MSc Program
Environmental Technology & International Affairs

What influences shifts in electricity production by different energy sources? An application of VAR models to analyse dynamics of electricity production and economic performance.

A Master's Thesis submitted for the degree of
“Master of Science”

supervised by
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Affidavit

I, **DAVID NIEL, BA**, hereby declare

1. that I am the sole author of the present Master's Thesis, "WHAT INFLUENCES SHIFTS IN ELECTRICITY PRODUCTION BY DIFFERENT ENERGY SOURCES? AN APPLICATION OF VAR MODELS TO ANALYSE DYNAMICS OF ELECTRICITY PRODUCTION AND ECONOMIC PERFORMANCE.", 60 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and
2. that I have not prior to this date submitted the topic of this Master's Thesis or parts of it in any form for assessment as an examination paper, either in Austria or abroad.

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Abstract

In this thesis, I analyse the dynamics in electricity production in relation to the development of a country's economic performance. I investigate how the amount of electricity production from different energy sources reacts to changes in the unemployment rate or manufacturing output. Conversely, I analyse if increases in these two economic variables lead to changes in the amount of electricity produced by one or more energy sources. Data of four European countries (Austria, Czech Republic, France and Germany) are used in separate Vector Autoregressive (VAR) models, covering the period 2000 - 2019. I can show that there are strong patterns of interrelatedness between different sources of electricity production – renewables, combustible and nuclear fuels – and I present evidence for causal relationships between manufacturing output and renewable electricity production. The goal of this study is to contribute to the knowledge of mechanisms governing the electricity market and the transition to renewable energies. It is shown that VAR models have great potential for further analysis of the dynamics of energy production. I also discuss possibilities of further research, including a comparison of energy market trends in different countries based on their geographic potential.

Table of Contents

Table of Abbreviations

AR	Autoregression
ADF-Test	Augmented Dickey-Fuller-Test
AUT	Austria
BIC	Bayesian Information Criterion (= SIC)
CF-E	Electricity from combustible fuels
CZR	Czech Republic
FRA	France
GER	Germany
GHG	Greenhouse Gas
IEA	International Energy Agency
ILO	International Labour Organization
IP	Industrial Production
IPCON	Industrial Production from Construction
IPMFG	Industrial Production from Manufacturing
IRF	Impulse Response Function
N-E	Electricity from nuclear energy
OECD	Organisation for Economic Co-Operation and Development
RCF	renewable energy from combustible fuels
RES	Renewable energy source
RES-E	Electricity from renewable energy source
SD	Standard deviation
SIC	Schwarz Information Criterion
UE	Unemployment Rate
VAR	Vector Autoregression

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1. Introduction

With the rise of public attention to the topic of climate change in recent years, there are many scientific discourses (re-)emerging. One such field which will become ever more relevant is the transition to renewable energies in both the general energy market and especially in the electricity sector. That discussion is also driven by the European Union's policy goals of achieving a renewable energy share of 32% of total consumption by 2030 and climate-neutrality by 2050.

According to the environmental scientist and energy historian Vaclav Smil, the difficulties and costs of as well as the time needed for the energy transition are strongly underestimated (Nysnø Klimainvesteringer, 2019). The objective of this thesis is to create new insights into the dynamics of energy production in order to understand the transition process better. As stated by Brauner (2019), the energy transition will have to be a process in which technological improvements, changes in consumer behaviour, and increased capacity for renewable electricity production go hand in hand. Out of these challenges, I will focus on electricity production. Electricity is especially important because the share of electricity of the total energy consumption will rise significantly with digitalisation and electric vehicles.

This thesis analyses the dynamics of electricity production in four different countries of the European Union. It scrutinises empirical data with the objective to generate knowledge on causal relationships between different economic variables such as unemployment rates or industrial output and amounts of electricity produced by different energy sources. The central method applied is a Vector Autoregressive Model (VAR model) which is a classical model of multivariate time series analysis. The application of a VAR model to this kind of data set is a relatively rare approach. This is due to the comparatively high data quality and observation quantity necessary for VAR models.

The geographic scope of this thesis is relatively limited to enable a comparative discussion of individual cases. Data is analysed from four countries over a period of 20 years (2000 - 2019). My goal is to answer the question of what caused the countries to increase or decrease certain sources of energy for electricity production. Three different forms of electricity production are analysed in this study: electricity from renewable energy sources (RES-E), from combustible fuels (CF-E) and from nuclear energy (N-E).

The four case countries Austria, Czech Republic, France and Germany, have been chosen based on several criteria. First of all, it was essential to compare countries for which the data was generated using the same standards. This was the case for all sources used (IEA, Eurostat & OECD). Secondly, I wanted to ensure that different energy pathways are represented without losing comparability between the countries. That meant that countries with very specific geographic potentials or limitations could not be included (e.g. Iceland, which has the unique benefit of vast access to geothermal energy). A third criterion was the need for comparability of energy data. Since I use aggregated variables of energy source categories (e.g. "combustible fuels" and not "coal", "natural gas" etc.) countries with very specific energy mixes within those categories would distort the picture. In this context, the exclusion of Sweden is explained in the chapter "Description of Data". The final consideration for the decision of inclusion or exclusion of countries was whether the data was suitable for the applied models without too many alterations. For instance, it could not be excluded that the series of Polish renewable electricity production contained a unit root even after one turn of differencing (see the chapter on (Non)-Stationarity and Unit Root testing). Poland was therefore not included as a case country.

I am building upon a broad fundament of scientific literature on economic drivers for renewable energy production and on literature analysing the impacts of different sources of energy on the above mentioned key economic indicators. Ohler (2015) and Wei et al. (2010), found that increased energy production from renewable energy sources (RES) has the potential to create new jobs. These findings are put to the test in new cases with other methodologies. Also, following the example of Sari et al. (2008), I test how industrial production is linked to different ways of electricity production.

I am able to show that there are significant relationships between the economic variables and changes in electricity production. Another important finding is, however, that there are no all-encompassing mechanisms which enable the formulation simplistic laws in the form of "If a country wants to improve A (e.g. the employment rate) it has to invest in B (e.g. renewable energies)".

The first chapter is dedicated to a discussion of existing research in the field of market dynamics in the energy sector. Here, I focus firstly on some assumptions about causal relations between economic variables and associated differences in the usage of energy sources. A second aspect explained in the literature review is the indication of fields where conflicting findings from different studies have been reported. Following the literature review, the next chapter focuses on the datasets used in the analysis. In this part, I briefly discuss which variables were excluded from the final models and why. After that, I explain the methodology used for modelling, testing and analysing the results. The chapter "results" includes the standard tests necessary to assess the applicability of a VAR model. After that, I will discuss the findings from the impulse response functions, which indicate the observed relationships between individual variables. I analyse individual country cases and explain how and why electricity production has changed in each of them. A more general discussion of the findings follows in the final chapter of this thesis where I try to synthesise the findings from the impulse response to draw a more comprehensive picture of the interrelation of economic factors and the electricity production. To conclude, I elaborate on further research potentials detected while studying the analysed field.

The following four hypotheses will be tested. They are based on the literature review and a general analysis of the data in combination with the epistemological potential of the applied methodology (VAR).

H1: "Different types of electricity production behave like communicating vessels."

This hypothesis follows evidence provided by Apergis and Payne (2012) which showed that there is a certain substitutability of different types of energy sources. If renewables increase other energy forms will decrease. In more mathematical terms, this leads to the expectation that *there is a tendency towards significant negative bidirectional relationships between RES-E and N-E & CF-E production.*

H2: Rising unemployment leads to an increase in electricity production from renewables.

Works by Ohler (2015) and Wei et al. (2010) have provided evidence pointing to such a relationship. Concerning the Impulse Response Functions, this hypothesis, therefore, assumes that *there is a significant positive response of RES-E following shocks to the unemployment rate.*

H3: Rising manufacturing output leads to an increase in electricity production from renewables and vice versa.

H4: Rising manufacturing output leads to an increase in electricity production from combustible fuels and nuclear energy and vice versa.

H3 and H4 both test the relationships of industrial production of the manufacturing sector (IPMFG) to different sources of energy. This hypothesis is founded on literature which established that economic output, in general, is closely related to energy production (Sari et al., 2008). Phrased in mathematical terms we, therefore, expect to find that (i) *there is a significant bidirectional positive relationship between CF-E and the industrial production index for manufacturing* and (ii) *there is a significant bidirectional positive relationship between RES-E and the industrial production index for manufacturing.*

2. Research

2.1. Literature Review

The topic of the renewable energy transition has been researched extensively from a variety of perspectives over the last decades. Many studies - this one included - try to find answers to the question of how this change can be brought to completion. Researchers both look at what circumstances facilitate the energy transition, and what complementary developments happen parallel to or are caused by this changeover. Most studies conduct cross-sectional comparisons to deduce the effects of specific variables on the share of renewable energies. Only a minority have applied methods of time series analysis. This is due to the somewhat limited availability of longitudinal data of high quality, fine temporal granularity and large geographic scope for energy production by source. The method of using a Vector Autoregressive Model for the analysis is therefore not the most common path taken and could, therefore, offer new insights. In the context of dynamics on the electricity market, VAR models have mostly been applied for short-term prediction models, e.g. relating weather conditions to electricity production (Bigerna 2018; Cavalcante et al. 2019). Though there are examples for the application of VAR models to long-term dynamics of energy production (Wada; 2017), there is still a high potential for new studies analysing specific cases.

All of the variables analysed in this thesis have proven to offer some explanatory power in other studies. Though the choice of variables is not new, there is still a high potential for additional insights into the matter. Previous studies have not always focussed on comparable countries, over comparable time frames and have not used the same methodology.

2.1.1. Economic Output and Renewables

Larger renewable energy production has often been put in relation to the economic potency of individuals or countries. Bollino (2008) found that individuals of higher income have a greater willingness to pay for electricity from renewables. These findings from the micro-level are also visible when checked for at the macro-level. Carley (2009) reports that for states in the USA, the gross state income correlates significantly with a higher renewable energy share. In the context of inter-country comparison, the concept of an “electricity ladder” is often mentioned. According to Burke (2010), the electricity ladder is a sequence of different energy sources which is typically followed when a country becomes more prosperous. After developing economies stop using locally accessible renewable sources (e.g. wood) as the primary energy carrier, according to the ladder, the progress goes via coal to natural gas and eventually to modern renewables and nuclear power. In his analysis of energy mixes of 133 countries, Burke shows furthermore that energy production from biomass, waste generated electricity and wind power increases with per capita GDP while the share of other renewable sources such as hydropower decreases. On the other hand, he also notes that increases in the shares of coal, natural gas and nuclear energy are also related to a rising GDP per capita. He additionally reports a substantial "endowment effect". Countries with a large resource potential for a specific type of fuel naturally tend to use this resource more extensively. Apergis and Payne have shown a positive bidirectional causality of renewable energy consumption and GDP growth for several Eurasian (2010) and Central American (2011) countries. The same authors have furthermore found such a bidirectional causality in an 80 country panel study from 1990 to 2007 (2012), but this time not only for renewable energies but also for non-renewables. Their data suggests a certain substitutability for both groups of energy technologies when it comes to impact from and on GDP growth. However, their data also indicates that the mere potential for substitution does not seem to incentivise a transition on its own. Countries with large shares of non-renewables are not expected to change their energy mix in favour of renewable sources. The finding hints to strong patterns of path-dependency which might also be expected as a result of this study.

2.1.2. Employment and Renewables

Another variable which is often discussed as either an influencing factor or as being influenced by renewable energy usage is the unemployment rate. Wei et al. (2010) compared a set of 15 individual studies with regards to the job creation potential of renewable energy sources during the period between 2001 and 2009. For the purpose of this thesis, their findings suggest the possibility of a bidirectional relationship between the unemployment rates and the share of renewable energies. First, they find that a higher unemployment rate can lead to more capacity building for renewable energy production after investments. In a second step, the authors find that more renewable energy production, in turn, leads to less unemployment. The authors also state that the positive effect on the job market is bigger from renewable energies than from fossil-fuels. This finding is supported by a study by Menegaki (2010) who finds boosts to employment by both RES (relatively stronger) and GHG emitting fuels (relatively weaker). Further literature research does, however, dampen such expectations to a certain extent. Apergis and Salim (2015) have conducted a study of 80 different countries and find a diverse picture of causes and effects between RE consumption and unemployment. While in many regions they do find job-creating potential from renewables, especially in EU countries they find positive effects of RE consumption on unemployment (i.e. higher consumption -> higher unemployment). Sari et al. (2007) found that both employment and industrial output are key determinants of both fossil fuel and renewable energy consumption. That means that typically economic variables move first and changes in the patterns of energy consumption follow later. Building on these findings, Ohler (2015) has shown that in the United States, higher unemployment rates lead to significant upticks in renewable energy capacity. She adds, however, that this effect decreases with increasing income. Additionally, she finds that in states with a larger manufacturing industry also a positive correlation between the unemployment numbers and relative RE capacity is found.

2.2. Methodology

2.2.1. A Brief introduction to time series analysis

In its most general form, a time series is a set of observations which have a natural order in time. These observations typically are reported at regular intervals. The most common intervals for macroeconomic data are years, quarters or months. This frequency is also called temporal resolution or granularity.

Time series analysis differs in some key points from other forms of econometric analysis. First of all, different data points are not independent of other observations, but each data point has a clearly defined temporal distance to any other data point in the series. Understanding how earlier observations influence later observations of the same or other variables is the key questions posed in a time series analysis. These dependencies over time can, however, be hidden or distorted by other mechanisms which are central to a time series and have to be considered in the analysis. A time series that is distorted by such a mechanism is called "non-stationary". In the following paragraph, I will briefly explain the meanings of trends and seasonality, which both lead to such non-stationarity and would, if unaccounted for, lead to wrong estimations by the VAR model. Since time-varying volatility (third a type of non-stationarity) is no issue at play in the data I use in this thesis, there is no subsection dedicated to this topic. In general, it has to be said that the VAR model applied in this study would not be equipped to estimate a process with volatility clusters successfully. Such behaviour would call for a Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model (developed by Bollerslev (1986)) which are widely used in financial econometrics.

2.2.2. (Non-)Stationarity and Unit Roots testing

As explained in the introduction to this chapter, there are some distorting mechanisms which can introduce patterns into a time series which prevent the meaningful application of the most common tools and models for the explanation of interdependencies of variables. If all influences from the mechanisms described in this chapter can be ruled out, a time series is called "stationary". Since the real world rarely produces a stationary series of observations, there are practical ways to deal with most issues of non-stationarity. Every method, however, goes with some kind of alteration of the dataset, which sometimes has its own disadvantages.

2.2.2.1. Seasonality

Regularly recurring cyclical patterns are indicators for a seasonal behaviour of a variable. Even though such a seasonal behaviour may be an interesting observation by itself, such seasonality generally distorts the analysis of real processes at work. A classic example of seasonality is the CO_2 concentration in the atmosphere measured at Mauna Loa in Hawaii. This curve underlies seasonal fluctuations that are clearly visible. (see figure 1) Even though it is straightforward for humans to adjust for this pattern and see the underlying trend upwards, this added "noise" makes it more difficult for a simple computer model to accurately describe what is happening. Conveniently there are many different techniques and algorithms which are well tested and can be used to adjust for such a seasonal pattern. One way is to use a rolling average over the whole year (or whatever the duration of the cyclical pattern is). Other, more elaborate algorithms aim to deconstruct the data into trend and cyclical components in order to generate a new seasonally-adjusted variable. In this study, I will use the method of seasonal-trend decomposition using locally weighted scatterplot smoothing (LOESS) or short STL Decomposition as will be explained below.

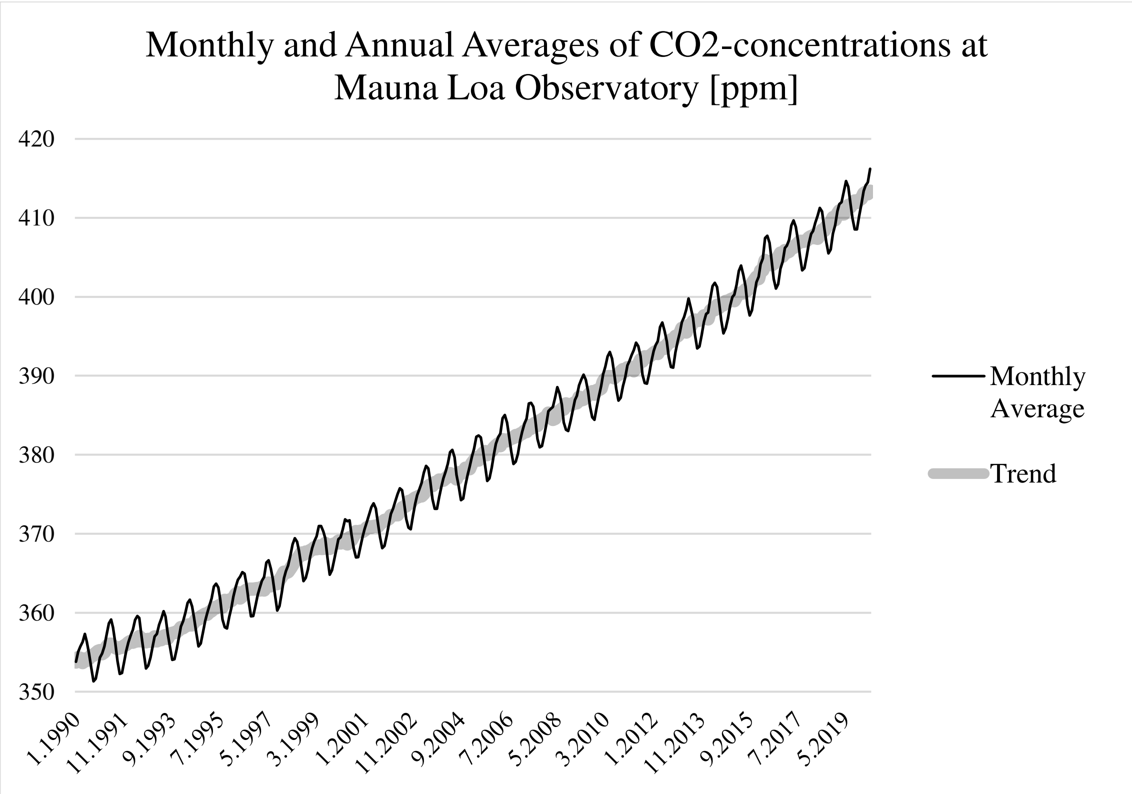

Figure 1: Atmospheric CO2-Concentrations at Mauna Loa Observatory. Graph recreated with data from Tans and Keeling (NOAA 2020).

2.2.2.2. Trend

A trend - or in more mathematical terms: a non-constant mean of a time series - also poses a problem to VAR models. Similarly to the above-described case of seasonality, a trend is an inherent influence on the expected values of a variable at a certain point in time. The most common way of adjusting a time series for trend effects is called differencing. Differencing is the simple step of subtracting each observed value from its predecessor. This procedure is similar to the differentiation in calculus. The new data points describe the change of a variable over one step in time. Since the first value cannot be subtracted from anything, one observation will be lost by this operation.

2.2.2.3. Unit Root testing

Before using a time series in a model, the possibility of non-stationarity has to be excluded. To do this, the Augmented Dickey-Fuller-Test (ADF-Test) is the most common tool used. The ADF-test is testing whether it is safe to reject the null hypothesis that a so-called unit root exists. A unit root is present if 1 is a root of the characteristic equation.[1]

2.2.3. Vector Autoregressive Models

This study uses a vector autoregressive model (VAR model) as the main tool to analyse the interdependencies between different variables about electricity production and economic performance of a country. This econometric tool was popularised mainly by the works of Christopher Sims (1980). VAR models can be seen as a multivariate expansion of simple autoregressive models (AR). AR-Models consist of optimised equations for calculating the best estimate of a value y_t by taking the sum of p past values, weighed (by coefficients β_p) according to their importance for describing the current value, a constant α, and a white noise error term u_t.

$$y_t = \alpha + \beta_1 \times y_{t-1} + \cdots + \beta_p \times y_{t-p} + u_t \tag{1}$$

VAR models generalise this idea and are not limited to a single variable but estimate time-lagged dependencies for several variables. *VAR models try to find out which variables influence which variables over which period in time.* This unintuitive sentence is maybe best illustrated by the general equation of a VAR model itself.

[1] This description is purposefully held very brief because a more detailed explanation would breach the thematic scope of this thesis. For a more detailed explanation on unit roots see: Kirchgässner, Gebhard, and Jürgen Wolters (2007).

$$y_t = v + A_1 \times y_{t-1} + \cdots + A_p \times y_{t-p} + u_t \quad (2)$$

In this equation, y_t is a vector containing the values of all K variables and v is a vector (also of size K) for the intercept terms. u_t is a vector of size K containing the unobservable errors for each variable within y_t. These errors are assumed to be generated by a zero-mean independent white noise process.

$$y_t = \begin{pmatrix} y_{1t} \\ \vdots \\ y_{Kt} \end{pmatrix}, v = \begin{pmatrix} v_1 \\ \vdots \\ v_K \end{pmatrix}, u = \begin{pmatrix} u_{1t} \\ \vdots \\ u_{Kt} \end{pmatrix} \quad (3)$$

This model takes into account the lagged values of y for each timestamp up to y_{t-p}. We, therefore, speak of a VAR(p)-model. A_1 to A_p are matrices of size K x K which contain the coefficients by which previous vectors are multiplied in order to best estimate the current y_t. Therefore, a VAR model can be written in its expanded form as follows:

$$\begin{pmatrix} y_{1t} \\ \vdots \\ y_{Kt} \end{pmatrix} = \begin{pmatrix} v_1 \\ \vdots \\ v_K \end{pmatrix} + \begin{pmatrix} A_{11t-1} & \cdots & A_{1Kt-1} \\ \vdots & \ddots & \vdots \\ A_{K1t-1} & \cdots & A_{KKt-1} \end{pmatrix} \times \begin{pmatrix} y_{1t-1} \\ \vdots \\ y_{Kt-1} \end{pmatrix} + \cdots + \begin{pmatrix} A_{11t-p} & \cdots & A_{1Kt-p} \\ \vdots & \ddots & \vdots \\ A_{K1t-p} & \cdots & A_{KKt-p} \end{pmatrix} \times \begin{pmatrix} y_{1t-p} \\ \vdots \\ y_{Kt-p} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ \vdots \\ u_{Kt} \end{pmatrix} \quad (4)$$

The coefficients of a VAR model are typically found by the ordinary least squares (OLS) regression. There are some important preconditions to take into account when using a VAR model. The first one is that usually, only stationary variables can be estimated successfully. Another precondition is related to the number of variables and lags included in the system.

2.2.3.1 Limits for VAR applicability

Due to the OLS-method, there is a technical limit for the applicability of VAR models. Any VAR cannot have more parameters, including one for the intercept $(Kp + 1)$ than data points available for the estimation $(T - p)$. T is the total sample size (temporal). Expressed as a formula, this gives us:

$$Kp + 1 \ \leq T - p \quad (5)$$

This yields after transformation:

$$K \leq \frac{T-1}{p} - 1 \tag{6}$$

As mentioned above, this is only the technical limit for a VAR. De facto any model that is close to that limit will not function properly due to a very high variance of the estimates. Therefore, similarly to the next discussion on lag inclusion, it is a general goal of reducing the number of variables to a minimum.

2.2.3.2. Lag Length Criteria

Related to the general formula on Vector Autoregressions (formula 4), one question remains: How many lags (previous time steps) should be included to estimate the parameters of the corresponding VAR model? The initial reaction might be to choose the largest number of lags possible because more information for the model means a better capability of the model to accurately predict the expected values. This notion is flawed for two reasons. Firstly, if one includes too many lags, the part of the data set which will be used for training the model, also gets smaller and smaller. In practice, the more important reason to reduce the number of lags is a scientific principle which is known for at least many hundred years. It is sometimes referred to as "Occam's Razor" and states that a scientific explanation should be as simple as possible for a given level of explanatory power. Even though the expected values become ever more accurate predictions with more lags included for fitting the model to the observations, the model becomes more complex and less testable. Since the 1970s, statisticians have come up with so-called information criteria (ICs) which are formulae which help to decide how many lags should be included without getting unnecessarily specific. All ICs compare the goodness-of-fit of a model to a "punishing-term" which gets larger with an increasing number of lags. The information criterion that I use in this thesis was developed by Gideon Schwarz (1978) and is either called the Schwarz Information Criterion (SIC) or the Bayesian Information Criterion (BIC). It states that the following expression shall be a minimum:

$$SIC = -2\left(\frac{l}{T}\right) + k\frac{log(T)}{T} \tag{7}$$

Here, T is the number of observations included for estimating the model, k is the number of parameters, and l is the log of the likelihood function produced by the model. The likelihood function is a term reflecting the goodness-of-fit of the data, so the better the model's quality, the lower the SIC will be. With more parameters k included the punishing term gets larger, and the whole expression gets bigger. With more lags included the rising T in the first term outweighs the decreasing second term and the expression also gets bigger. Therefore the model's lags should be chosen where SIC is at a minimum.

2.2.4. Granger Causality

Granger causality is a concept which is used to generate a first indication whether knowledge of previous data of one variable helps to predict another variable better than only with knowledge of its own previous values. It is named after its inventor Clive Granger (1969). For this purpose, a two-step process of t-tests (to check if individual variables are helping to explain others) and F-tests (to check if all other variables together help explain a variable) is used to determine granger causality. It is important to stress that granger causality does not imply real causality. The expression: "Variable y_i granger causes variable y_j" simply says that variable y_j is better predicted when variable v_i is included in the sample than without it. It does not imply any causation in the sense that one variable directly influences another one. Any real causation still must be explained by different means.

2.2.5. Impulse Response Functions (IRF)

An impulse response function (IRF) is used to measure the dynamic relationships of variables within a VAR model more precisely. The principle at work in an impulse response analysis is the following: A unit impulse is applied to a variable $v_{i,}$ and subsequently, its effects on all variables are individually measured for each following lag. A unit impulse is defined as a shock of the size of one standard deviation (SD) of the error term u_i of v_i. Since the error terms for different variables tend to be correlated amongst each other, it has to be ensured that the applied impulse is independent of all other variables.

There are several ways of de-correlating an impulse to make it independent. I will use so-called generalised impulses. This method was developed by Pesaran and Shin (1998). It works by applying matrix transformations in a way that the impulse is genuinely independent of the other variables within the error term.

For logged and differenced variables the values of the IRF are interpreted as follows: On average, all else held constant, a shock of the size of one standard deviation of u_i in variable v_i, p time periods ago, will cause variable v_j to increase/decrease by x per cent. The applied method of generalised impulses does not differentiate between the sizes of effects from negative and positive shocks. A positive response, thus, has to be interpreted as a response in the same direction as the assumed shock.

2.2.6. Residual Autocorrelation Test

After a model has been built and estimated, a final step is to check for residual autocorrelation. The goal is to create a model which does not show any patterns within the errors of the model's expected values when compared to the actual values. Such patterns would indicate that there is more information in the data which is not sufficiently considered by the model. For VAR models with more than 100 observations, the Ljung-Box-Test is the established way of controlling for residual autocorrelation. It was developed by Greta Ljung and George Box (1979). As will be shown later, under the specific circumstances of this thesis, the judgement of this test has to be taken with a grain of salt (see subchapters: Trend components & Tests on the applicability of the model).

More detailed explanations on all applied tests and models can be found in the works of Lütkephol (2005 & 2007) and Kirchgässner, Gebhard, and Jürgen Wolters (2007).

2.3. Description of Data

The data used for this thesis were extracted from different well-established databases between April 1st 2020 and May 6th 2020. The data used for the time series analysis encompass the period from January 2000 to December 2019. In total, 240 months are considered. For each variable, there is one observation per month.

The VAR model for three countries (France, Germany and the Czech Republic) considers a total of 6 variables; the Austrian model only consists of 5 variables because there is no need for the inclusion of electricity production from nuclear energy as an explanatory factor. The VAR models with nuclear energy run on a total of 1440 (= 240 x 6) data points; the Austrian model runs on 1200 (= 240 x 5) data points.

For the time series, there was no need of altering any data set with respect to its temporal granularity since all utilised data was initially reported with a monthly frequency. All data used in this thesis is transformed using the natural logarithm in order to enable the interpretation of results of the IRF as percentage changes to the variables.

In this chapter, I will explain the origin and format of all data sets used for this thesis. And I will also critically reflect on the assumptions associated with the use of these data sets where necessary. Furthermore I will briefly discuss a number of variables which I have considered but finally have not proven to be useful in the context of this model. This is done to serve the secondary goal of this thesis, which is to offer insights into the learnings from the research.

2.3.1. Data on electricity production

All data on electricity production stems from the database of the International Energy Agency (IEA) which collects, on a monthly basis, the total amounts of electricity produced from different fuels. The unit of this data set is GWh. This data set goes back until January 2000. The geographic scope of the dataset encompasses all OECD countries. There was one major change in the collection method in January 2016. Before, only four categories of energy source were reported. After that date, much more differentiated data was provided, especially in the field of renewable energy sources. Nevertheless, for several reasons, I decided to use the data from the old categorisation for the VAR model. The first reason for this is the advantage of using a longer time period. Furthermore, fewer variables also mean more simplicity in the model.

Therefore, fewer coefficients have to be estimated, and thus the model can be expected to be less prone to errors due to fewer degrees of freedom.

According to information provided by the IEA, the collection of data did not change much over time. However, a few minor modifications occurred in the data composition over the observed period. These changes and other known imprecisions are enumerated in Appendix B.

2.3.1.1. Trend components

For the VAR model, all variables on electricity production have been transformed into trend-variables. Together with the seasonal adjustment of data, which is a standard prerequisite for times series analysis, this is an additional alteration of the raw data material from the IEA. This transformation yields some advantages and some disadvantages.

The decision of using the trend-component of the data rather than simply the seasonally adjusted data was taken due to the high volatility of the amounts of electricity production. This volatility is not only produced by regular and predictable seasonal effects but also due to ungeneralisable effects which are unpredictable either on the long-term like weather phenomena or on the short term such as fluctuations in consumption. The smoothing of data helps to filter out the short-term volatility and enables the VAR model to focus more on long-term developments which are influenced by economic variables. One possible interpretation is that the trend-variables are an indicator of the level of installed electric energy production capacity which is ready for usage at a given moment. Since this installed capacity can be expected to be related to economic impulses, it seems tenable to use this approach. In further research with variables which control for meteorological circumstances and consumption patterns, it could be possible to prove or disprove this assumption. Figure 2 shows an exemplary comparison of the raw data, the seasonally adjusted data and the trend data of the share of renewable energy sources in electricity production in the Czech Republic.

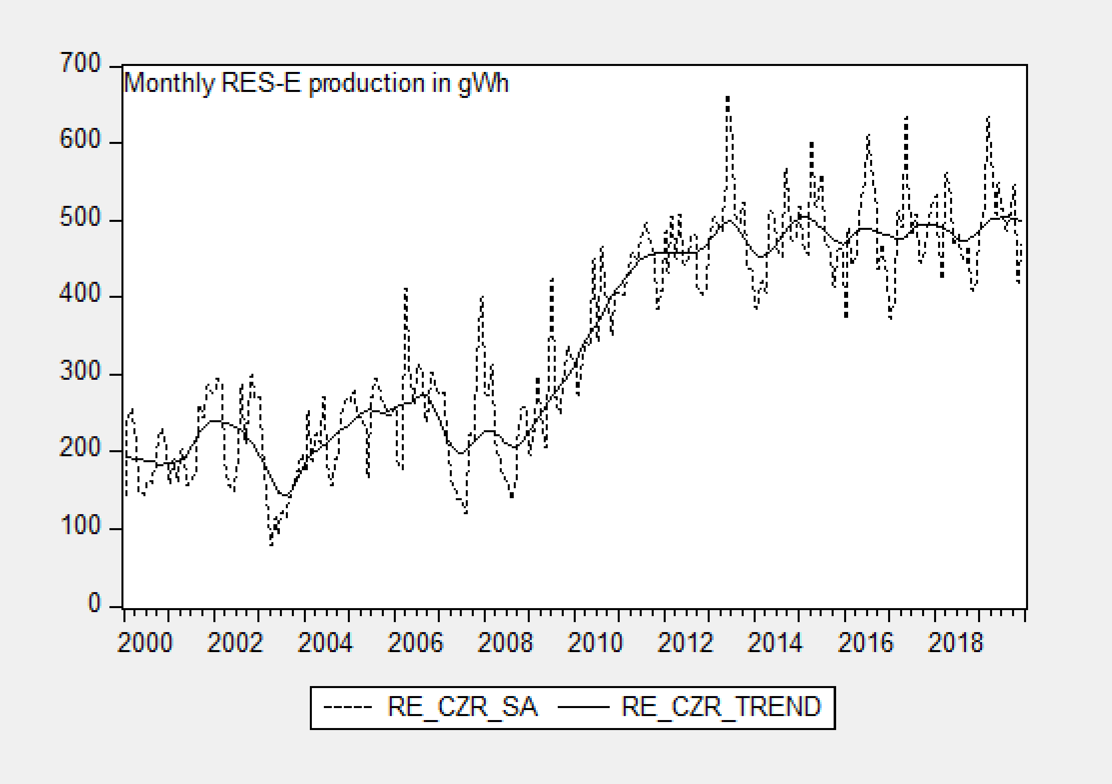

Figure 2: Comparison of seasonally adjusted and trend of Czech RES-E production

The downside of using these trend variables is also clear. A researcher has to acknowledge the fact that any alteration applied to the dataset represents an unnatural influence on what is analysed. Especially smoothing brings about a specific issue in time series analysis. In the post-estimation-test for residual autocorrelation, a model which uses such a trend-component will produce a significant amount of patterns which the model did not account for. Typically this would call for the inclusion of more lags in order to include the present patterns into the prediction model. In the case of this study, there are good reasons for not including more lags, as will be explained in the subchapter on the applicability of the model.

For all variables, the trend components were filtered out using the STL Decomposition method in EVIEWS. This method was developed by Cleveland et al. (1990). STL Decomposition assumes that the value of a variable at a given point in time Y_t is the sum of three components: The seasonal component S_t, the trend component T_t, and the Remainder R_t.

$$Y_t = S_t + T_t + R_t \tag{8}$$

Each component is then estimated using a double recursive process where an algorithm follows an inner loop to estimate the seasonal effects and the trends and an outer loop estimates the remainder.

2.3.1.2. Electricity production from renewable energy sources (variable code: re_country_trend)

The amount of electricity production from renewable energy sources (RES-E) is the sum of the two categories “Hydro” and “Geothermal/Other” from the IEA data set. One decision which had to be taken was whether renewable energy should be measured in total electricity produced from renewables or as the share of renewables of all forms of energy. Using the relative values would facilitate to analyse the transition to a “greener” electricity production. However, there is a severe disadvantage which eventually convinced me of using the absolute value of RES-E: The simultaneous use of relative and absolute values would lead to a reduced quality of the results from the impulse response functions. This is due to the fact, that a decrease in the percentage of RES-E could be either a direct result of an increase of total RES-E or an indirect result of an increase of another fuel.

According to IEA information, the variable hereby called “amount of renewable energy in the electricity production” includes the net generation of hydro facilities, including pumped storage production, geothermal, solar PV, solar thermal, wind, tide, wave, ocean and other non-combustible sources (IEA 2020). Even though this definition is close to the common definition of renewable energy sources, there is some small incongruence to be addressed. Energy used for pumped storage plants may also come originally from non-renewable sources. The subchapter “Further Discussion on data suitability” contains a more detailed discussion on this issue.

2.3.1.3. Electricity produced from combustible fuels (variable code: cf_country_trend)

The IEA definition of that term is: “Production from fossil fuels (primary coal, coal products, peat and peat products, oil shale and oil sands, crude oil, NGL, oil products, natural gas) and combustible renewables and wastes (solid biofuels, biogases, liquid biofuels, industrial and municipal waste).” (IEA 2020). Similarly to the issue with the RES-E variable, this is not a 100% congruent accumulation of non-renewable energy sources. Biofuels which are generally considered as renewable (even though they contribute to CO2 emissions) are part of this variable. That point was taken into account for the decision on which countries to include in this study. Countries with very large shares of renewable electricity production from combustible fuels (RCF) can distort the general meaning of this variable when compared to other countries. To account for this issue, Table 1 shows the average RCF share for the 4 case countries in the period where the data is available. Further data for Austria (were the RCF-share is the relatively highest) indicates that this share is slightly lower for the period since 2000 (E-Control 2020), but it was not possible to quantify this share on a monthly basis for each country. The subchapter “Further Discussion on data suitability” contains a more detailed discussion on this issue.

Table 1: Average shares and standard deviations of electricity produced by RCF of electricity produced by combustible fuels. (IEA 2020)

	Average RCF (2016-2020)	S. Dev. RCF
France	13%	6%
Germany	13%	2%
Austria	27%	10%
Czech Republic	10%	1%

2.3.1.4. Electricity produced from nuclear energy (n_country_trend)

The IEA definition is: “Electricity produced using heat generated from nuclear fission.” (IEA 2020) The nuclear energy variable also was generated using the trend component of the raw data. Of the four case-countries, only the Czech Republic, Germany and France produced electricity with nuclear energy during the observed period. Therefore in the VAR model for Austria, this variable is not included.

2.3.1.5. Total electricity produced (te_country_trend)

According to the definition of the IEA, this variable contains the sum of production from different energy sources excluding own use of power plants. This value is calculated before exports and imports and is a precursor to total electricity supplied. Any potential production from any unofficial independent grid system would probably not be included in each countries reporting, however, research has not provided any indication that such systems exist to a significant extent in one of the tested countries.

Just as the other energy-related variables, the trend component is used in the VAR models.

2.3.2. Economic Factors

2.3.2.1. Industrial Production of the manufacturing sector (ipmfg_country)

For this study, one problem was the lack of monthly GDP data. GDP is typically reported quarterly or annually. Many different variables have been proposed as a proxy for GDP, but no single variable will ever be able to grasp the whole picture. It has been frequently shown that there is a very high correlation between GDP and industrial production indexes (Humpe & Macmillan 2009, Nishat & Shaheen 2004). Therefore, for the purpose of this study, I have decided to follow the example of using an industrial production index as a monthly alternative to GDP (e.g. Kim, Ki & Choi 2019, Forson & Janrattanagul 2013).

Other studies (e.g. Ohler 2015) have shown that industrial production offers explaining value for developments on the energy market. For this study, the Industrial Production Index published by the OECD was used. This data set is standardised with the year 2015 set to 100. In the process of model building, three different versions of this variable have been tested: (i) Manufacturing (IPMFG), (ii) Construction (IPCON), and (iii) the total Industrial Production (IP = IPMFG + IPCON). These tests have revealed that IPMFG (Manufacturing only) has the strongest explanatory power.

2.3.2.2. Unemployment (UE_country_m)

As discussed in the literature review, many studies have already tested and found a causal relationship between unemployment rates and different forms of energy production. In this study, the data on the UE-rate was retrieved from Eurostat (Eurostat 2020). For all countries, the share of unemployed (according to ILO-criteria) per active population between 15 and 75 was used. The data from Eurostat was already adjusted for seasonal effects; therefore, no secondary alteration of the dataset was needed. It is important to note at this point that when changes to the variable "UE" are described as, e.g., + 0,8%, this cannot be interpreted as the UE rising from, e.g., 5% to 5,8%. This formulation indicates a 0,8% increase calculated from the previous percentage value. In the mentioned example, this would be a change from 5% to 5,04%.

2.3.2.3. Unused Economic Variables

During the building and fine-tuning process of the VAR models, many initially promising variables had to be discarded. Two reasons were mostly responsible for such exclusions. Either the temporal resolution was too low, or no significant effects were detected in any of the four country-models when the variables were included in the model.

Out of a lack of data with higher granularity, it could not be checked if changes in state income from ecological taxation (annual data) had an impact on changes in the energy mix of electricity production.

Also, data on specific prices of energy sources could not be used because it was not possible to objectively translate existing data to match the format (method of aggregation) of the electricity data provided by the IEA.

Previous research has shown that research and development expenditures can help renewables to penetrate the commercial market and de-risk the private sector (Zhou & Gu, 2019). In trying to test such potential, a variable on R&D investment in the energy sector was unsuccessfully tested. No significant impact on the other variables was detected. These exclusions, of course, do not mean that there is no real-world impact of these variables, but the only study with a larger sample size could dive deeper into answering this question.

2.3.3. Unused field of variables: Political & Social Variables

The initial outline for this thesis was larger than the final scope of the present study. I decided to include a discussion on learnings from the research-design-process to draw a broader picture of the considerations that went into the model.

One goal was to include variables on the social and political environment of a country to the policy outcome of a change in renewable energy usage. This quest proved not to be possible with the applied methodology. All attempts to use data on how pro-environment an acting government is carried no reliable fruits. This was due to the fact that the changes in government are rather infrequent and evaluations on how pro-environment a party is do not exist for a sufficient period in time. Additionally, it would have been hard to quantify and compare to the power structure within a coalition government.

As an alternative to assessing the government's positioning on environmental issues, it was further attempted to check if the public opinions influenced RES-E production.

Even though previous studies raised doubt about any effects of environmental consciousness to boost RES-E production (Marques et al. 2010), it would have been interesting to re-check this finding ten years later. Therefore, I tested if the biannual data from the standard Euro barometer could help as an indicator of how important environmental issues are in a country. Also, here the coarse granularity would have been an issue, but eventually, other reasons were decisive for the exclusion. Even though the Eurobarometer aims for high continuity in the questionnaires, this is not the case for environmental issues. This is because the environmental issues discussed have changed strongly over time. While today climate change is at the centre of the attention in 2005 (when at first environment-related questions where included in the survey) other issues like bio-diversity where more salient issues concerning the environment. Big infrastructural projects like large hydropower plants, therefore, are probably not uniformly influenced by changes in the importance of environmental protection.

2.3.4. Further discussion on data suitability

Every finding of a study is only as good as the data sets used for the analysis are. It was, therefore, of the utmost importance to do thorough research for the highest quality of data. The analysed material had to both carry meaningful information for the research question and be accessible for a sufficient timeframe with a sufficient temporal resolution. These two prerequisites naturally generate a certain contradiction. Since the methods of data collection get changed and improved over time, there will often be an alternative data set of higher quality for a shorter time frame. In the case of this study, this especially was true for the data on hydropower and combustible fuels which both cannot be assigned completely into the categories of renewable and non-renewable energy sources. An exact categorisation is only possible for the data from 2016 onwards. Nevertheless, I decided to go for the longer time frame with data of lesser quality. This decision was taken out of a number of reasons. This thesis can be seen as a preliminary investigation in the applicability of VAR models to data of electricity production and macroeconomic variables for different countries. In the case of success, further research can build upon the presented findings and elaborate on them on different levels. For example, more countries could be included, or the better data from post-2015 can be analysed in a more detailed fashion. Any later, additional research has the added benefit of being able to include a larger temporal sample size which improves the reliability of the findings. Yes, the technical limitations of a VAR model (as explained previously) would not have been exceeded in an analysis of the period between of January 2016 and December 2019 but together with the distortion from the trended variables the probability of generating a wrong picture was too large. In order to limit the effect of the inexact categorisation of renewables, the no countries were chosen for the analysis where the amount of a) biofuels of combustible fuels are very high (e.g., Sweden) or b) the amount of undeclared electricity is transformed into hydropower via pump storage is high.

2.4. Results

2.4.1. Tests on the applicability of the model

As explained in the methodology chapter, some important tests have to be made accompanying a time series analysis with a VAR model.

For every variable used in the VAR model, the null-hypothesis of containing a unit root could be rejected after one turn of differencing (Tables in appendix A). The Schwarz Information Criterion was used to calculate the best lag length for the four individual VAR models. The Austrian model is constructed using 3 lags (i.e. the model works best when including data of the 3 previous months for the estimation), the models for the three other countries needed 4 lags according to the SIC. The block exogeneity tests to check the variables for Granger causality are presented in appendix A and offer an initial overview of dependencies. Lastly, the Ljung-Box test for residual autocorrelation was applied to all models and showed highly significant cases of autocorrelation. Under normal circumstances, this would indicate a poorly fit model, and it would be recommended to increase the number of lags. However, as discussed before, this residual autocorrelation is not worrying for this thesis. The reason for these additional patterns in the data, which are not accounted for by the model, is the smoothing of electricity data. The trend-components are calculated in a way that filters out the natural volatility to a point where the autocorrelation test rightly assumes a poorly fit model. Since I have used the SIC to assess the right lag-lengths for the model, it would be unwise to try to artificially increase the goodness of fit of the model by including more observations.

2.4.2. Impulse Response Functions - Austria

According to the general intention of this thesis, the analysis of the impulse responses predominantly focuses on influencing factors for changes in RES-E production. Nevertheless, a brief discussion on the other effects will also be included for completeness.

Very clear impulse responses can be seen for each of the variables to its own lagged values. All electricity production variables clearly show a long-lasting positive response to shocks of up to 7 months before. The two economic variables also have an influence on their own later values, but they seem to follow some kind of cyclic behaviour since the very strong positive responses to shocks at lag one are followed by negative responses to a shock at the lags two (for IPMFG) and three to four respectively (for UE).

As expected, the IRF shows that if CF-E goes up, RES-E goes down. An effect in the other direction (a negative response of CF-E to RES-E) is also noticeable, but it is a bit weaker. This can be explained by decisions of market participants which strongly depend on the behaviour of competing market participants.

Also, some evidence for interdependencies between the electricity variables and economic variables is shown by the model.

2.4.2.1. Renewables and Industrial Production

A small but still significant (when considering ± 2 standard errors) upward response is detected for RES-E in Austria in the case of an increase of one standard deviation in industrial output in the manufacturing sector. Exactly spoken we can say: All other things held constant, a shock of one standard deviation in industrial output is on average followed by a 0,03% (lag 1) increase in the RES-E production. For Austria, this would mean that for an average month an increase of renewably produced electricity for more than 3400 average households[2] can be expected.

There is also evidence for a significant effect going the other way as well: All other things held constant, a shock of 1 SD in RES-E production is on average followed by a 0,23% increase in Industrial production in the manufacturing sector.

[2] The average production from 2019 was taken as the average month. There a 0,03% increase in RES-E production would have meant 0,9 GWh more from renewables. For the average household 4415 kWh annual consumption are assumed (Österreichs Energie; 2019)

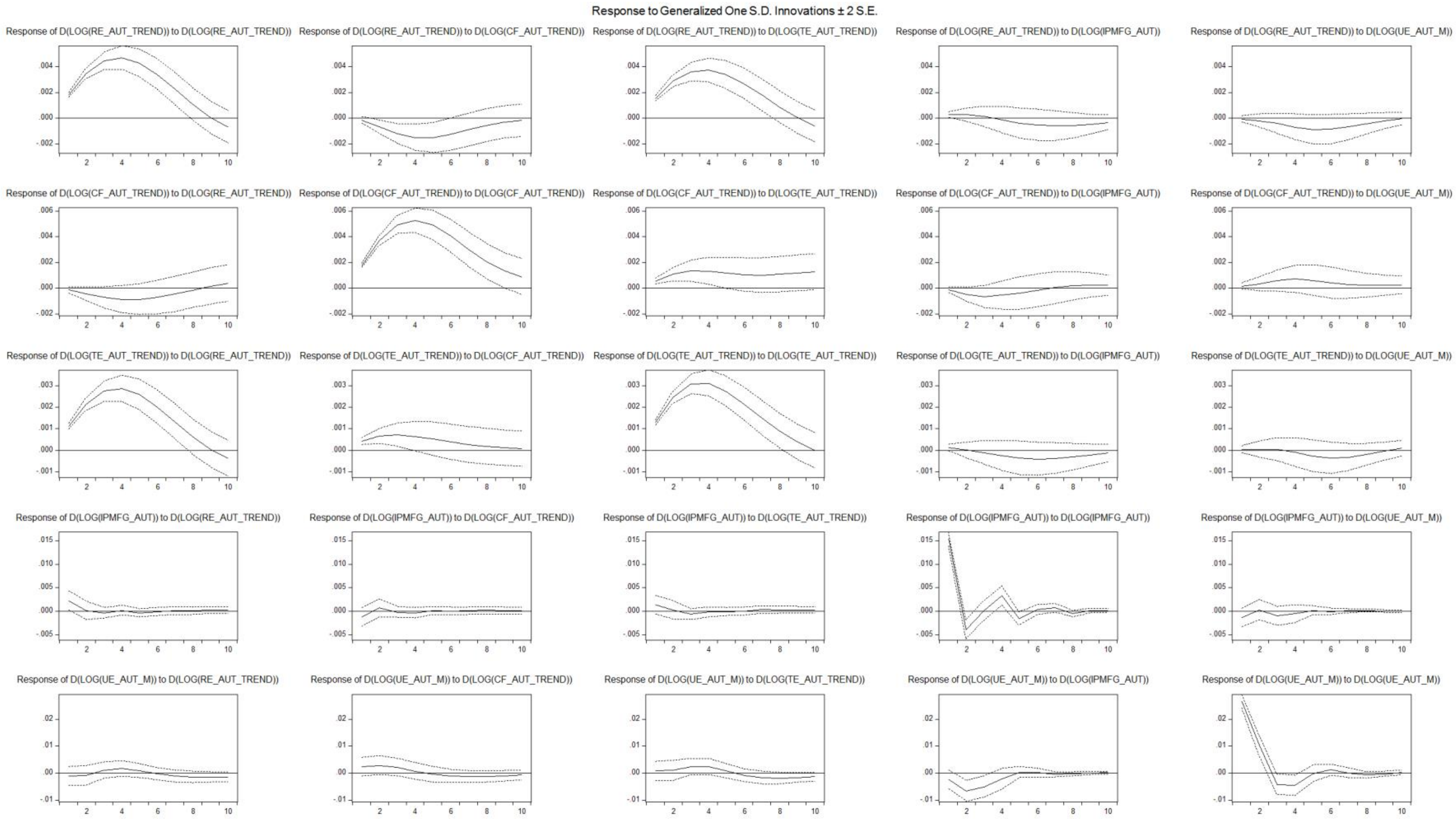

Figure 3: Impulse Response Functions: Austria. The continuous line represents the average response to positive shocks of 1 SD for each lag, the dotted lines represent ±2 standard errors of this value.

2.4.2.2. Renewables and Unemployment in Austria

Contrary to expectations (e.g. grounded in the work of Ohler (2015)), there is no evidence for a positive response of renewable electricity production to higher unemployment. There is even a weak non-significant indication that higher unemployment leads to less renewable electricity over the following months. The model's data furthermore shows no evidence of an effect in the other direction, where an increase in the share of renewable energy would affect the unemployment rate.

2.4.3. Impulse Response Functions - Czech Republic

The VAR model for the data on the Czech Republic draws the picture of a renewable electricity sector, which is relatively independent of economic factors. This is probably related to the low share of renewables in the energy mix of the country's electricity production. The impulse response analysis shows no meaningful influences between the economic variables (unemployment rate and manufacturing output) and RES-E production. However, the model shows an interesting relationship between nuclear electricity and combustibles. Production from nuclear energy seems to shrink a few months after a positive shock to combustible fuels. But the opposite is true for the reverse direction: More production from nuclear energy leads to a (weak) positive effect on production from combustible fuels after 1 month.

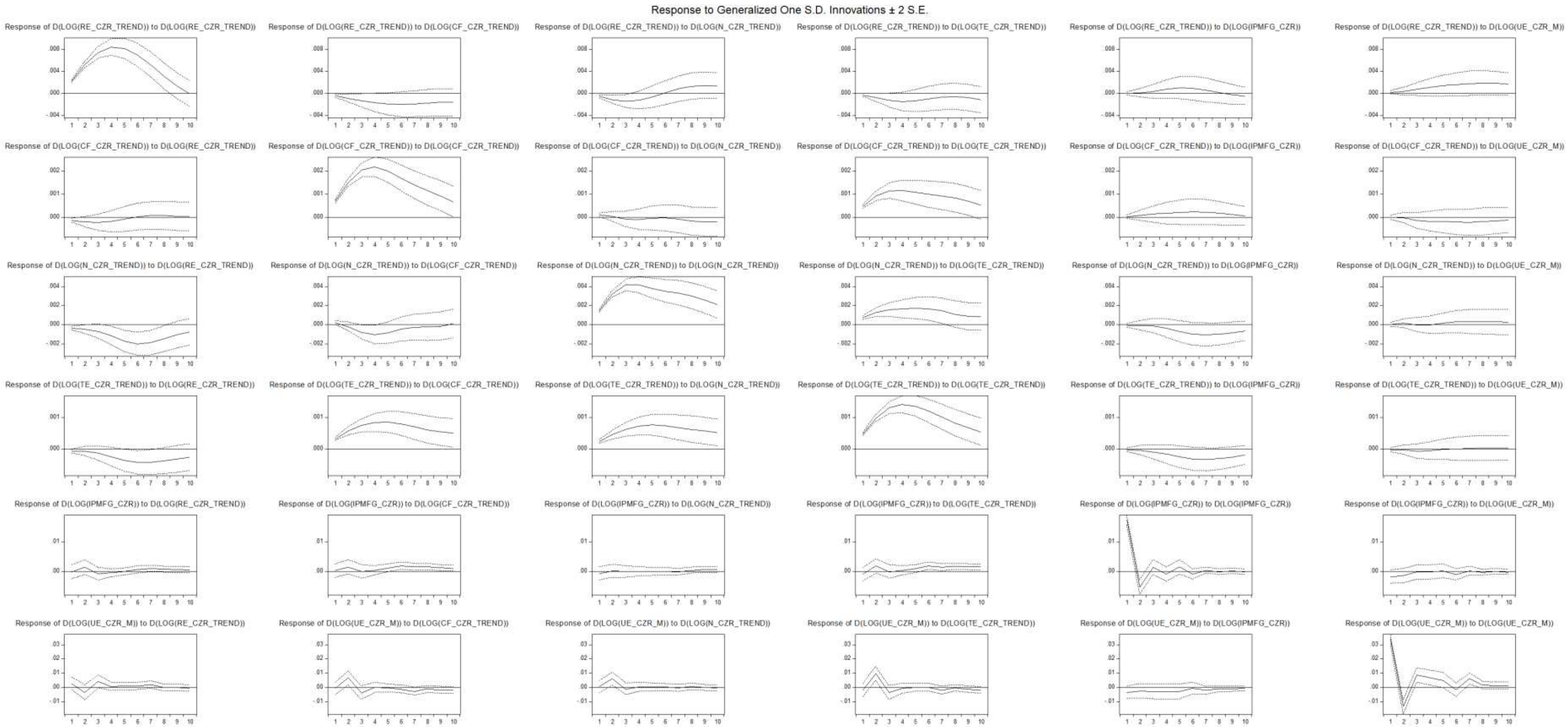

Figure 4 Impulse Response Functions: Czech Republic. The continuous line represents the average response to positive shocks of 1 SD for each lag, the dotted lines represent ±2 standard errors.

2.4.3.1. The Czech electricity sector and the economy

The impulse response functions for both manufacturing output and the unemployment rate show significant responsiveness to the non-renewable energy production in the Czech Republic. The manufacturing output seems to be influenced by shocks to electricity production by combustible fuels 6 months ago. All else held constant a shock of 1 SD on average results in a 0,19% shift in manufacturing output.

The unemployment rate is also significantly influenced by electricity production. 2 months after a shock of one standard deviation to electricity production from both combustibles and nuclear energy, the unemployment rate rises by 1%.

2.4.4. Impulse Response Functions - France

The results from the French VAR model show an electricity system with an electricity sector clearly dominated by nuclear energy. RES-E production is negatively influenced by rising numbers in combustible fuels and nuclear energy. Also, in general, a rise in total electricity production is followed by a drop in the share of renewable electricity.

There is a highly interesting, yet not strongly significant, relationship between electricity sources and industrial production. While the IRF hints to the possibility that IPMFG is increased at lag 2 by rising CF-E, the opposite seems to be the case for rising nuclear electricity where a slight reduction of IPMFG is found. This is especially interesting since nuclear energy is the only form of electricity which experiences significant upward development after industrial production increases. A very long-lasting positive impulse response can be detected for total nuclear electricity production after a shock of one standard deviation to industrial production. All other aspects held constant, this impulse response will reach up to 0,09% for a lag of 6 months.

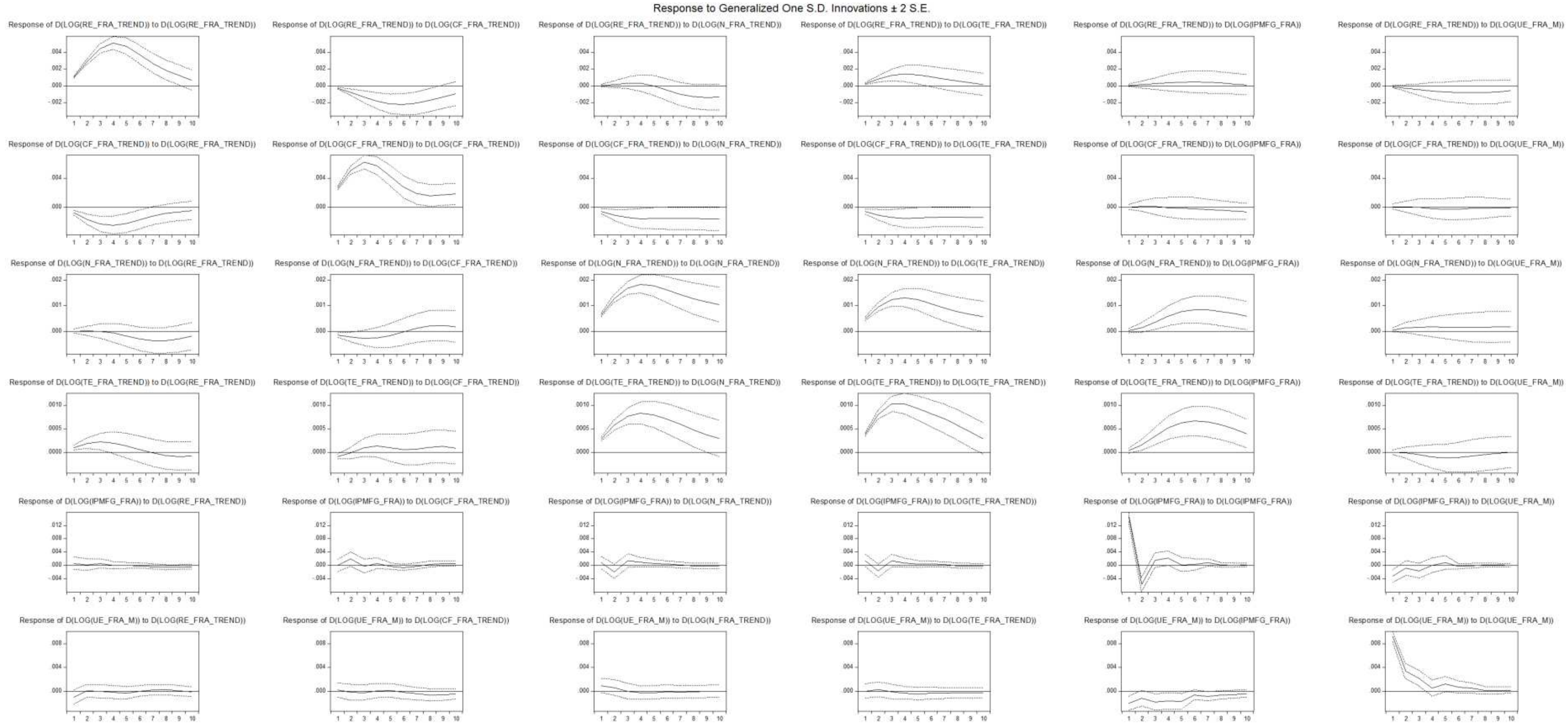

Figure 5:Impulse Response Functions: France. The continuous line represents the average response to positive shocks of 1 SD for each lag, the dotted lines represent ±2 standard errors

2.4.4.1. Electricity and Unemployment in France

There is a weakly significant indication that positive shocks to renewable energy might lead to a reduction of unemployment at lag one. All other variables held constant, an increase by 1 SD in the RES-E production on average leads to a drop in the unemployment rate by 0,10%. This is the opposite of the UE-rates response to shocks to nuclear electricity where a weakly significant increase can be detected. Changes in combustible fuels do not seem to influence the labour market.

Another, however not 100% waterproof finding is that rising unemployment rates seem to have - if any - a reducing effect on RES-E production.

2.4.5. Impulse Response Functions - Germany

Also for Germany, the electricity-related variables show patterns of interrelatedness. The model shows that the RES-E is significantly negatively influenced by increases in electricity from combustible fuel production in the last four months. All else held constant, a negative response of -0,12% to positive shocks in CF-E are reported on average.

Interestingly, however, no such pattern is detectible for increases in electricity from nuclear energy. On the other hand, increases in RES-E production often is followed by negative responses by both nuclear and combustible fuels.

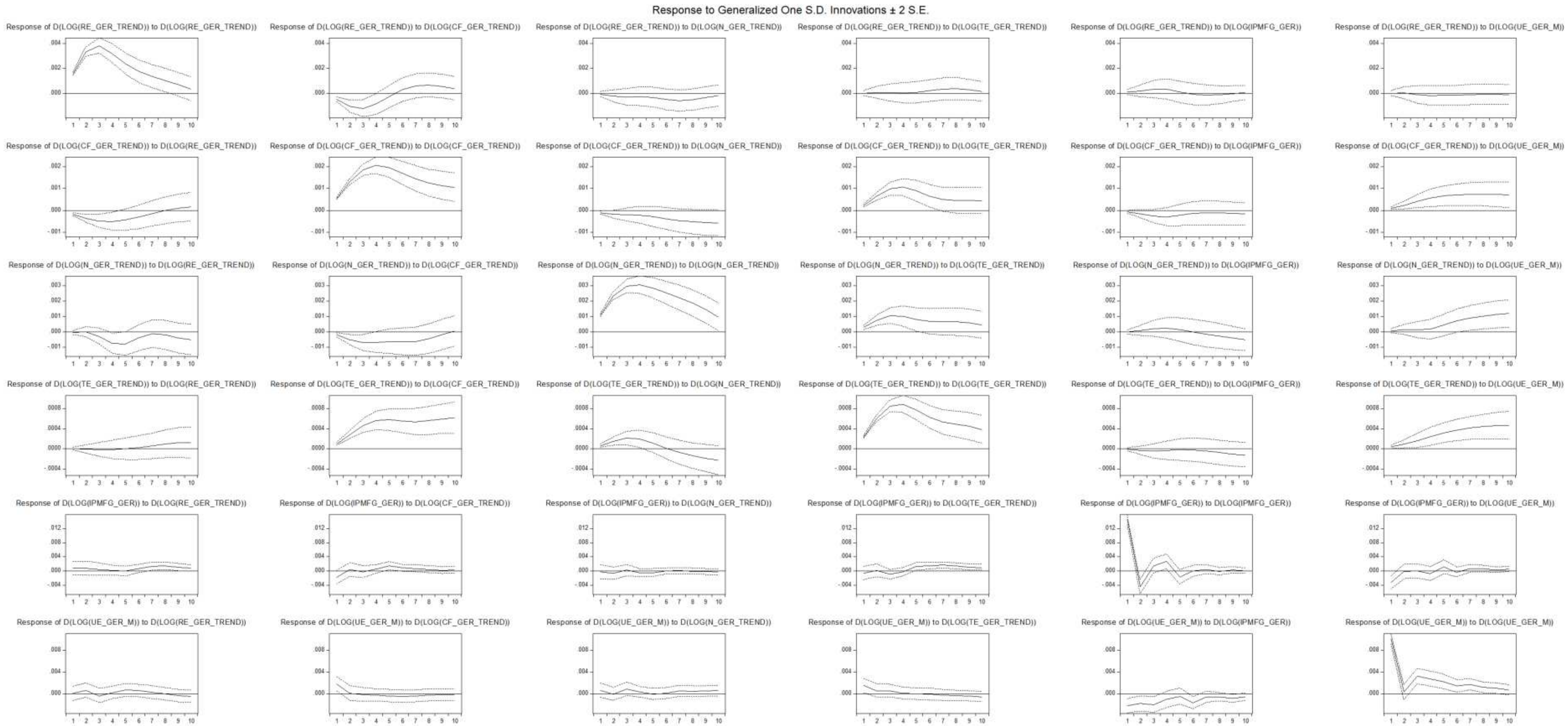

Figure 6: Impulse Response Functions: Germany. The continuous line represents the average response to positive shocks of 1 SD for each lag, the dotted lines represent ±2 standard errors.

2.4.5.1. The unemployment rate's responses to different sources of energy

The VAR model did not detect significant influences of increases in the share of renewable energies on the unemployment rate or the other way round. For lag 1 however, the model reports that an increase of 1 SD in combustible fuels will result, all other things held constant, in an uptick in the unemployment rate by 0,18% on average. Since RES-E production and the variable for nuclear electricity do not show such a relationship, a similar effect of the unemployment rate to an increase in total electricity production can be attributed to the same effect caused by combustible fuels. Also, an effect in the other direction is reported. German CF-E production seems to increase by an average of +0,07% if the unemployment rate increases by 1 SD.

One additional interesting (yet rather puzzling) finding is that the electricity production from nuclear energy seems to increase by an average of up to 0,12% assuming a 1% increase of unemployment for the lags 7-10.

2.4.5.3. Renewables and industrial production

The model furthermore reports slight indications for a relationship between output from the manufacturing sector and renewables. At a lag of 8 months, an average increase of 0,15% in IPMFG typically follows a shock of 1 SD to RES-E. The IRF does not show any signs of this being a two-way relationship since no significant responses of RES-E to IPMFG show up in the respective function.

3. Analysis of the Hypotheses, Conclusion and Discussion

3.1. Analysis of the Hypotheses

In general, it can be said that the VAR model provided some useful insights into the dynamic mechanisms at play in the electricity production sector of the 4 countries. I will discuss each of the initially formulated hypothesis individually and then shed light on some additional findings. For a quick overview of the significant interactions, table 2 shows the respective maximal responses for each pair of variables.

Table 2: Maxima (absolute value) of significant effects for each pair of variables.

Austria		Shocks by...					
		re	cf	n	te	ipmfg	ue
Responses by...	re	0,47%	-0,15%		0,37%	0,03%	
	cf		0,53%		0,13%		
	n						
	te	0,29%	0,07%		0,31%		
	ipmfg	0,23%				1,53%	
	ue					-0,65%	2,65%

France		Shocks by...					
		re	cf	n	te	ipmfg	ue
Responses by...	re	0,51%	-0,22%		0,14%		
	cf	-0,25%	0,62%	-0,16%	-0,15%		
	n		-0,02%	0,18%	0,13%	0,09%	
	te	0,02%	-0,01%	0,08%	0,10%	0,07%	
	ipmfg					1,45%	-0,32%
	ue					-0,20%	0,92%

Czech Republic		Shocks by...					
		re	cf	n	te	ipmfg	ue
Responses by...	re	0,84%	-0,13%	-0,14%	-0,13%		
	cf	-0,01%	0,22%	0,01%	0,11%		
	n	-0,20%	-0,11%	0,42%	0,17%		
	te	-0,04%	0,09%	0,08%	0,14%		
	ipmfg		0,19%		0,19%	1,74%	
	ue		0,67%	0,61%	0,96%		3,40%

Germany		Shocks by...					
		re	cf	n	te	ipmfg	ue
Responses by...	re	0,38%	-0,12%				
	cf	-0,05%	0,21%	-0,01%	0,11%		0,07%
	n	-0,08%	-0,07%	0,31%	0,11%		0,12%
	te		0,06%	0,02%	0,09%		0,05%
	ipmfg	0,15%	0,15%		0,17%	1,45%	-0,32%
	ue		0,18%		0,15%	-0,23%	1,01%

3.1.1 H1: There is a tendency towards significant negative bidirectional relationships between RES-E and N-E & CF-E production.

This hypothesis finds broad but not full support from the analysis of the impulse response functions. Rising amounts of renewable electricity are followed by lower production of electricity from combustion and nuclear power. For combustible fuels, this is demonstrated in the cases of the Czech Republic, Germany and France. A drop in nuclear electricity is only detected in Germany and the Czech Republic. The dominant French nuclear sector seems not to be influenced by changes to RES-E. Due to the lack of nuclear power in Austria, this country was not part of this comparison.

A similar effect is also detected in the other direction. In every one of the four countries, a shock to combustible fuels is answered by a change in the opposite direction of RES-E production. Only in the Czech Republic, such a relationship between nuclear energy and renewables was shown by the IRF.

The main explanation for this effect, as described by Apergis and Payne (2012), is the substitutability of different types of energy sources. If one type of fuel is increased for whatever reason, chances are that the other fuels get displaced from the market. This can be due to direct effects: E.g., One technology starts working at cheaper marginal costs, and thus the other technologies lose their foothold in the market. Or it can be a consequence of two indirectly related effects: E.g., A new policy favours one type of fuel over the other, and therefore the balance is tilted in the direction of one technology.

3.1.2. H2: There is a significant positive response of RES-E following shocks to the unemployment rate.

Such behaviour was not detected by the VAR model. Contrary to expectations, no significant effect showed up in the IRF.

A slight indication of a similar effect can be seen in the Czech case; however, this was not significant considering 2 standard errors.

Finally, it has to be said that this lack of evidence does not mean that the effects described by Ohler (2015) and Wei, Patadia and Kammen (2010) do not work for these European countries. These results just mean that there is a lack of empirical findings where such cause-effect relationship occurred during the observed period.

3.1.3. H3: There is a significant bidirectional positive relationship between RES-E and the industrial production index for manufacturing.

A bidirectional relationship was only found in the Austrian data. In this country, IPMFG and RES-E seem to positively influence each other. Germany is the only other country where any significant relationship between these two variables can be confirmed. However, the relationship does not work in both directions. Industrial production increases after a positive shock to renewable energy but a related effect is not observed in the opposite direction.

3.1.4. H4: There is a significant bidirectional positive relationship between CF-E and the industrial production index for manufacturing.

Based on this analysis, the assumption of a bidirectional reinforcing relationship has to be rejected completely. Especially the expectation of bidirectional behaviour was not met. While in the Czech Republic and Germany the IPMFG reacts positively to shocks to CF-E production, there is not a single case where combustible fuels increase or decrease significantly after a shock to IPMFG. In Austria and France, no relationship at all is observed.

3.2. Concluding Remarks

In this thesis, I tried to analyse some aspects of the market dynamics of electricity production in four exemplary countries. As expected, no overarching general principles were found, but some interesting relationships could be observed. The electricity market is a complex field, and, for this thesis, many simplifications had to be made. In general, it could be shown that changes in electrical energy production from nuclear and combustible fuels offered the best explanatory power on changes in the production from renewables. In comparison, the two economic variables used in this study – manufacturing and unemployment - are only weakly linked to the dynamics in the electricity production market.

Another goal of the study was the use of the Vector Autoregressive Model to the statistical analysis of data in energy policy. At present, there are still some limitations, but there is a high potential for further research using VAR models. The main reason for optimism is the expected increasing quality of available data. In a few years, analysing more accurately renewable electricity production versus non-renewable production will become possible. Increased availability of high-quality data also offers the possibility of analysing countries which could not be included in this thesis because their energy mix was too dissimilar from the other countries in the comparison. A broader geographic scope of the study would then, in turn, open up even more possibilities for deeper insights into the reasons for a successful energy transition.

Oaklef et al. (2019) created a tool for the estimation of the development potential for different energy sources on a global level at a spatial resolution of 1km. The inclusion of such data would offer more insights into the question to what extent resource abundance pre-defines the path a country takes.

Additionally, a broader scientific approach, including sociological data, could yield more insights into the effects of political developments and the changing relevance of climate issues. Furthermore, meteorological data could be brought into the analysis to control for natural effects causing the high volatility in the measured electricity production data.

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List of tables

List of Figures

Appendix A: Accompanying Tests

Block Exogeneity Wald Tests – Granger Causality

VAR Granger Causality/Block Exogeneity Wald Tests			
Country: Austria			
Sample: 2000M01 2019M12			
Included observations: 236			
Dependent variable: D(LOG(RE_AUT_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(CF_AUT_TREND))	1 072 684	3	0.0133
D(LOG(TE_AUT_TREND))	2 038 618	3	0.5644
D(LOG(IPMFG_AUT))	7 379 223	3	0.0607
D(LOG(UE_AUT_M))	3 489 190	3	0.3222
All	2 355 935	12	0.0233
Dependent variable: D(LOG(CF_AUT_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_AUT_TREND))	8 960 774	3	0.0298
D(LOG(TE_AUT_TREND))	1 049 806	3	0.0148
D(LOG(IPMFG_AUT))	5 662 026	3	0.1293
D(LOG(UE_AUT_M))	4 133 786	3	0.2474
All	2 132 342	12	0.0458
Dependent variable: D(LOG(TE_AUT_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_AUT_TREND))	1 771 146	3	0.0005
D(LOG(CF_AUT_TREND))	1 688 737	3	0.0007
D(LOG(IPMFG_AUT))	7 017 234	3	0.0714
D(LOG(UE_AUT_M))	3 468 961	3	0.3248
All	2 899 762	12	0.0039
Dependent variable: D(LOG(IPMFG_AUT))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_AUT_TREND))	2 675 933	3	0.4443
D(LOG(CF_AUT_TREND))	2 220 051	3	0.5280
D(LOG(TE_AUT_TREND))	3 065 560	3	0.3816
D(LOG(UE_AUT_M))	0.872672	3	0.8320
All	5 751 534	12	0.9281
Dependent variable: D(LOG(UE_AUT_M))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_AUT_TREND))	0.258743	3	0.9676
D(LOG(CF_AUT_TREND))	0.149981	3	0.9852
D(LOG(TE_AUT_TREND))	1 189 122	3	0.7556
D(LOG(IPMFG_AUT))	1 327 039	3	0.0041

All	2 243 354	12	0.0329

VAR Granger Causality/Block Exogeneity Wald Tests			
Country: Czech Republic			
Sample: 2000M01 2019M12			
Included observations: 235			
Dependent variable: D(LOG(RE_CZR_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(CF_CZR_TREND))	6 083 409	4	0.1930
D(LOG(N_CZR_TREND))	5 435 627	4	0.2454
D(LOG(TE_CZR_TREND))	9 654 265	4	0.0467
D(LOG(IPMFG_CZR))	5 711 407	4	0.2218
D(LOG(UE_CZR_M))	4 281 560	4	0.3692
All	3 127 705	20	0.0516
Dependent variable: D(LOG(CF_CZR_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_CZR_TREND))	1 971 051	4	0.7411
D(LOG(N_CZR_TREND))	1 435 382	4	0.0062
D(LOG(TE_CZR_TREND))	5 489 152	4	0.2407
D(LOG(IPMFG_CZR))	1 298 850	4	0.8616
D(LOG(UE_CZR_M))	7 066 447	4	0.1324
All	5 113 234	20	0.0002
Dependent variable: D(LOG(N_CZR_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_CZR_TREND))	2 208 057	4	0.0002
D(LOG(CF_CZR_TREND))	4 047 182	4	0.0000
D(LOG(TE_CZR_TREND))	7 696 508	4	0.1033
D(LOG(IPMFG_CZR))	4 738 465	4	0.3152
D(LOG(UE_CZR_M))	1 144 473	4	0.0220
All	1 127 626	20	0.0000
Dependent variable: D(LOG(TE_CZR_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_CZR_TREND))	6 331 863	4	0.1757
D(LOG(CF_CZR_TREND))	2 912 803	4	0.0000
D(LOG(N_CZR_TREND))	1 260 702	4	0.0134
D(LOG(IPMFG_CZR))	5 085 619	4	0.2786
D(LOG(UE_CZR_M))	7 778 715	4	0.1000
All	5 627 574	20	0.0000
Dependent variable: D(LOG(IPMFG_CZR))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_CZR_TREND))	9 280 966	4	0.0544

D(LOG(CF_CZR_TREND))	1 844 105	4	0.7644
D(LOG(N_CZR_TREND))	0.678886	4	0.9539
D(LOG(TE_CZR_TREND))	7 015 581	4	0.1351
D(LOG(UE_CZR_M))	3 503 806	4	0.4773
All	3 452 091	20	0.0228
Dependent variable: D(LOG(UE_CZR_M))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_CZR_TREND))	4 425 187	4	0.3515
D(LOG(CF_CZR_TREND))	4 413 664	4	0.3529
D(LOG(N_CZR_TREND))	4 941 810	4	0.2933
D(LOG(TE_CZR_TREND))	3 508 368	4	0.4766
D(LOG(IPMFG_CZR))	6 589 114	4	0.1593
All	3 594 815	20	0.0156

VAR Granger Causality/Block Exogeneity Wald Tests			
Date: 05/21/20 Time: 11:25			
Sample: 2000M01 2019M12			
Included observations: 235			
Dependent variable: D(LOG(RE_FRA_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(CF_FRA_TREND))	1 617 882	4	0.0028
D(LOG(N_FRA_TREND))	2 728 800	4	0.0000
D(LOG(TE_FRA_TREND))	1 730 216	4	0.0017
D(LOG(IPMFG_FRA))	0.215274	4	0.9946
D(LOG(UE_FRA_M))	0.369183	4	0.9849
All	3 820 927	20	0.0083
Dependent variable: D(LOG(CF_FRA_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_FRA_TREND))	6 005 086	4	0.1988
D(LOG(N_FRA_TREND))	3 019 385	4	0.5546
D(LOG(TE_FRA_TREND))	1 765 611	4	0.7788
D(LOG(IPMFG_FRA))	2 924 894	4	0.5705
D(LOG(UE_FRA_M))	0.772952	4	0.9420
All	1 554 190	20	0.7446
Dependent variable: D(LOG(N_FRA_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_FRA_TREND))	6 309 569	4	0.1772
D(LOG(CF_FRA_TREND))	3 072 029	4	0.5458
D(LOG(TE_FRA_TREND))	1 034 211	4	0.9046
D(LOG(IPMFG_FRA))	1 285 882	4	0.0120
D(LOG(UE_FRA_M))	3 650 926	4	0.4553
All	2 736 458	20	0.1253

Dependent variable: D(LOG(TE_FRA_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_FRA_TREND))	5 407 413	4	0.2480
D(LOG(CF_FRA_TREND))	4 900 866	4	0.0000
D(LOG(N_FRA_TREND))	1 460 875	4	0.0056
D(LOG(IPMFG_FRA))	1 685 836	4	0.0021
D(LOG(UE_FRA_M))	2 945 190	4	0.5670
All	9 138 153	20	0.0000
Dependent variable: D(LOG(IPMFG_FRA))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_FRA_TREND))	4 823 110	4	0.3059
D(LOG(CF_FRA_TREND))	5 854 336	4	0.2103
D(LOG(N_FRA_TREND))	3597930	4	0.4631
D(LOG(TE_FRA_TREND))	0.384008	4	0.9838
D(LOG(UE_FRA_M))	1 083 641	4	0.0285
All	2 972 369	20	0.0745
Dependent variable: D(LOG(UE_FRA_M))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_FRA_TREND))	2 176 332	4	0.7034
D(LOG(CF_FRA_TREND))	1 016 678	4	0.9073
D(LOG(N_FRA_TREND))	2 268 015	4	0.6866
D(LOG(TE_FRA_TREND))	2 276 295	4	0.6851
D(LOG(IPMFG_FRA))	7 870 769	4	0.0964
All	1 396 709	20	0.8322

VAR Granger Causality/Block Exogeneity Wald Tests			
Date: 05/21/20 Time: 11:26			
Sample: 2000M01 2019M12			
Included observations: 235			
Dependent variable: D(LOG(RE_GER_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(CF_GER_TREND))	4 990 231	4	0.2883
D(LOG(N_GER_TREND))	7 698 605	4	0.1033
D(LOG(TE_GER_TREND))	2 459 846	4	0.6518
D(LOG(IPMFG_GER))	6 408 933	4	0.1706
D(LOG(UE_GER_M))	3 821 026	4	0.4308
All	2 323 761	20	0.2773
Dependent variable: D(LOG(CF_GER_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_GER_TREND))	0.904213	4	0.9240
D(LOG(N_GER_TREND))	3 935 804	4	0.4148
D(LOG(TE_GER_TREND))	1 465 861	4	0.0055
D(LOG(IPMFG_GER))	7 605 221	4	0.1072

D(LOG(UE_GER_M))	7 150 013	4	0.1282
All	3 873 272	20	0.0072
Dependent variable: D(LOG(N_GER_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_GER_TREND))	5 096 132	4	0.0000
D(LOG(CF_GER_TREND))	6 871 270	4	0.1428
D(LOG(TE_GER_TREND))	1 091 302	4	0.0276
D(LOG(IPMFG_GER))	2 881 268	4	0.5779
D(LOG(UE_GER_M))	9 179 069	4	0.0568
All	8 220 597	20	0.0000
Dependent variable: D(LOG(TE_GER_TREND))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_GER_TREND))	1 385 050	4	0.8468
D(LOG(CF_GER_TREND))	1 469 298	4	0.0054
D(LOG(N_GER_TREND))	4 809 069	4	0.3075
D(LOG(IPMFG_GER))	3 169 515	4	0.5299
D(LOG(UE_GER_M))	1 220 839	4	0.0159
All	3 840 518	20	0.0079
Dependent variable: D(LOG(IPMFG_GER))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_GER_TREND))	6 945 310	4	0.1388
D(LOG(CF_GER_TREND))	5 371 179	4	0.2513
D(LOG(N_GER_TREND))	2140005	4	0.7100
D(LOG(TE_GER_TREND))	1 510 143	4	0.0045
D(LOG(UE_GER_M))	2 349 318	4	0.6718
All	3 984 145	20	0.0052
Dependent variable: D(LOG(UE_GER_M))			
Excluded	Chi-sq	df	Prob.
D(LOG(RE_GER_TREND))	3 216 094	4	0.5223
D(LOG(CF_GER_TREND))	3 876 447	4	0.4230
D(LOG(N_GER_TREND))	1 718 505	4	0.7874
D(LOG(TE_GER_TREND))	2 328 995	4	0.6755
D(LOG(IPMFG_GER))	1 409 618	4	0.0070
All	3 144 296	20	0.0496

Residual Autocorrelation – Ljung-Box-Tests

VAR Residual Portmanteau Tests for Autocorrelations					
Null Hypothesis: No residual autocorrelations up to lag h					
Country: Austria					
Sample: 2000M01 2019M12					
Included observations: 236					
Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df

1	1 503 579	---	1 509 977	---	---
2	4 031 432	---	4 059 436	---	---
3	5 601 130	---	5 649 344	---	---
4	8 495 383	0.0000	8 593 499	0.0000	25
5	1 118 107	0.0000	1 133 732	0.0000	50
6	1 393 229	0.0000	1 416 031	0.0000	75
7	1 554 688	0.0003	1 582 425	0.0002	100
8	1 852 927	0.0004	1 891 128	0.0002	125
9	2 074 879	0.0013	2 121 881	0.0006	150
10	2 603 864	0.0000	2 674 272	0.0000	175
11	2 976 149	0.0000	3 064 757	0.0000	200
12	3 269 418	0.0000	3 373 738	0.0000	225
13	3 480 016	0.0000	3 596 613	0.0000	250
14	3 624 187	0.0003	3 749 875	0.0001	275
15	3 831 093	0.0008	3 970 824	0.0001	300

*Test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: No residual autocorrelations up to lag h

Country: Czech Republic

Sample: 2000M01 2019M12

Included observations: 235

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	7 520 121	---	7 552 259	---	---
2	3 533 865	---	3 560 957	---	---
3	5 471 451	---	5 523 599	---	---
4	7 941 585	---	8 036 505	---	---
5	1 062 830	0.0000	1 078 162	0.0000	36
6	1 312 361	0.0000	1 334 231	0.0000	72
7	1 734 531	0.0001	1 769 363	0.0000	108
8	2 166 779	0.0001	2 216 845	0.0000	144
9	2 433 288	0.0012	2 493 967	0.0005	180
10	2 959 849	0.0002	3 043 931	0.0001	216
11	3 308 476	0.0006	3 409 678	0.0002	252
12	3 807 463	0.0002	3 935 516	0.0000	288
13	4 077 355	0.0011	4 221 212	0.0002	324
14	4 406 270	0.0023	4 570 963	0.0004	360
15	4 854 692	0.0014	5 049 959	0.0002	396

*Test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: No residual autocorrelations up to lag h					
Date: 05/21/20 Time: 11:34					
Sample: 2000M01 2019M12					
Included observations: 235					
Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	7 551 562	---	7 583 833	---	---
2	4 759 480	---	4 797 079	---	---
3	7 065 385	---	7 132 802	---	---
4	8 984 733	---	9 085 386	---	---
5	1 126 870	0.0000	1 141 900	0.0000	36
6	1 451 328	0.0000	1 474 860	0.0000	72
7	2 010 393	0.0000	2 051 089	0.0000	108
8	2 465 032	0.0000	2 521 750	0.0000	144
9	3 110 765	0.0000	3 193 198	0.0000	180
10	3 488 704	0.0000	3 587 935	0.0000	216
11	3 780 970	0.0000	3 894 553	0.0000	252
12	4 229 454	0.0000	4 367 171	0.0000	288
13	4 538 185	0.0000	4 693 980	0.0000	324
14	4 870 528	0.0000	5 047 377	0.0000	360
15	5 175 641	0.0000	5 373 293	0.0000	396
*Test is valid only for lags larger than the VAR lag order.					
df is degrees of freedom for (approximate) chi-square distribution					

VAR Residual Portmanteau Tests for Autocorrelations					
Null Hypothesis: No residual autocorrelations up to lag h					
Date: 05/21/20 Time: 11:34					
Sample: 2000M01 2019M12					
Included observations: 235					
Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	1 201 743	---	1 206 879	---	---
2	3 722 566	---	3 749 340	---	---
3	5 848 535	---	5 902 800	---	---
4	7 248 170	---	7 326 671	---	---
5	1 026 826	0.0000	1 041 241	0.0000	36
6	1 293 171	0.0000	1 314 565	0.0000	72
7	1 580 351	0.0012	1 610 562	0.0007	108
8	2 051 829	0.0006	2 098 656	0.0003	144
9	2 626 852	0.0001	2 696 578	0.0000	180
10	2 949 701	0.0003	3 033 775	0.0001	216
11	3 373 863	0.0003	3 478 767	0.0001	252
12	3 794 314	0.0002	3 921 844	0.0000	288
13	4 130 694	0.0006	4 277 921	0.0001	324
14	4 666 972	0.0001	4 848 172	0.0000	360

15	4 986 318	0.0003	5 189 291	0.0000	396

*Test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

Appendix B: Country Notes accompanying the IEA dataset (IEA 2020)

Austria:

- Monthly reporting does not include production from geothermal, therefore it is estimated by the IEA Secretariat based on annual submission since January 2003.
- Monthly reporting does not include production from solar, therefore it is estimated by the IEA Secretariat based on annual submission since January 2003.
- Monthly reporting does not include production from other non combustible fuels, therefore it is estimated by the IEA Secretariat based on annual submission since January 2003.

Czech Republic:

- Monthly reporting did not include production from other non combustible fuels, therefore it was estimated by the IEA Secretariat based on annual submission from January 2004 until December 2008.

France:

- Includes Monaco. Since January 2018 it includes the French overseas territories: French Polynesia, Guadeloupe, Guyane, Martinique, New Caledonia, Reunion, Saint Pierre and Miquelon.
- Monthly reporting does not include production from solar, therefore it is estimated by the IEA Secretariat based on annual submission since January 2000.
- Monthly reporting does not include production from other non combustible fuels, therefore it is estimated by the IEA Secretariat based on annual submission since January 2000.
- Monthly reporting did not include production from wind, therefore it was estimated by the IEA Secretariat based on annual submission from January 2000 until December 2004.

Germany:

- Combustible Fuels production is estimated from monthly submissions of production from main electricity producers.
- Monthly reporting did not include production from solar, therefore it was estimated by the IEA Secretariat based on annual submission from January 2000 until December 2001.

- Monthly reporting did not include production from wind, therefore it was estimated by the IEA Secretariat based on annual submission from January 2000 until December 2001.
- Due to an increase in survey coverage since January 2017, the level of production and the growth rate shown may be different than actual.