
                                        'Value':past_forecast,
                                        'Scenario':scenario})

    # include current results in overall results dataframe
    consumption_all = consumption_all.append(consumption_current, ignore_index=True)

    # print total and annual growth
    print(country,":")
    print('Difference:␣', round((total[2050]−total[2017])/total[2017]*100,2), '%')
    print('Avg.␣annual␣growth:␣', round(statistics.mean(impact_rel.total)*100,2), '%')

    # print summarized results
    print(results_summary)

    # create dataframe with current statistical results
```

```
        statistics_current = pd.DataFrame({'Country':country,
                                           'Sector':sector,
                                           'Factor':results_summary.index,
                                           'Coeff':results_summary['coeff'],
                                           'P-Value':results_summary['p-values'],
                                           'Scenario':scenario})

        # add Log-Likelihood Value to statistics results
        statistics_current = statistics_current.append({'Country':country,
                                                        'Sector':sector,
                                                        'Factor':'LLF',
                                                        'Coeff':model.llf}, ignore_index=True)

        # add adj. R2 Value to statistics results
        statistics_current = statistics_current.append({'Country':country,
                                                        'Sector':sector,
                                                        'Factor':'R2_adj',
                                                        'Coeff':model.rsquared_adj}, ignore_index=
                                                            ↪ True)

        statistics_all = statistics_all.append(statistics_current, ignore_index=True)

        ## end of loop over countries and sectors


# In[12]:


consumption_all.head()


# In[13]:


csv_out_path = 'I:\\Products␣-␣Power\\2050␣extension\\2050␣Demand\\Industry␣(SebR)\\Outputs\\
    ↪ IndustrialDemand_results.csv'


# In[14]:


consumption_all.to_csv(csv_out_path)


# In[15]:


csv_out_path_stats = 'I:\\Products␣-␣Power\\2050␣extension\\2050␣Demand\\Industry␣(SebR)\\Outputs\\
    ↪ IndustrialDemand_results_stats.csv'


# In[16]:
```

```
statistics_all.to_csv(csv_out_path_stats)


# In[17]:


csv_out_path_effects = 'I:\\Products␣-␣Power\\2050␣extension\\2050␣Demand\\Industry␣(SebR)\\Outputs\\
    ↪ IndustrialDemand_results_effects.csv'


# In[18]:


effects_all.to_csv(csv_out_path_effects)


# In[19]:


print('--------------------done----------------------')
```