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The Impact of Governmental Energy Research and Development Investments on Economic Growth

A Structural VAR Analysis for Germany

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Abstract

Germany exhibits one of the world's largest governmental budgets for supporting the energy transition through direct policy tools, such as *R&D* investments. While governmental investments in the German renewable energy sector are commonly rationalised against the background of reducing CO_2 emissions and ensuring energy security, economic implications have received less attention. Next to identifying the importance of the economic impact of governmental *R&D* investments to provide justification for the allocation of public financial resources, we contribute to existing literature by determining the impact of renewable and fossil fuel energy *R&D* investments on economic growth in a structural Vector Autoregressive Model. Using impulse response functions and forward error variance decompositions, we find a significant negative impact of renewable energy *R&D* on economic growth, which is transmitted through the channels capital and price. No significant impact of a shock in fossil fuel *R&D* on economic growth has been observed. The results are robust to various sensitivity checks and we additionally extend our model by analysing the effectiveness of governmental *R&D* investments in changing the energy consumption mix. The results provide evidence for an adverse effect of fossil fuel *R&D* on renewable energy consumption and a positive impact of renewable energy *R&D* on both forms of energy consumption. The underlying estimation of the economic impact of governmental energy *R&D* in this study provides key insights for the policy design in the German energy sector.

Keywords: Renewable Energy, Fossil Fuel, R&D, Economic Growth, Vector Autoregressive Model, Germany

JEL classification: C32, O44, Q43, Q48

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List of Abbreviations

AIC	Akaike Information Criterion.
BIC	Bayesian Information Criterion.
FEVD	Forecast Error Variance Decomposition.
FF	Fossil Fuel Energy.
GDP	Gross Domestic Product.
IEA	International Energy Agency.
IRF	Impulse Response Function.
OLS	Ordinary Least Squares.
R&D	Research & Development.
RD&D	Research, Development & Demonstration.
REN	Renewable Energy.
SD	Standard Deviation.
SVAR	Structural Vector Autoregressive Model.
VAR	Vector Autoregressive Model.
VECM	Vector Error Correction Model.

1. Introduction

In recent years, global warming and other environmental concerns have raised a fierce public discussion about the usage of conventional energy sources. While this expresses the need for constant CO_2 emission reduction, renewable energy sources are often seen as the solution to growing global energy demand. In the debate on the transition to renewable energy sources, Germany is often mentioned as a role model in the retreat from fossil fuels by employing renewable energy technologies. Along a short-term nuclear power phase-out, the German government targets a total energy consumption with 60% gained from renewable sources by 2050 (Renn and Marshall 2016).

It is widely acknowledged that the transition to alternative energy technologies requires not only large efforts by the general public, private sector and other organisations, but also assigns an important role to governments and their policy tools to incentivise and guide the change of energy composition (Wong, Chang and Chia 2013a). Technology-push policies, such as governmental research and development ($R\&D$) programs, have been found to be effective in sustaining long-term cost reductions and are therefore a crucial direct policy tool for increasing the share of renewable sources in the energy composition of a country (Nemet and Baker 2009).[1]

While the energy transition is essential for reasons, such as a secure energy supply and climate change, the costs and economic implications are to a large degree undiscovered. Today, most of the costs of the energy transition are paid by the end-consumers through higher electricity prices and general taxes. Over the last years, a growing body of empirical literature has evolved on the economic implications of the energy transition. Most scholars have looked at the relationship between consumption and economic growth and observe uni- and bidirectional effects using panel data sets. Only few empirical studies explored the R&D-growth nexus and find both positive and negative effects of governmental investments in the renewable energy sector on economic growth. The consensus on these relationships is, that promoting energy R&D stimulates economic growth through technological progress. As a side effect, guiding resources to energy R&D may imply less resources that can be used for other factors of production and therefore harms economic growth.

This paper investigates the impact of renewable energy investment on economic growth and compares it with the effect of investments in traditional energy sources. The assessment helps policy makers to provide justification for the allocation of public financial resources. Moreover, the time lag between investment and impact is discussed. Since the impact of energy R&D on economic growth is taken via distinct transmission channels, the impact on the variables capital, labour and energy price is displayed. Furthermore, investments in the renewable energy sector are expected to decrease traditional energy consumption. This crowding-out effect of traditional energy consumption is investigated in an extension of the primary analysis.

The principal aim of this paper is to study the energy R&D-growth nexus in a structural Vector Autoregression framework. To the best of our knowledge, no paper has yet studied the relationship between governmental energy R&D investments and economic growth by

1. Technology-push instruments influence the supply of new knowledge (Taylor 2008 p.2830).

utilising this methodology. We undertake a time series analysis of Germany specifically and thereby differentiate this study from related literature, which bases the analysis on panel data. Capturing the endogenous nature of the underlying macroeconomic variables, the applied model has been proven as particularly suitable to account for simultaneous relationships and reverse causality (Gottschalk 2001).

The main result of the analysis using impulse response functions and forecast error variance decompositions is, that we find a negative and deferred impact of governmental renewable energy R&D investments on economic growth. Both the capital and price channel turn out to be important in transmitting the effects from renewable energy R&D investments on economic growth. Furthermore, this study cannot find evidence for a significant impact on economic growth caused by a shock in governmental energy R&D investments in the fossil fuel sector. In the extended model, we can additionally confirm the importance of renewable energy R&D investments as a policy tool to change the energy consumption mix.

The structure of this thesis is as follows: Chapter 2 provides a research context on the current political discussion of the energy transition in Germany and explains the transmission channels of governmental energy R&D on economic growth, thus highlighting the importance and relevance of renewable energy R&D for policy making in Germany. In Chapter 3, we present a literature review, summarising existing empirical studies that have investigated the economic impact of renewable and non-renewable energy sources. Further, Chapter 4 introduces a theoretical model that serves as a rationale for the econometric analysis. Chapter 5 describes the underlying data used in this research and corresponding descriptive statistics are presented. After that, we outline the empirical methodology and model specification in Chapter 6 and 7, respectively. In Chapter 8, impulse response functions and forecast error variance decompositions, which are received from the structural vector autoregressive model, are displayed and discussed. Subsequently, we test the robustness of our model and introduce an extension of the analysis in Chapter 9 and 10, respectively. Chapter 11 summarises the results from the empirical analysis. Subsequently, Chapter 12 discusses policy implications and limitations of the research design. The conclusion is presented in Chapter 13.

2. Research Context

2.1 The Energy Transition and Current Political Discussion in Germany

The energy transition in Germany, also known as *Energiewende*, reaches back to the 1970s and 1980s during which the ecological movement, the oil crisis and accidents, such as Chernobyl, triggered a change of thinking in society and politics. When environmental awareness increased over the years, renewable energy technologies became part of energy policies on a larger scale. Until then, Germany has been mainly using fossil fuels and lignite in particular for its energy supply.[2] Following several policy reforms, the energy transition in Germany started to become more tangible in the form of a planned retreat from fossil fuel towards renewable energy sources. Despite the start of the gradual phase-out in the beginning of the 21st century, fossil fuels still remain important for Germany today. Strong resistance against the energy transition comes from the coal industry itself, which, due to strong labour unions and lobbying power, possesses substantial political influence (Renn and Marshall 2016). After the nuclear accident in Fukushima in March 2011, the initial plan to use nuclear energy to bridge the phase-out of fossil fuels was not at issue anymore.

Generally, the energy transition in Germany stands for an increase in the supply of renewable energy as an alternative to traditional energy sources and for an improvement in energy efficiency (BMWi 2015).[3] Changing the composition of energy sources is rationalised by three key reasons: climate protection, energy security and cost-effectiveness (economic benefits) (BMWi 2012).

The first argument in favour of the energy transition in Germany is the reduction of CO_2 emissions by increasing the consumption of environmentally-friendly energy sources, such as wind, hydro or solar technologies. This is the most prominent motive that is used in order to promote a change towards renewable energy sources, as it especially leverages the awareness of the environment by society. Mitigating the climate change with the help of a shift in energy supply is also directly embedded in Germany's climate targets.[4]

Energy security is the second rationale for a shift in energy consumption. As global energy consumption is steadily rising and fossil fuel resources will deplete in the foreseeable future, the dependency of countries with less natural resources on countries with a greater amount of natural resources will increase. In order to avoid this development, a transition in the energy consumption towards renewable energy sources is inevitable; in particular for countries that have limited natural energy resources. Thus, the outcome of the energy transition with regard to the security of energy supply is defined through targets and, in this way, also ensures transparency of the likely impact of the shift towards renewable energy sources.[5]

The last argument commonly used to rationalise the German energy transition is cost-effectiveness. The energy transition as an engine for economic growth through higher employment, technological progress and competitiveness creates incentives for the change, and simultaneously, represents an important element of Germany's energy politics. In contrast to the first two aspects, the argument of economic benefit is not integrated in the targets set by the German government, making it difficult to understand and to anticipate the economic consequences of the transition.

2. Germany has the second largest lignite reserves worldwide after Russia and was globally the largest producer with 178 million tonnes in 2015, which is 17,4% of the total lignite production (Statista 2016; BGR 2015).

3. "Energy efficiency is a way of managing and restraining the growth in energy consumption. Something is more energy efficient, if it delivers more services for the same energy input, or the same services for less energy input" (IEA 2014 p.17).

4. Reduction of CO_2 emissions by 40% until 2020, by 55% until 2030, 70% until 2040 and between 80% and 95% until 2050 (base year: 1990) (BMWi 2016c).

5. "An increase in the share of renewable energy consumption to 18% until 2020, 30% until 2030, 45% until 2040 and 60% until 2050 of total energy consumption in Germany" (BMWi 2016c).

In order for Germany to achieve its targets, the government applies a set of instruments that are based on five platforms: 1) Energy efficiency, 2) Energy grids, 3) Electricity market, 4) Energy transition in buildings, 5) Research and innovation (BMWi 2016c). While all platforms and their corresponding tools pursue a certain purpose, the research and innovation platform performs a particularly important contribution in reaching long-term objectives. Its overall aim is to support an increasing deployment of renewable energy sources while ensuring a secure and cost-effective transition towards renewable energy.

The importance of governmental energy R&D as driving factor of economic growth is derived from its contribution to knowledge accumulation that subsequently leads to technological progress. The driving factor of technological change in general is embedded in learning through research (Aghion and Howitt 1992; Grossman and Helpman 1993) and the concept of learning by doing (Stokey 1988; Young 1991). While learning through research includes inventions, innovations and development of technologies, learning by doing is mainly related to learning effects through economies of scale, utilisation and the general commercialisation and diffusion of technology (Jamasb 2007). In accordance with this observation, learning through research leads to cost-cutting learning effects in relatively infant industries, such as the renewable energy sector, that are not matched by learning rates of capacity expansions (Koseoglu, Berg and Lacerda 2013). In electricity generating technologies specifically, it has further been shown that learning by research has an effect on technological progress over a longer time horizon compared to learning by doing that has its impact shortly after its application (Jamasb 2007; Koseoglu, Berg and Lacerda 2013). A further assumption behind governmental R&D is that cost-cutting learning effects spill over to the whole energy sector through knowledge-spillover effects (Rave, Triebswetter and Wackerbauer 2013). This argument is also a key assumption in the endogenous growth theory by Romer (1986), which states that knowledge spillovers among producers may allow for endogenous economic development. The theory further states that policy measures, such as subsidies for R&D, play a key role in increasing economic growth. In accordance with this, "governments regularly subsidise R&D for branches of knowledge, where wide diffusion of the resulting knowledge seems especially important" (Parker 2012 p.6).

Research and innovation funding by the German government specifically aims at reducing the production costs of renewable energy and hence contributes to the increase in renewable energy consumption. Moreover, financial governmental support for R&D programs in the renewable energy sector is an effective and flexible instrument, which allows to absorb some of the risks of investing into energy R&D. In this way, it triggers and accelerates technological changes that are system relevant and central to the expansion of renewable energies (BMWi 2016a). Besides the investment risk and carbon lock-in effects, market imperfections, such as negative externalities of fossil fuels (e.g. CO_2 emissions) that may not be included in the resource price, justify the importance of governmental intervention for adjusting the energy market (Rave, Triebswetter and Wackerbauer 2013).[6]

6. "It is asserted that this condition, termed carbon lock-in, creates persistent market and policy failures that can inhibit the diffusion of carbon-saving technologies despite their apparent environmental and economic advantages" (Unruh 2000 p.817).

In accordance with the previous assumptions, renewable energy sources historically "[...] have received a commitment that is stronger and more consistent than in any other energy R&D area" (Runci 2004 p.14). From 2013 until 2016, the German government spent 3.5 billion euros in projects that enhance research and development process of modern energy technologies (BMBF 2016). More than 90% of these investments flow into the development of renewable energy sources and the improvement of energy production efficiency, with around 50% of the investments being allocated to the expansion of renewable energy sources (BMWi 2014). Since most of the climate targets of the energy transition in Germany are focused on the expansion of renewable energy sources, rather than the energy consumption efficiency, we concentrate on the investigation of funds that directly flow into the R&D of energy production.

The research and innovation platform is not only important for the development of renewable energy sources, but has also been addressed to support the fossil fuel energy sector in the past. Since fossil fuel lignite is considered a natural reserve and lignite coal reserves are a main tool to secure energy supply in Germany, it is classified as strategically important to maintain the competitiveness of the sector. Further, the coal industry accounts for many jobs and thus possesses strong political bargaining power. For this reason, the government is supporting the fossil fuel sector until today through subsidies, such as R&D investments.

2.2 Transmission Channel of Governmental R&D on Economic Growth

In the following paragraph, we outline the main transmission channels from governmental R&D to economic growth in order to better understand the rationale and mechanisms behind the estimated impact, which is presented in Chapter 8.[7] As depicted in Figure 1, governmental R&D follows a direct and indirect transmission channel towards economic growth. In our study, we consider governmental energy R&D investments in the renewable energy sector ($R\&D_{REN}$) and the fossil fuel sector ($R\&D_{FF}$).

The direct channel, which we call *investment effect*, is characterised by R&D activities that trigger current costs and capital expenditures.[8,9] Providing financial resources for R&D activities in the renewable energy and/or fossil fuel domestic sectors leads to an increase in current costs and capital expenditures (IEA 2011). The investment effect evolves as the spending on labour and capital are required in order to conduct R&D activities in the first place.[10] Independent of the outcome of the research activities, the injection of financial grants to labour and capital expenditures alone directly impacts the economy.

The second transmission channel works through energy consumption. As displayed in Figure 1, the indirect effect of R&D on economic growth hinges on the success of R&D

7. We assume the transmission mechanism to primarily work through capital, labour and price (consumption) but expect that the effect of a change in governmental R&D may work through other channels as well.

8. Current costs are defined as labour costs "[...]as well as non-capital purchases of materials, supplies and equipment to support R&D performed in a given period" (OECD 2015 p.366).

9. Capital expenditures include spending on "major fixed assets used in R&D programs, [...]including land, buildings, instruments and equipment" (OECD 2015 p.367).

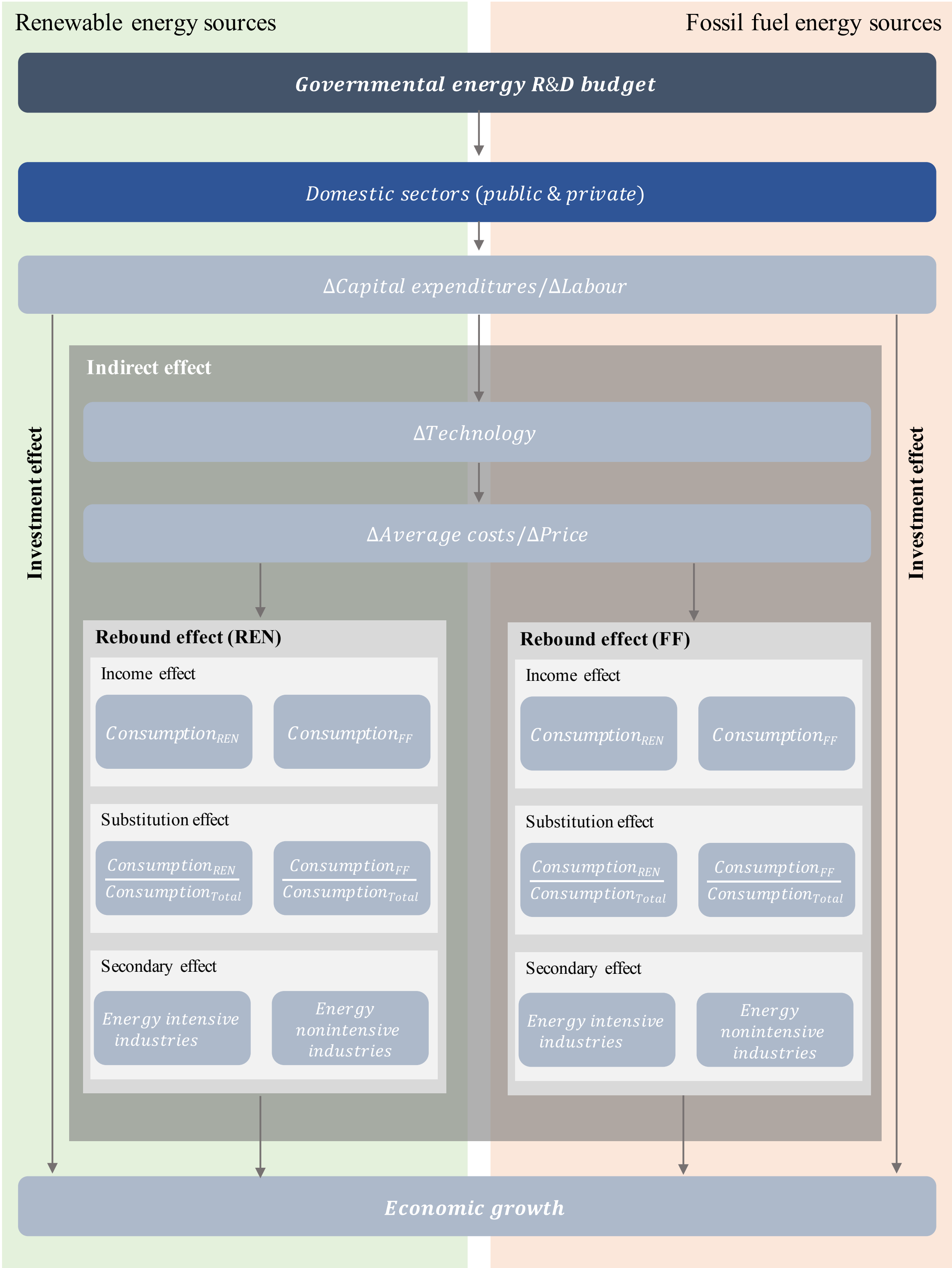
10. We assume that R&D budgets are entrusted for a specific purpose; i.e. R&D on renewable energy and fossil fuel technologies.

programs. More specifically, while the investment effect is dependent on the direct input variables, such as capital and labour, the indirect effect will be determined by the outcome of the R&D programs and likely to have a lagged effect due to the lengthiness of the R&D process (Rouvinen 2002). According to the endogenous growth theory, output from R&D activities is technological progress. One of the major consequences of such technology advancements is the reduction of average costs per energy unit through efficiency and lifetime improvements. Nemet and Baker (2009) find that R&D programs are more effective in cost reduction than learning by doing activities and that R&D programs are critical for cost reductions in the long-term. Triggered by a change in average costs, a shift in energy use can be observed (Nemet and Baker 2009). In economic theory, this effect is called *rebound effect* (Greening, Greene and Difiglio 2000). Three separate mechanisms determine the size and the direction of the effect: *income*, *substitution* and *secondary effects*.

The income effect is characterised by a change in the consumption of energy sources, which is caused by increased efficiency or lifespan through technology advances, which in turn decreases the costs and consequently alters the consumption behaviour (O'Sullivan, Sheffrin and Perez 2014). Generally, one can assume that this change in behaviour will lead to an increase in the consumption of all inputs, including energy sources. This offsets to some extent the reduced consumption due to efficiency gains.

The substitution effect between renewable energy and fossil fuel consumption is caused by a shift in relative prices of respective energy sources and hence changes the composition of energy consumption with regard to renewable energy and fossil fuel. For example, renewable *R&D* may lead to a reduction in renewable energy price and thus changes the price relationship between renewable energies and fossil fuels. As a reaction to this shift, the market will decide to increase renewable energy consumption as a substitute for fossil fuels (Sorrell 2007).

The third effect is called secondary effect. This effect describes the transmission channel outside the energy sector. A reduction in the price of energy sources may reduce the production costs and subsequently the price of intermediate and final goods throughout the economy (Sorrell 2007). This would lead to increased consumption of the respective products and services, thereby further increasing energy consumption. In particular, energy-intensive industries are likely to gain from secondary effects that are triggered through R&D. Other secondary effects for example, are increased purchasing behaviour of other services and goods. The effect of consumption on economic growth closes the indirect transmission channel of R&D on economic growth.



Source: Own illustration

Figure 1: Transmission Channel

3. Literature Review

Most studies, which have estimated the economic consequence of the energy transition specifically for Germany, look at the effect of increasing renewable energy sources on employment. This is also in line with the observation made in Section 2.1, that states the emphasised importance of employment effects following the energy change as a proxy for the economic benefits in Germany. While the study by O'Sullivan et al. (2009) outlines an increase in employment due to deployment of renewable energy technologies, several empirical studies conclude that long-term net employment effects are negligible (Frondel et al. 2010). The main reason for this are the adverse effects of an increasing share of renewable energy technologies on employment in other parts of the energy sector. Since our research focuses on the overall effect of energy R&D on economic growth, we will present studies in the following sections that have looked at the impact of energy R&D and energy consumption on economic growth holistically.

3.1 Consumption-growth Nexus

The economic impact of renewable energy has been primarily investigated by studies, which show the relationship between energy consumption and economic growth. More precisely, researchers have focused on finding empirical evidence for the *growth*, *feedback* and *conservation hypothesis* (Tugcu, Ozturk and Aslan 2012).[11]

Focusing on the growth hypothesis, Inglesi-Lotz (2015) determines the impact of renewable energy consumption on economic growth for OECD countries. The findings indicate a long-run equilibrium relationship between renewable energy consumption and gross domestic product (GDP), revealing that rising renewable energy consumption positively impacts GDP. These results confirm that deploying renewable energy resources does not harm economic growth and renewable energy consumption can be justified not only by environmental but also supported by economic arguments. This finding is further confirmed by a study of the top 38 renewable energy consuming countries, in which Bhattacharya et al. (2015) find that long-run output elasticities indicate a significant positive impact of renewable energy consumption for 57% of the selected countries, among them Germany. Further, the findings suggest that output elasticity with respect to non-renewable energy consumption is larger than with respect to renewable energy consumption (Bhattacharya et al. 2016). The energy growth hypothesis is therefore confirmed for both renewable and non-renewable energy consumption and indicates a stronger effect of non-renewable energy consumption on economic growth. Thus, increasing renewable energy consumption does not negatively impact economic growth, but is subject to opportunity costs, being the reduction in non-renewable energy consumption.

According to economic theory, the impact of energy consumption on economic growth is subject to reverse causality. While most studies determine uni-directional effects, Pala

11. "Growth hypothesis: Uni-directional causality from energy consumption to economic growth. Feedback hypothesis: Bi-directional causality between energy consumption and economic-growth. Conservation hypothesis: Uni-directional causality from economic growth to energy consumption" (Tugcu, Ozturk and Aslan 2012).

(2016) estimates the bi-directional causality with Granger causality tests. The finding is a bi-directional short-term causality between energy consumption and economic growth for OECD countries. This supports the feedback hypothesis, which says that economic growth is energy dependent but also a major driver of energy consumption.

The study of renewable and non-renewable consumption in G7 countries by Tugcu, Ozturk and Aslan (2012) analyses the energy consumption-growth nexus differentiating between energy technologies. In the framework of the classical production function, bi-directional causality is found between both renewable and non-renewable energies and economic growth for Germany and all other studied countries. This suggests that both renewable and non-renewable energy consumption impact economic growth and proves the existence of reverse causality in this relationship.

Energy consumption is a variable on the market's demand side, which can be mainly influenced through demand-pull schemes.[12] To draw further conclusions about the supply-side of the market, few studies on energy R&D and its impact on economic growth have been undertaken.

3.2 R&D and Economic Growth

Studying energy R&D and its impact on economic growth has been subject to the production function framework, as this enables to account for endogenous technological change through R&D and controls for other production factors. Using a panel-analysis of 20 OECD countries, Wong, Chang and Chia (2013a) find a positive and significant impact of $R\&D_{FF}$ on economic growth for all investigated countries, including Germany. They argue that most countries remain highly dependent on fossil fuels and therefore $R\&D_{FF}$ is found to have a large impact on economic growth. However, the study also reveals significant and positive effects of $R\&D_{REN}$ on economic growth in countries with no oil reserves. The authors acknowledge that this is in line with the theory of energy security, which shows the importance of renewable energy consumption in countries without oil reserves. For countries with oil reserves, $R\&D_{REN}$ reveals a negative effect, while $R\&D_{FF}$ significantly drives economic growth. Assuming that the economic performance of countries with oil reserves heavily depends on non-renewable energy resources, the strong impact of $R\&D_{FF}$ on economic growth can be well explained. Likewise, investing in renewable energies is likely to involve high opportunity costs for countries with fossil fuel reserves and may subsequently be a possible explanation for the negative impact of $R\&D_{REN}$ on economic growth (Wong, Chang and Chia 2013a). Similarly, the authors mention that different opportunity costs may also imply a substitution effect between renewable energy and fossil fuel consumption that differs for countries with and without fossil fuel reserves. Finally, the article demonstrates a larger impact of energy R&D in comparison to energy consumption on economic growth. The authors explain this result by the efficiency improvement of R&D programs that is not directly achieved through energy consumption.

12. Demand-pull instruments affect the size of the market for a new technology (Taylor 2008 p.2830).

In a later study, the authors Wong, Chang and Chia (2013b) investigate the impact of energy R&D on energy consumption and the extent to which economic growth impacts energy R&D. The scholars find that $R\&D_{FF}$ and $R\&D_{REN}$ activities can be used to change the consumption energy mix of an economy. The study shows that higher $R\&D_{FF}$ investments promote the usage of fossil fuel and reduces the consumption of renewable energies. Contrary, an increase in $R\&D_{REN}$ significantly reduces the consumption of fossil fuel, confirming the relevance of $R\&D_{REN}$ activities in changing the mix of energy consumption (Wong, Chang and Chia 2013b). The second part of the study shows that economic growth has a positive and significant impact on fossil fuel consumption, but no significant effect on renewable energy consumption was detected. Nevertheless, an indirect effect of economic growth on energy consumption through renewable energy R&D is observed (Wong, Chang and Chia 2013b). According to the findings, an increase in economic growth leads to a significant increase of $R\&D_{REN}$ investments. Both articles by Wong, Chang and Chia (2013a; 2013b) confirm the importance of R&D for policies that are directed towards changing the energy mix of an economy.

3.3 Contribution to Academic Research

The current state of academic research has mostly investigated the relationship between renewable energy consumption and economic growth. In this analysis, various scholars differentiate between the economic impact of renewable and non-renewable energy consumption. Next to demand-pull subsidies and other factors influencing the demand-side of the market, governmental interventions can directly affect energy supply. Thus, the importance of further research investigations on the energy supply-side has been widely acknowledged. Here, the impact of technological advancement, stemming from R&D activities, has a major impact on energy production and therefore on economic growth. The energy sector is an industrial sector and highly dependent on technology, which gives R&D activities particular importance (Nemet and Baker 2009).

The authors Wong, Chang and Chia (2013a) have studied the relationship of R&D on economic growth for a panel data set of 20 OECD countries. Country clusters have been applied with respect to oil reserves and non-oil reserves in order to absorb important country characteristics. Due to national differences in the composition of energy supply and a large variation in energy policies, it is important to study the impact of energy R&D on a country level. Our study investigates the impact of energy R&D on economic growth at the German national level. This enables the research to account for country-specific policy implementations and to include national characteristics with regard to the energy market. Furthermore, Germany is one of the leading countries in the transition to renewable energy consumption and is in possession of one of the largest governmental energy R&D budgets (IEA 2006).

In light of the time consuming process of energy transition, it is important to consider the full spectrum of this development. As Germany has been one of the first countries engaging in $R\&D_{REN}$, it is possible to extend the empirical analysis to the largest time series data set studied up to now in the field, ranging from the years 1974-2014. Considering the long history of governmental energy R&D in Germany, it is important to place the analysis into the full context and to account for major structural changes in environmental policy.

While previous research has mainly focused on interpretations of empirical models that incorporate cointegration, for example the application of the Ordinary Least Squares (OLS) model in Wong, Chang and Chia (2013), this paper focuses on the interpretation of impulse response functions (IRFs) derived from a structural vector autoregressive model (SVAR). This form of analysis has become a popular tool in empirical Macroeconomics and is especially well suited to investigate the relationship between endogenous variables (Gottschalk 2001). In particular, it allows us to analyse the impact of unexpected policy changes, represented by structural shocks, on economic growth. In light of the upcoming national elections in Germany in 2017, potential unexpected changes to Germany's political direction, also with regard to energy policies, receive more attention. This provides particular relevance of an IRF analysis, which decomposes unexpected shocks. Furthermore, IRFs offer insights on the temporal devolution of response paths. To the best of our knowledge, no study has yet analysed the impact of energy R&D on economic growth within a dynamic framework, such as the SVAR-model, and outlined the temporal occurrence of response to structural shocks. Accordingly, this thesis answers the following research questions, by estimating the impact of energy R&D on economic growth in the context of a new methodology and country-specific data:

1. What is the impact of renewable and fossil fuel energy R&D investments on economic growth?

    1.1. Is there a difference between the impact of renewable energy R&D and fossil fuel R&D?

    1.2. What is the time period lag for the impact of such investments?

2. What is the impact of the respective energy R&D investment on the consumption of fossil fuel and renewable energy sources?

4. Theoretical Framework

As a theoretical foundation for the subsequent empirical analysis, the following chapter explores the connection between energy consumption, R&D investments in the energy sector and the level of economic activity in a theoretical framework. The classical production function, described by Cobb and Douglas (1928), can be used as foundation to explain economic activity, given the input variables labour (L_t) and capital (K_t). The variable A_t expresses total factor productivity, indicating the economy's long-term technological change with regard to labour and capital productivity (Cobb and Douglas 1928). As we are analysing technological change in energy production irrespective of change in total factor productivity, in equation (1) A_t is transformed into the constant A. Furthermore, in this specific research we are interested in analysing the impact of energy composition of an economy and thus the

Cobb-Douglas production function is expanded by the variable E_t, which describes gross energy consumption by the economy. Furthermore, α and β express output elasticity of capital and labour, respectively:

$$Y_t = A\ K_t^{\alpha}\ L_t^{\beta}\ E_t^{\gamma} \tag{1}$$

As energy can be sourced from renewable and fossil fuel technologies, the variable energy consumption can be split into its components. Here, we use the energy sources as perfect substitutes, which explains the functional form:

$$Y_t = A\ K_t^{\alpha}\ L_t^{\beta}\ (S_t + N_t)^{\gamma} \tag{2}$$

The variable S_t is the sum of consumption of energy sourced from renewable energy sources and N_t is the sum of consumption of energy sourced from fossil fuel energy sources.

We continue by taking the respective energy consumption function for renewable and fossil fuel energy in a standard constant elasticity Cobb-Douglas-type functional form, as proposed by Madlener et al. (2011). For simplicity, we adjust the output elasticity of the respective energy demand, taking into consideration our prior assumption of perfect energy substitution, by stating that the different energy demands have equal elasticity with respect to output (θ). The renewable energy consumption in equation (3) is given below, in which s_t is the renewable energy-specific technology factor, $P_{s,t}$ is the renewable energy price and $P_{n,t}$ is the price of the substitute (fossil fuel) energy:

$$S_t = s_t\ P_{s,t}^{\mu}\ P_{n,t}^{\zeta}\ Y_t^{\theta} \tag{3}$$

Equation (4) is the function of fossil fuel consumption in which n_t is the fossil fuel energy-specific technology factor. We note that $P_{s,t}$ and $P_{n,t}$ are included in both functions, which is due to the cross-price elasticity:

$$N_t = n_t\ P_{n,t}^{\lambda}\ P_{s,t}^{\rho}\ Y_t^{\theta} \tag{4}$$

The parameters μ, ζ, λ, ρ are the respective demand elasticities with regard to energy price. In the consumption of an energy source, the energy-specific technology factor has a significant relevance, which motivates further analysis of the variable. Acknowledging the study of Griliches (1984), the technology stock factors s_t and n_t are measured by accumulation of knowledge from R&D (R_t). A declining balance formula for development of the technology factor is used, in which technology stock depreciates at rate $\delta_{x,t}$, where x is either renewable energy (s) or fossil fuel energy (n):

$$s_t = R_{t-1}^{s} + (1 - \delta_{s,t})\ s_{t-1} \tag{5}$$

$$n_t = R_{t-1}^{n} + (1 - \delta_{n,t})\ n_{t-1} \tag{6}$$

One can now see in equations (5) and (6) that technology stock (s_t) depends on depreciated technology stock from the prior period s_{t-1}. Taking equations (5) and (6) into the prior time period, $t-1$, and substituting it into the original equation, provides a continued inter-temporal expression. This can be undertaken with infinite repetition. For reasons of simplicity and the purpose of demonstration, we will assume in the following context constant depreciation of knowledge stock, $\delta_{x,t} = \delta_{x,t-1} = \delta_x$, and a constant growth rate in R&D activities over time, $R^x_{t-1} = R^x_{t-2}(1 + g_x)$.

As the solutions are symmetric for renewable and fossil fuel energy technology stock, the equation is solved for renewable energy technology stock (s_t) first:

$$s_t = R^s_{t-1} + (1-\delta_s)R^s_{t-2} + (1-\delta_s)^2 R^s_{t-3} + ... = \sum_{x=0}^{\infty} R^s_{t-1-x}(1-\delta_s)^x = R^s_{t-1} \sum_{x=0}^{\infty} \left(\frac{1-\delta_s}{1+g_s}\right)^x \quad (7)$$

It can be demonstrated that technology stock can be expressed by R&D in time period t, R^s_t.

$$s_t = R^s_{t-1} \sum_{x=0}^{\infty} \left(\frac{1-\delta_s}{1+g_s}\right)^x = R^s_{t-1} \left(1 + \frac{1-\delta_s}{1+g_s} + \left(\frac{1-\delta}{1+g_s}\right)^2 + ...\right) =$$

$$= R^s_{t-1} \frac{1}{1 - \left(\frac{1-\delta_s}{1+g_s}\right)} = R^s_{t-1} \frac{1+g_s}{g_s+\delta_s} = \frac{R^s_t}{g_s+\delta_s}$$

The factor of the geometric series is $z = \frac{1-\delta_s}{1+g_s}$, which by definition has to be $-1 < z < 1$ and can be assumed for positive growth rates. Once these rearrangements for both energy technology forms are undertaken, one can observe following expressions for technology stock (s_t, n_t) in form of R&D (R^s_t, R^n_t):

$$s_t = \frac{R^s_t}{\delta_s + g_s} \quad (8)$$

$$n_t = \frac{R^n_t}{\delta_n + g_n} \quad (9)$$

Taking the results from (8) and (9) for substitution into (3) and (4), respectively, we receive energy consumption functions, which incorporate R&D. Furthermore, one can substitute energy consumption in (10) and (11) into the production function to see the dependency of output on R&D in equation (12):

$$S_t = \frac{R^s_t}{\delta_s + g_s} \; P^{\mu}_{s,t} \, P^{\zeta}_{n,t} \, Y^{\theta}_t \quad (10)$$

$$N_t = \frac{R^n_t}{\delta_n + g_n} \; P^{\lambda}_{n,t} \, P^{\rho}_{s,t} \, Y^{\theta}_t \quad (11)$$

$$Y_t = A \; K^{\alpha}_t \; L^{\beta}_t \; \left(\frac{R^s_t}{\delta_s + g_s} \; P^{\mu}_{s,t} \, P^{\zeta}_{n,t} \, Y^{\theta}_t + \frac{R^n_t}{\delta_n + g_n} \; P^{\lambda}_{n,t} \, P^{\rho}_{s,t} \, Y^{\theta}_t\right)^{\gamma} \quad (12)$$

Solving this equation for Y_t enables us to see that we can write the equation in the following form:

$$Y_t = \left(A\ K_t^{\alpha}\ L_t^{\beta} \left(\frac{R_t^s}{\delta_s + g_s}\ P_{s,t}^{\mu}\ P_{n,t}^{\zeta}\ + \frac{R_t^n}{\delta_n + g_n}\ P_{n,t}^{\lambda}\ P_{s,t}^{\rho} \right) \right)^{\frac{1}{1-\theta\gamma}} \tag{13}$$

For our further empirical analysis we take equation (13) as foundation for the econometric modelling. The expression for output containing the variables of interest is therefore:

$$Y = f\left(K, L, R^n, R^s, P\right) \tag{14}$$

Due to practical concerns with regard to modelling energy prices, the combined price $P = f(P_s, P_n)$ for the renewable and fossil fuel resources is included in the analysis. Since nuclear energy in Germany has been subject to a strong exogenous shock, being the political decision of a nuclear power phase-out by 2022, financial resources and political commitment to advance this technology have been substantially reduced. This motivates an exclusion of funds historically devoted to nuclear energy and R&D investments in nuclear technology from our model and analysis. In the following research, we distinguish between non-renewable energy, identified by energy sourced from fossil fuels, and renewable energy, including energy sourced from solar, wind, bio-fuel etc. In the following chapter, we will proceed by explaining the composition of the variables in equation (14) and displaying descriptive statistics, before proceeding with the modelling approach in Chapter 6.

5. Data Descriptives

5.1 Calculation and Transformation of Variables

The variables GDP (Y) and gross capital formation (K) are sourced in nominal million euro from the World Bank (2016) for the time period 1974-2014. Yearly active labour force (L) in million persons for the same time period was retrieved from the German Federal Statistical Office (DStatis 2016). We notice that the records prior to 1990 are accounting for West-Germany and from 1991 records indicate labour force for the entire country after the unification. Furthermore, the German household electricity price (P) in euro/mWh is received from the International Energy Agency database (IEA 2016). The household electricity price has been chosen due to the incorporation of both renewable and non-renewable sources.

In the following analysis energy research, development and demonstration (*RD&D*) is used as a proxy for the previously described energy *R&D* investments. The database of the International Energy Agency (IEA) provides detailed information on the governmental *RD&D* budget, which is devoted to the different energy sectors. These budget figures are measured in million euro and generally revised on a year to year basis, which restricts the analysis to yearly data. Governmental energy *RD&D* budgets are submitted by each national administration on an annual questionnaire (IEA 2011). The IEA states that "*RD&D* budgets are calculated by identifying all budget items involving *RD&D* and measuring their content in terms of funding" (p.17). Then governmental *RD&D* budgets are used in the domestic market by public establishments, business enterprises, private non-profit organisations and higher education programs. Energy *RD&D* covers "basic research to enhance technologies, applied research, experimental development and demonstration related to the production, storage, transportation, distribution and rational use of all forms of energy" (IEA 2011 p.16). *RD&D* investments directed to fossil fuel energy include the resources oil, natural gas and coal whereas the investments directed to renewable energies include energy sourced from solar, wind, ocean energy, bio-fuels, geothermal, hydroelectricity and other renewable sources (IEA 2006).

To avoid biased results through fluctuations in currency value, all variables given in nominal euro are adjusted with a GDP deflator. Therefore, the annual inflation for Germany from the World Data Bank is used to construct a GDP deflator with base year 2011. All monetary values before 2002 are transferred to euro by a constant exchange rate, due to the change in currency from deutsche mark to euro, which has been accounted for in the database. Further, we take the logarithmic form of all variables to smooth skewness, to treat potential heteroskedasticity, to linearise a non-linear relation and to enable interpretations with regard to elasticities.

5.2 Descriptive Statistics

In Table 1 we display the variables of interest in their mean, standard deviation and min/max for the period 1974-2014. One can observe large differences in the size of the mean and standard deviation of the variables. These differences are partly reduced by taking the logarithmic form of the variables.

Variable	Unit	Mean	Std. Deviation	Min	Max
GDP	Real million €	2,074,374.45	459,146.05	1,319,639.53	2,783,868.51
Fixed Gross Capital Formation	Real million €	457,504.95	74,884.52	312,097.65	558,644.16
Labour Force	Absolut count in million	34.65	6.13	26.23	42.60
Govt. Fossil Fuel RD&D	Real million €	91.11	95.38	1.38	303.73
Govt. Renewable Energy RD&D	Real million €	109.85	62.87	1.27	285.75
Household Electricity Price	Real €/mWh	188.76	34.35	147.44	284.63

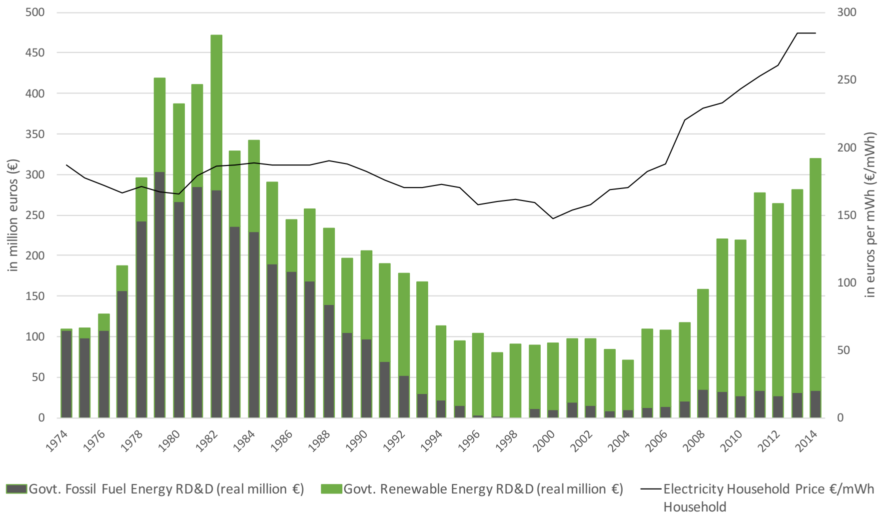
Source: Authors' rendering of data from IEA (2016), World Bank (2016) and DStatis (2016)

Table 1: Summary Statistics of Input Variables

We notice that $RD\&D_{REN}$ is larger in its mean and smaller in standard deviation than $RD\&D_{FF}$. This can be explained by the increasing importance of the renewable energy sector in Germany and the overall reduced support for fossil fuels over the studied period. Moreover not only the size but also the consistency with respect to $RD\&D_{REN}$ can be justified by the political reinforcement due to the primary concern of energy security. Note that the maximum of $RD\&D_{FF}$ with 303.73 million euros in year 1979 reveals the importance and high dependency of Germany on fossil fuel resources in the past.

In Figure 2 it can be seen that, while the overall sum of renewable and fossil fuel governmental $RD\&D$ is largest, with over 450 million euros in year 1982, it constantly decreases from then until it reaches its low in year 1997. Due to increasing governmental renewable energy budgets, the overall governmental $RD\&D$ budget steadily climbs up again with few exceptions until year 2014. Further note that the share of renewable sources rises from year 1989 continuously until year 2014. This observation can be reasoned by the energy transition in Germany that build momentum around the unification with a rising commitment to invest in renewable energy sources and to reduce the support for fossil fuel sources.

Another interesting observation is that the electricity price seems to be positively correlated with $RD\&D_{REN}$. This relationship could possibly explain the problematic sentiment in Germany and the increased interest for the actual economic effects of the energy transition.



Source: Authors' rendering of data from IEA (2016)

Figure 2: Governmental Energy $RD\&D$ and Electricity Price in Germany

6. Empirical Methodology

6.1 Endogenous Relationship of Variables

Macroeconomic variables tend to be subject to reverse causality, which qualifies as one of the main sources of endogeneity bias.[13] This means that the flow of causality is not simply uni-directional from the regressor to the regressands, but rather mutual (Wooldridge 2003). In statistical terms, the problem of endogeneity refers to the violation that the error term, $\epsilon_{i,t}$, will be contemporaneously correlated with the regressors, $X_{i,t}$ (Wooldridge 2003).[14] The vector autoregressive model (VAR) methodology is an attempt commonly applied in Macroeconomics to account for reverse causality "[...] by making assumptions that allow the dynamic

13. Further forms of endogeneity bias, being omitted variable bias and measurement error, are discussed in Chapter 9 and 12, respectively.

14. I.e. $E = (\epsilon_{i,t}|X_{i,t}) \neq 0$.

relationships of the respective variables to be estimated consistently" (E. Sims 2013 p.12). In other words, we define an identification of zero restrictions in order to exactly identify the system of equations (cf. Section 6.3). By applying zero restrictions to the contemporaneous effects, we can also account for reverse causality in the variables. After having defined these identifying restrictions for the contemporaneous effects, the error terms, $\epsilon_{i,t}$, have no contemporaneous effects on the regressors, $X_{i,t}$, anymore, which allows to estimate the dynamic relationships through a system of equations, using the OLS method (E. Sims 2013).

6.2 The Vector Autoregressive Model

The identification of a VAR-model with lag length p starts from the so-called structural form equation:

$$Bx_t = \Gamma_0 + \Gamma_1 x_{t-1} + \Gamma_2 x_{t-2} + ... + \Gamma_p x_{t-p} + \epsilon_t \tag{15}$$

where we display the function $Y_t = f\left(K_t, L_t, R_t^n, R_t^s, P_t\right)$ from Chapter 4 in vector form $x_t = [R\&D_{FF,t},\ R\&D_{REN,t},\ K_t,\ L_t,\ P_t,\ Y_t]'$. This is a (6 x 1) vector in logarithmic form of the variables of interest: fossil fuel energy R&D, renewable energy R&D, capital, labour force, electricity price, and GDP. The logarithmic form of the variables is displayed in Figure 11 in the Appendix A.1. In equation (15), Γ_i for $i = 1, 2...p$ is the respective (6 x 6) coefficient matrix, Γ_0 determines the (6 x 1) vector of intercepts and ϵ_t denotes the (6 x 1) vector of error terms. The structure of the system incorporates feedback because all variables are allowed to effect each other and hence the model suits the economic interpretation of the variables (Enders, 2010). The contemporaneous effects are arranged on the left hand side of the equation and determined by the (6 x 6) matrix B:

$$B = \begin{pmatrix} 1 & b_{11} & b_{12} & b_{13} & b_{14} & b_{15} \\ b_{21} & 1 & b_{22} & b_{23} & b_{24} & b_{25} \\ b_{31} & b_{32} & 1 & b_{33} & b_{34} & b_{35} \\ b_{41} & b_{42} & b_{43} & 1 & b_{44} & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 & b_{45} \\ b_{61} & b_{62} & b_{63} & b_{64} & b_{65} & 1 \end{pmatrix} \tag{16}$$

The system of equations (15) is not in the reduced-form equation, as the variables have contemporaneous effects. Thus, the VAR-model has to be transformed into a more useful form through pre-multiplication by B^{-1}, also known as the *standard* form (Enders 2010):

$$x_t = A_0 + A_1 x_{t-1} + ... + A_p x_{t-p} + e_t \tag{17}$$

in which $A_0 = B^{-1}\Gamma_0$, $A_i = B^{-1}\Gamma_i$, and $e_t = B^{-1}\ \epsilon_t$. The VAR-model consists of a system of equations, in which six variables are regressed, using OLS estimation, on lagged and contemporaneous factors. Therefore, all variables are treated endogenously in this model and the standard form does not underlie any restrictions. Here, it is very important to acknowledge that dynamic feedback effects matter in this analysis. An increase in output can positively contribute to more financial resources devoted to governmental R&D. At the same time, governmental investments in R&D intervene in markets and advance technological growth, which is allowed to favourably influence output.

6.3 Identification

Before inferences from the model can be drawn, a predefined identification has to be implemented. Since in equation (17) a reduced form equation is estimated, the structural shocks have to be recovered. According to statistical theory, the problem is to take the observed values of e_t from equation (17) and to restrict the system to recover ϵ_t through $\epsilon_t = B\ e_t$. As described by Enders (2010), it is necessary to impose $\frac{n^2-n}{2}$ restrictions on the VAR-model, which is then defined as a SVAR-model. Given the six variables of the VAR-model from Section 6.2, fifteen restrictions have to be imposed to receive exact identification. In the following Table 2, the chosen contemporaneous restrictions are displayed. $R\&D_{FF}$ (FF), $R\&D_{REN}$ (REN), capital (K), labour force (L), and electricity price (P) are used in abbreviations. A zero entry means that the variable in the column does not have a contemporaneous effect on the row variable. Thus, the identification restricts an impact of one variable on the other only during the same period. The dot in the table indicates that a contemporaneous effect is admitted and a parameter is estimated. The presented identification is built on the lower triangular Cholesky decomposition. This chosen form imposes a certain selection of *causal ordering* on the variables as the first shock affects all variables within the same period and further variables are sorted in decreasing order of exogeneity (E. Sims 2013). While the SVAR-model enables other forms of orderings, the (lower) triangular Cholesky decomposition is regularly applied in econometric time series analysis (Enders 2010). The recursive structure of the Cholesky decomposition further reflects to a large extent the properties of the transmission channel in Section 2.2 and hence can be justified on theoretic grounds.

The chosen ordering of $FF_t \rightarrow REN_t \rightarrow K_t \rightarrow L_t \rightarrow P_t \rightarrow Y_t$ is motivated by economic theory, the transmission channel outlined in Section 2.2 and related literature in the field of Energy Economics. In Table 2 we see that the variable FF in the first row is contemporaneously exogenous. As mentioned in Section 5.1, R&D budgets are allocated on an annual basis (IEA 2011). Thus, governments decide before commencement of the year on the size and allocation of public funds and thus FF and REN are contemporaneously independent of the variables capital, labour, price and GDP. Because the energy budget allocation in Germany is done in the year prior to the actual spending, both FF and REN are allowed to contemporaneously influence all other variables in the system, but not vice versa as the decision on the size and allocation of energy budgets has already been decided in the previous period. The underlying ordering of FF and REN has been chosen due to recent research findings that have shown that "subsidies to fossil-fuel technologies continue to dwarf those to renewable energy" (Bridle and Kitson 2014 p.18). This implies that investments in clean energy sectors, among them *R&D* spending, are distorted when fossil fuel energy sectors are subsidised. Bridle and Kitson (2014) accentuate that "fossil fuel subsidies impair the competitiveness of renewable energy, create large barriers to entry for new technologies, undermine investments by enhancing the attractiveness of fossil fuel technologies and distort prices, which do not fully reflect costs" (p.18). These observations are based on the assumption that FF is priorly ordered to REN and hence define the underlying ordering as follows: $FF_t \rightarrow REN_t$ (Lechtenböhmer, Kristof and Irrek 2004). Furthermore, ordering identifications in empirical studies commonly assume that "[...] the policy variable does not respond within the period to the other endogenous variables" (Kilian 2011). The general intuition behind this assumption is time lags of decision making in politics and adjustment costs (Kilian 2011). Blanchard and Perotti (2002), for instance, assume that government spending does not respond to any contemporaneous effects of other endogenous variables.

As discussed in the transmission channel in Section 2.2, $R\&D$ investments cause capital expenditures and changes in employment. As per definition, FF and REN activities lead to a direct change in capital expenditures and current costs, which includes labour costs (IEA 2011). Because the injection of financial grants in $R\&D$ contemporaneously effects capital and labour, both variables are ordered after FF and REN. Since capital is accumulated through investments, which are subject to planning lags and because labour supply can be flexibly adjusted to demand, we place capital before labour in the current period, as previously done by Roberts (2005). The author argues that capital is not influenced contemporaneously by variables, such as labour, because of longer planning lags for investments. For instance, "it takes some time for the decision on capital expenditures to be made and for the new capital to be installed, so measured capital expenditures responds with a delay" (Kilian 2011 p.8). Roberts (2005) further allows capital to impact other variables, assuming that capital is, mechanically, a component of aggregate spending.

Both capital and labour expenditures directed to $R\&D$ in the energy sector improve the respective technology stock, which consequently impacts the production costs in the energy sector. As described in the transmission channel in Section 2.2, this may change the resource (energy) price. Due to this underlying economic rationale and since we assume planning lags, we order price on the fifth position so that the energy price cannot contemporaneously impact R&D, capital and labour.

Lastly, we place the economy's output at sixth order and therefore define a fully endogenous variable. This is also in line with the general theory on SVAR modelling by E. Sims (2013), who notes that variables, such as output, tend to be endogenous and therefore ordered last.

	FF	REN	K	L	P	Y
FF	1	0	0	0	0	0
REN	.	1	0	0	0	0
K	.	.	1	0	0	0
L	.	.	.	1	0	0
P	.	.	.	.	1	0
Y	.	.	.	.	.	1

Table 2: Restrictions on Contemporaneous Effects: B^{-1} Matrix

It is important to notice that speaking in the context of ordering about endogeneity and exogeneity, the terms are solely related to contemporaneous impacts, as lagged effects are not restricted by the implied zero-identifications. To account for a potential ordering bias, the contemporaneous restrictions will be altered during robustness tests in Section 9.2.

The structural VAR-model in combination with an IRF analysis is preferred to alternative models, as for example the regular VAR-model or structural equation modelling, in answering our research questions. Thereby, an IRF analysis enables us to determine the effect that an unexpected shock in $R\&D_{REN}$ or $R\&D_{FF}$ has on economic growth and illustrates the response paths in a graphical and dynamic form. These shocks simulate structural changes in policy making, which are common in the field of Energy politics and are often caused by changes in government or environmental incidents (Renn and Marshall 2016). Furthermore, the impulse response paths based on SVAR estimations describe the magnitude, transmission mechanisms and time lagged impacts of structural shocks. Lastly, a SVAR-model allows for causality inference, while controlling for reverse causality in the relationship of variables of interest. In order to analyse how the variable output reacts to shocks in $R\&D_{REN}$ and $R\&D_{FF}$, IRFs are plotted in Chapter 8.[15]

7. Model Specification and Diagnostic Tests

7.1 Model Specification

The underlying data consists of six time series from 1974 to 2014. Furthermore, the model accounts for structural breaks observed in the series by including dummy variables.[16] In this analysis, the structural breaks represent the start of the energy transition in 1979, the unification of Germany in 1990, the continuation of financial aid to the coal industry in 1998 and the Renewable Energy Sources Act in 2000.[17] These structural breaks in the history of energy policies in Germany can also be observed visually in the data (cf. Figure 11 in Appendix A.1). Before we start with the SVAR-model analysis, the first step includes testing each individual time series for a unit root.[18] Testing for unit roots in the time series is important for the model specification, as a process containing a unit root is non-stationary (Enders 2010). Here, the augmented Dickey-Fuller test is applied, which indicates that all series are unit root processes.[19] Taking the first difference of the series, reveals that all variables are difference-stationary and therefore we can conclude that the series are integrated of order $I(I)$. The property that all variables are integrated of the same order enables possible cointegration, which will be taken into consideration in Section 9.1.

Based on the proposition of C. A. Sims (1980) and Sims, Stock and Watson (1990), we proceed in our estimation without first differenced variables, even though the variables contain unit roots. This is sustained, as our primary interest is the interrelation of variables and first differencing causes elimination of important information. E. Sims (2013) further summarises

15. For a derivation of the estimated formula of the IRFs, see Appendix A.2.3.

16. Dummy variable: An indicator of value [0/1] that sorts data into mutually exclusive categories.

17. The key elements of the Renewable Energy Sources Act in 2000 are: "long-term and regularly adjusted remuneration/feed-in tariffs, priority feed-in and grid connection rights and the EEG surcharge for electricity consumers" (BMWi 2016b).

18. Unit root: "Any sequence that contains one or more characteristic roots that equal unity is called a unit root process" (Enders 2010 p.30).

19. To see the detailed explanation and foundation of the augmented Dickey-Fuller test see Enders (2010) Section 4.7.

that "[...] as long as there are lagged variables included in the model the problem of a spurious regression can be neglected, and even if there is cointegration, an estimation in levels is still robust" (p.20).

To fit the correct specification of the SVAR-model, we subsequently determine the optimal lag selection. Statistical theory provides several information criteria that determine the optimal lag selection. The advantages of a higher lag specification, being higher interaction between the variables, have to be measured against the exposure to overspecification. We consider the Akaike (AIC), Bayesian information criterion (BIC) and the Likelihood-ratio. Due to constraints in the model specification, the maximum lags permitted are $p = 3$, as models with higher lag lengths become impracticable. The AIC and the Likelihood-ratio jointly indicate a lag length of $p = 3$, while the BIC indicates a lag length $p = 1$ (cf. Appendix A.2.1). We proceed with the selection of $p = 3$, as Enders (2010) recommends the AIC for small to medium sample sizes.

7.2 Diagnostic Tests

Next to the optimal lag selection, it is also an important condition that the residual series of the model follow a white noise process.[20] Thus, a Lagrange multiplier test is applied to test if remaining autocorrelation can be found in the residuals, ϵ_t, of the SVAR-model.[21] To confirm the choice of $p = 3$ in Section 7.1, we apply the test to the models with $p = 1$, $p = 2$, $p = 3$. Using the Lagrange multiplier test, we find confirmation that the lag selection $p = 3$ selects a suitable model, as the test fails to reject the null hypothesis of no remaining autocorrelation up to the fourth lag at a 10% significance level (cf. Appendix A.2.2). For the SVAR-models $p = 1$ and $p = 2$ we find that the null hypothesis of no remaining autocorrelation can be rejected at the 10% and 5% significance level, respectively. Furthermore, anticipating inflated standard errors of an overspecified model, we compare the coefficient standard errors of all three models and diagnose no major differences. A further condition for the specification of the model is stability.[22] This condition is important for the interpretation of the model, as only results derived from a stable model can be used for valid inference. If a SVAR-model is stable, "it is invertible and has an infinite-order vector moving-average representation, which enables the creation of IRFs" (Lütkepohl and Krätzig 2004 p.165). The selected SVAR(3)-model also satisfies the stability condition, as all eigenvalues lie within the unit circle. Therefore, one can proceed with the SVAR-model imposing the selection of $p = 3$ lags.

20. "A sequence, (ϵ_t), is a white noise process if each value in the sequence has a mean of zero, has a constant variance, and is uncorrelated with all other realisations" (Enders 2010 p.51).

21. "The Lagrange multiplier test is build on an X^2 asymptotic distributions and K^2 degrees of freedom, where $K \times x$ is the vector of residuals and tests for the autocorrelation of the residuals in SVAR-models" (Johansen 1995).

22. The stability of the model is tested with the eigenvalue stability condition. As shown by Lütkepohl (2005) a SVAR-model "[...] is stable if the modulus of each eigenvalue of A(B) is strictly less than one" (p.260).

8. Results and Interpretation

8.1 Impulse Response Functions

By imposing restrictions on matrix B^{-1}, a VAR-model is transformed into a SVAR-model. This allows interpretations for the initial structural equations and decomposes the impact of structural shocks, ϵ^{j}_{t-i}, which enables plotting orthogonalised IRFs in the following diagrams. Orthogonalising the error terms of the equation, also known as *shocks*, is required to assure that the error terms tracked by IRFs are uncorrelated (Ronayne 2011). IRFs offer an interpretation of the response in one variable to a one-unit shock in itself or another variable. Since the input variables are inserted in logarithmic form, a one-unit standard deviation (SD) shock to one variable is followed by a response path determined in percentage points. The blue inner solid line in the diagram marks the point estimate, while the outer bands in red determine a 95% confidence interval. In general, we note that most response paths to a one-unit SD shock are rather small in their magnitude. Still, this does not neglect the importance of the impact, but is rather caused by the substantial difference in size of the variables.

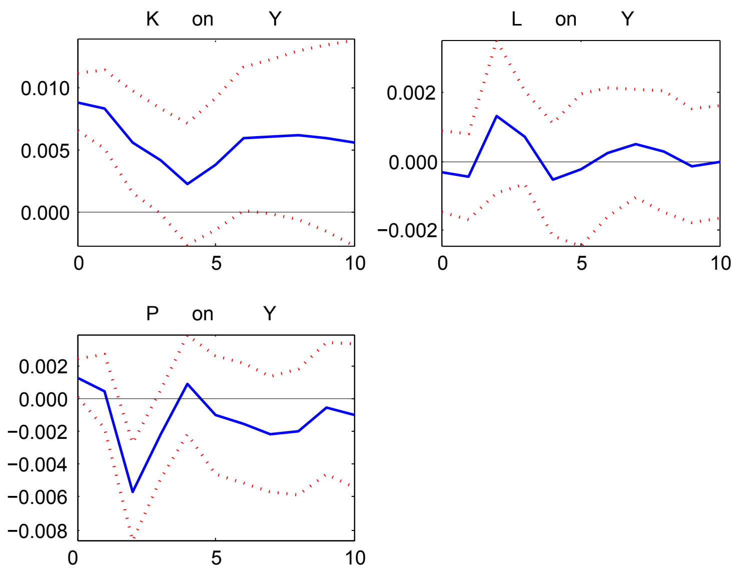
8.1.1 Impulse in Capital, Labour, Price

The chosen production function, enables a critical assessment of the analysis of structural shocks to the variables of interest, as it incorporates the variables capital, labour and output, whose interrelation has been extensively proven and examined (Romer 1986). The first graph in Figure 3 shows that K has a significant positive impact on Y. We find that a one-unit SD increase in capital, leads to an approximate 0.01% immediate increase in total output. Y then slowly decays back to its low at around 0.0025% after three periods and slowly increases again in order to gradually decay to zero over the remaining time periods. After period three, the response path becomes insignificant. The positive significant and immediate impact is in line with the production function, which suggests a positive impact of capital on economic growth.

Shocks to the variable labour do not reveal an impact on Y, as the 95% confidence interval fully covers the zero line. While this result seems puzzling from a theoretical point of view, it can be explained by the characteristics of the underlying data for the variable labour force, which exhibits relatively low SDs and hence low variation for the given standard errors in the sample (cf. Section 8.2). Similarly, Bhattacharya et al. (2015) find a positive but insignificant response of output to changes in labour in their analysis of long-run output elasticity for Germany. Studies by Wong, Chang and Chia (2013a) divide all variables by labour force to receive the *per labour force* form, which is solely a suitable alternative for the analysis of coefficients, but unsuitable for IRF analyses due to the interpretation of response paths to structural shocks.

Incorporating the electricity price, also enables the assessment of an additional transmitting variable. While P has a significant and negative impact on Y between the periods one and three, no significant impact can be observed in the other periods. More specifically, a one-unit SD increase in P has its greatest effect with a negative 0.006% impact on Y in the second period. This inverse relationship between price and output has been observed in related literature, which concludes that "higher electricity prices raise costs particularly in energy-intensive sectors and this spills over to the whole economy" (European Commission 2011 p.32). The insignificant instantaneous effect of prices may be explained by lagged spillover effects (Ockenfels 2007). Energy demand is generally inelastic to price changes in the short-run and thus consumption behaviour alters with deferral (Boug 2000). Hence, the implications of a price increase can only be observed with a time lag.

These findings confirm that shocks to capital and price significantly impact economic growth in Germany, in a way it is predicted by theory, but shocks to labour do not have a significant impact on output.



Note: The one standard deviation shocks are in the variables capital (K), labour (L) and price (P). The response path is in the variable output (Y). The time horizon on the x-axis is 10 years and the y-axis is given in percentage change. While the blue line is the point estimate, the dotted red lines are the 95% confidence bands.

Figure 3: IRF - Response Variable: Y

8.1.2 Impulse in Renewable Energy R&D

We further notice in Figure 4 a delayed, significant and negative impact on Y following a positive shock in $R\&D_{REN}$ in the time frame of three to five years after the initial shock. A one-unit SD increase in $R\&D_{REN}$ leads to a 0.008% decrease in Y in period four. Outside the time period of three to five years after the impulse, the impact on Y is not significant. This finding is in accordance with the study by Wong, Chang and Chia (2013a), who find a significant negative impact of $R\&D_{REN}$ on economic growth for countries possessing large fossil fuel reserves. The authors show that "[...] when countries do not lack important energy endowment and do not face energy security issues either, which could threaten their sustainable economic growth" investments in renewable energy sources instead of fossil fuels involve high opportunity costs and may harm economic growth (Wong, Chang and Chia, 2013a p.59). Germany has the second largest lignite reserves worldwide and was globally the largest producer with 178 million tonnes in 2015 (Statista 2016; BGR 2015). The country therefore still largely depends on its traditional fossil fuel industry, which could explain the opportunity costs and the corresponding adverse effect arising from $R\&D_{REN}$ investments.

Additionally, the period lag of three to five years reflects the lengthiness of the $R\&D$ process. From the point of investment to technology progress and the actual noticeable effect on output, several years usually pass by. Other studies confirm this assumption and show that $R\&D$ has a lagged impact on output (Ravenscraft and Scherer 1982; Rouvinen 2002).

In order to better understand how the impulse from $R\&D_{REN}$ triggers through the economy, we also analyse how $R\&D_{REN}$ impacts capital, price and labour in Figure 4.

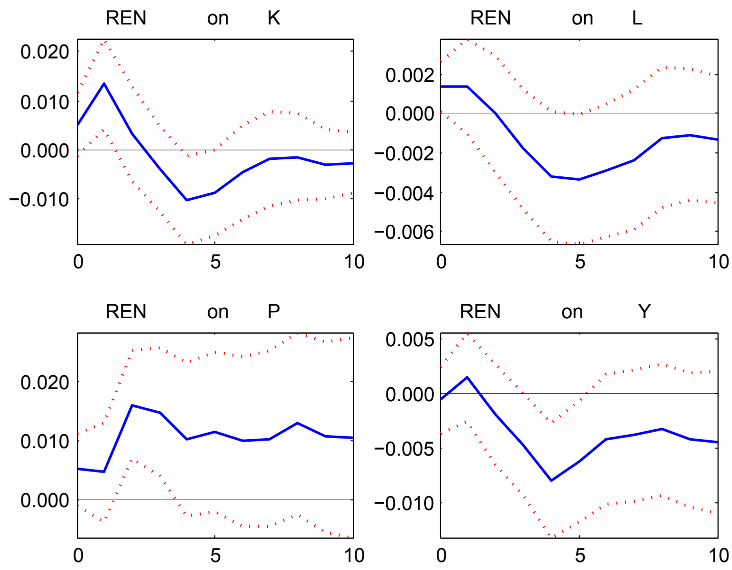
The overall reaction of K is characterised by a positive increase shortly after a shock in $R\&D_{REN}$ reaching its peak in period one, which is then followed by a steady decrease towards its trough in period four and a slow decay to the zero line afterwards. While the one-unit SD increase in $R\&D_{REN}$ in period zero leads to a significant 0.0125% increase in K after the first period, a significant decrease in K by 0.01% in period four can be observed. The significant positive effect on capital can be explained by the investment effect, but the negative significant effect in period four deserves further attention. Governmental investments in $R\&D_{REN}$ are crowding out investments in other areas, like for example transport, infrastructure, or manufacturing (IRENA 2016). The crowding out effect "refers to the possibility that the investments needed for increased renewable energy deployment compete with and displace investments elsewhere in the economy" (IRENA 2016 p. 27). Further, the study by IRENA (2016) shows that a reduction of capital available to other sectors can lead to full crowding out, which subsequently results in a negative impact on economic growth (IRENA 2016). Furthermore, $R\&D$ expenditures in infant industries, such as the renewable energy sector, lead to a significant reduction in the costs for energy production, particularly in the first periods of development. As a consequence, less capital expenditures are required in the future, which explains the negative impact on fixed capital formation (IEA 2006). Overall, the investment effect positively impacts capital in the short-run and investing in renewable energy sources may result in deferred future investments and a negative effect on capital may be the consequence.

In Figure 4, we also note that $R\&D_{REN}$ has an overall positive and significant effect on P between two and four years after the impulse. A one-unit SD increase in the impulse variable, $R\&D_{REN}$, results in a 0.015% increase in P. While the effect remains positive, the size is not significant before two and after four years of the initial shock of $R\&D_{REN}$ on P. The positive effect of $R\&D_{REN}$ on the price may not be expected, but it can be elucidated by the environmental regulations embedded in the German energy transition. Governmental investments in $R\&D_{REN}$ support the renewable energy sector through technology advancements and a potential reduction of energy production costs. Consequently, the deployment of an increasing share of renewable energy technologies is facilitated, which will be discussed further in the extended model in Chapter 10. This is in line with the aim to increase the energy production from renewable sources. Policy reforms and laws incorporated in the Renewable Energy Sources Act determine the compensation of renewable energy producers through additional payments, which are defined in incentive plans over a time period of 20 years (Bruns et al. 2009). These payments are financed through premiums, which increase the electricity price and partly transfer the costs of the energy transition to end-consumers (BDEW 2016).[23] Additionally, integrating renewable energies into the German electricity grid results in infrastructure costs due to the high supply volatility and the lower voltage levels of renewable energy sources (BNetzA 2016). In particular, the increased supply volatility of renewable sources relative to conventional energies requires *redispatch* measures that imply higher integration costs, that are reflected in increasing electricity prices (Vahlenkamp et al. 2016).[24] In order to better understand the two opposing effects of decreasing production costs and price increasing effects, future research may focus on disaggregating the electricity price to see each individual component and its development after a shock in $R\&D_{REN}$.

$R\&D_{REN}$ has almost no significant effect on labour, except for years four to six. In this respective period, we notice a small negative and significant impact on labour after the initial shock in $R\&D_{REN}$ investments. A similar observation has been made by researchers from the Ifo Institute for Economic Research (2011), who conclude that investing in the German energy sector results in overall negative net employment effects. This finding is also confirmed for the renewable energy sector through a study by Gkatsou et al. (2014), who estimate a net job reduction for Germany, caused by an increase in the renewable energy share. Along with these findings, our study does not provide evidence for an overall net employment increase caused by $R\&D_{REN}$ investments. In contrast to this, industry experts often highlight the potential of job creation in the renewable energy sector. While this may be true, employment in industries, such as the lignite production, is likely to decrease because of a higher energy share in renewable energy sources. It is therefore important to consider net employment effects and recognise adverse effects of $R\&D_{REN}$ on employment in other parts of the energy sector.

23. Around 55% of the electricity price are induced by the government, which uses part of the proceedings to drive the energy transition (BDEW 2016).

24. Redispatch measures are interventions in the energy production of power plants (Vahlenkamp et al. 2016).



Note: The one standard deviation shock is in the variable $R\&D_{REN}$ (REN). The response paths are in the variables capital (K), labour (L), price (P) and output (Y). The time horizon on the x-axis is 10 years and the y-axis is given in percentage change. While the blue line is the point estimate, the dotted red lines are the 95% confidence bands.

Figure 4: IRF - Impulse Variable: $R\&D_{REN}$

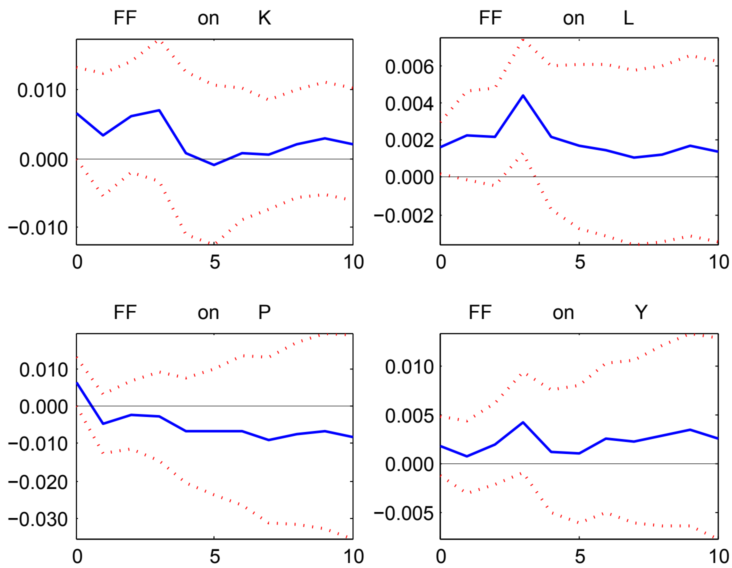
8.1.3 Impulse in Fossil Fuel Energy R&D

Contingent on the investment effect and anticipated technology improvements, a positive impact of $R\&D_{FF}$ on output is expected. The point estimates in the fourth graph in Figure 5 shows a positive impact of $R\&D_{FF}$ on economic growth, which has also been observed by Wong, Chang and Chia (2013a), who find a significant positive impact on economic growth for countries with fossil fuel reserves. However, due to the statistical insignificance in our results we cannot find evidence for an impact of $R\&D_{FF}$ on Y. The insignificant impact might be explained by the fact that investing into R&D in mature industries is less efficient, as stated by Koseoglu, Berg and Lacerda (2013), who explain that “R&D funding should start from a maximum value at the beginning of innovation phase when learning is greatest and decline over time as the technology reaches maturity in the market” (p.538).

In Figure 5 we observe that $R\&D_{FF}$ has a significant impact on L. Over the respective ten periods, the impulse from $R\&D_{FF}$ leads to a significant positive increase of 0.005% in L after three years. This confirms the deferred impact of R&D investments. An increase in governmental R&D investments can lead to lagged technology improvements in the fossil fuel sector, which have net employment enhancing effects in the economy. Contrary, the impact of $R\&D_{FF}$ on fixed capital investments is statistically insignificant. Therefore, we cannot find evidence for the expected impact stemming from $R\&D$ investment in the fossil fuel energy sector. Also, we cannot find statistical evidence for an impact of $R\&D_{FF}$ on price, which would be expected following long-term technology improvements.

While the observed insignificant impacts of $R\&D_{FF}$ may be due to statistical imprecision, which could be caused by sample or measurement errors, it could also imply that $R\&D_{FF}$

has no impact on economic growth. This is why more specific research on the separate fossil fuel technologies incorporated in $R\&D_{FF}$ is required to derive conclusions. It would provide further insights on which of the different fossil fuel technologies have a significant impact and potential reasons why this is the case. This is necessary in order to understand the observed insignificant impacts on the aggregate level.



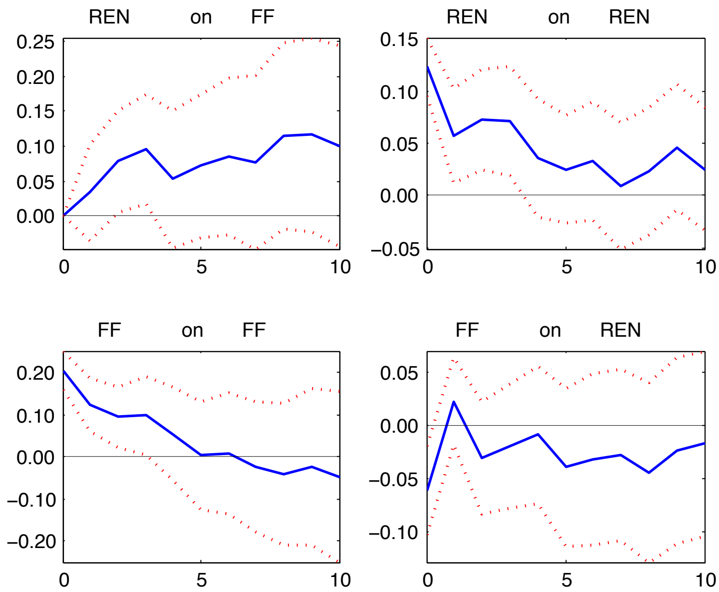
Note: The one standard deviation shock is in the variables $R\&D_{FF}$ (FF). The response paths are in the variables capital (K), labour (L), price (P) and output (Y). The time horizon on the x-axis is 10 years and the y-axis is given in percentage change. While the blue line is the point estimate, the dotted red lines are the 95% confidence bands.

Figure 5: IRF - Impulse Variable: $R\&D_{FF}$

8.1.4 Relationship between Renewable and Fossil Fuel Energy R&D

While overall governmental $R\&D$ budgets are dependent on various factors, the different sector budgets are expected to be related. Governmental financial resources are limited and Bridle and Kitson (2014) determine a negative impact of fossil fuel related subsidies on renewable energy subsidies, which partly consist of governmental $R\&D$ investments. This adverse effect of $R\&D_{FF}$ on $R\&D_{REN}$ investments is confirmed by the empirical finding in Figure 6, as an instant negative response of 0.05% in $R\&D_{REN}$ is significant. This finding shows that a shock to $R\&D_{FF}$ comes at the cost of $R\&D_{REN}$, as this investment is reduced in the same period as the shock. This may be due to the competitive allocation of governmental budgets and the conflicting interests of political reforms. In most cases, subsidy payments, which are allocated to R&D, are limited and have to be separately assigned to the different sectors. The fossil fuel sector remains dominant in the German energy production and thus can exert negative impact on R&D in the renewable sector (Renn and Marshall 2016).

Contrary, a shock to $R\&D_{REN}$ reveals a significant positive impact of 0.1% in $R\&D_{FF}$, which is occurring in the second and third year. This demonstrates that financial support to the renewable energy sector is followed by an allocation of financial resources to the fossil fuel sector. Due to political energy security concerns, the maintenance of the fossil fuel industry, aside a growing renewable energy sector, is a primary political objective. Furthermore, the traditional coal industry in Germany possesses strong political influence due to large employment numbers, tax payments, lobbying networks and political representation, which exhibits a strong position in energy policy decision making (Renn and Marshall 2016). The explicit structural identification specified in Section 6.3 constrains the contemporaneous impact of a shock in $R\&D_{REN}$ on $R\&D_{FF}$ to being equal to zero. This is a necessary constraint required by the model, but prevents conclusions about a contemporaneous impact of $R\&D_{REN}$ on $R\&D_{FF}$. As specified in Section 6.3, this ordering was chosen as Bridle and Kitson (2014) find that "fossil fuel subsidies impair the competitiveness of renewable energy, create large barriers to entry for new technologies, undermine investments by enhancing the attractiveness of fossil fuel technologies and distort prices, which do not fully reflect costs" (p.18).



Note: The one standard deviation shock and the impulse response paths are in the variable $R\&D_{REN}$ (REN) and $R\&D_{FF}$ (FF). The time horizon on the x-axis is 10 years and the y-axis is given in percentage change. While the blue line is the point estimate, the dotted red lines are the 95% confidence bands.

Figure 6: IRF - Impulse Variable: $R\&D_{REN}$ & $R\&D_{FF}$

8.2 Forecast Error Variance Decompositions

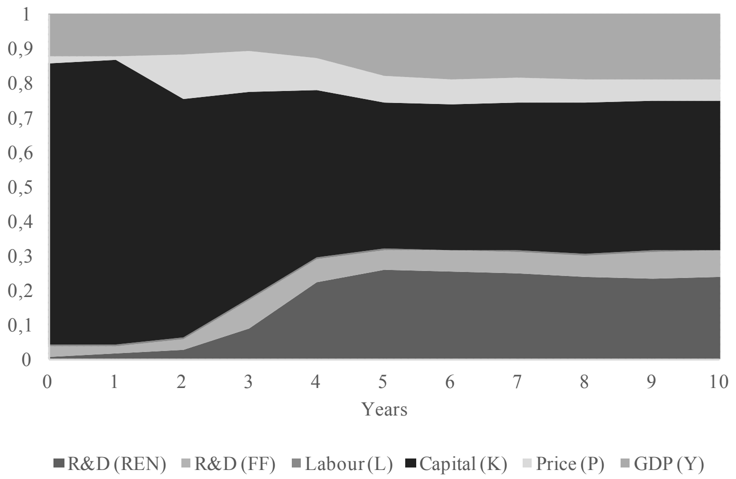
IRFs display the response path of one variable to a one-unit SD increase of another variable. Since the SD of variables differs in size, we cannot directly compare the relevance of individual shocks. Therefore a forecast error variance decomposition (FEVD) "[...]can be used to compute the proportion of the movement in a series that is due to its own shocks versus the parts that are due to shocks from the other variables" (Enders 2010 p.314). Through this statistical method the relative importance of a specific shock to a response variable is determined. Thus, FEVDs can be used to confirm the magnitude of impact on one variable caused by a shock to another and to verify the observed transmission channels.[25]

From Figure 7 we can conclude that a shock to capital is clearly dominant over the entire period of time. The second most important shock accounting for forecast error variance of output is the shock to $R\&D_{REN}$. Here, we notice that the proportion steadily rises from around 0% to reaching an approximate steady maximum level of 25%. This represents the time lagged impact of $R\&D$, which was also found in the IRF analysis. We also notice the proportion of below 10% that is assigned to shocks in $R\&D_{FF}$ and L, which confirms the insignificance of shocks to these variables to account for forecast error variance of Y. Also the proportion of price starts at the zero bound but sharply increases to around 10% between the first and second forecast period, which underlines the relevance of the impact from price to output. Summarising, $R\&D$ partly affects the economy's performance through the channels capital and price, as outlined in Chapter 2.

From Figure 14, 15 and 16 in the Appendix A.2.5, we conclude that the respective FEVD of capital, labour and price is partially explained by shocks in $R\&D_{REN}$ and $R\&D_{FF}$. This shows the importance of the variables $R\&D_{REN}$ and $R\&D_{FF}$ and the respective impact by governmental allocation of financial resources. Enders (2010) points out that "in applied research it is typical for a variable to explain almost all of its forecast variance at short horizons and smaller proportions at longer horizons", as it can be observed in Figure 14 and 16. The proportion of a shock in $R\&D_{REN}$ with its impact on movement in capital steadily rises up to a level of approximate 25%, which can be seen in Figure 14. The relevance of a shock to $R\&D_{REN}$ with its impact on movement in price in Figure 16 rises significantly between the first and third period confirming the time demanding R&D process. $R\&D_{FF}$ accounts for a sizeable proportion of the forecast error variance of labour, as illustrated in Figure 15.

Overall, this confirms the identified transmission channels from the IRF analysis, as a shock to $R\&D_{REN}$ accounts for a larger proportion of the movement in price and capital, while a shock to $R\&D_{FF}$ explains approximate 20% of forecast error variance of labour.

25. For a derivation of the estimated formula of the FEVD, see Appendix A.2.4.



Note: The proportion of movement in the sequence of Y explained by shocks to the other variables and itself.

Figure 7: FEVD: Output

9. Robustness

In the following chapter, we perform a sensitivity check of the applied SVAR-model by testing for the model's robustness with regard to cointegration, ordering, confounding variables bias and overspecification.

9.1 Robustness with Respect to Cointegration

In following section, we extend the analysis of the SVAR-model by allowing for one or more cointegrating relationships among the selected variables.[26] Testing the set of variables for cointegration allows us to determine whether long-run relationships exist that are linked through common stochastic trends. The main prerequisite of the existence of cointegrating relationships is that all variables included in the model are integrated of order n, I(n). The importance to test for cointegration lies in the assumption that estimating a SVAR-model in levels, which contains one or more cointegrating ranks leads to a misspecification error (Enders 2010). This misspecification error would result in wrongly estimated IRFs.

We choose Johansen (1995) methodology to specify a Vector Error Correction Model (VECM) that provides valid estimates. In the course of the SVAR-model specification, we identified all six variables to be unit root processes and therefore conclude that all variables are integrated of the same order (i.e. $I(I)$), which satisfies the prerequisite. Before cointegrated variables are estimated, one needs to define the lag length, as the test of cointegration is sensible to the lag selection (Enders 2010). We follow the most common approach and use the same lag length as specified in the traditional SVAR-model in levels, choosing $p = 3$ (Enders 2010). After that, we specify the number of ranks (r) by computing trace statistics

26. Variables are said to be cointegrated, if there is "[...] a linear combination of integrated variables that is stationary" (Enders 2010 p.356).

based on the eigenvalues of the system.[27] Johansen's methodoloy begins with testing for zero cointegrating relationships ($r = 0$) and increases the number of cointegrated relationships until the first null hypothesis is accepted (Johansen 1995). This procedure determines two cointegrating relationships in the system of equations (cf. Appendix A.3.1). We define the normalisation restrictions using the methodology by Lütkepohl and Krätzig (2004) and normalise on the variables, $R\&D_{REN}$ and P, accordingly.

After we confirm that our selected variables are all non-stationary processes and find two stationary long-run relationships, we estimate following VECM:

$$\Delta x_t = \Gamma_0 + \alpha(\beta' x_{t-1} + \mu) + \sum_{i=1}^{p-1} \Gamma_i \Delta x_{t-i} + \gamma + \epsilon_t \tag{18}$$

where Γ_0 determines the 6×1 vector of intercepts, α is a 6×2 matrix of adjustment coefficients, $(\beta' x_{t-1} + \mu)$ is a 6×2 vector of cointegrating relationships allowing for constant means, $\sum_{i=1}^{p-1} \Gamma_i \Delta x_{t-i}$ represents the short-run dynamics, γ is a linear time trend in the undifferenced data and, lastly, ϵ_t replicates a white noise process.

Before we illustrate and compare the cumulative IRFs from the VECM with the IRFs from the SVAR, we validate our estimates by conducting several diagnostic tests (cf. Appendix A.3.2). Because the IRFs of the VECM are based on first differenced variables, we need to estimate the cumulative IRFs.[28] We then qualitatively compare the cumulutative IRFs of the VECM with the IRFs of the SVAR-model in order to test for the robustness of the SVAR-model with respect to cointegration.

When comparing the IRFs of the SVAR-model with the VECM in Appendix A.3.3, two observations can be made. First, the shape of the impulse response paths in the two models is similar. Secondly, we can observe slight differences between the IRFs of the two models with respect to the magnitude of the impulse. While the size of the impulse response path of Y for a SD shock to capital, price and $R\&D_{FF}$ is similar for the two models, it is marginally different for the SD unit shock to L and $R\&D_{REN}$. In comparison with the SVAR-model, a structural shock to labour leads to an opposing and overall positive response path of output in the VECM. Further, the structural shock of $R\&D_{REN}$ leads to a greater positive and smaller negative impact on output, when compared with the IRFs based on the SVAR-model. Incorporating the cointegrating equation into the model, the negative impact in year four remains persistent. Because of this difference in the magnitude of the impulse response paths, we cannot preclude a bias from omitting the cointegrating relationships.

Allowing for cointegrating relationships increases the number of parameters in the model and consequently causes a reduction in the precision of estimates, thereby only enabling qualitative assessment. Since the shape of the IRFs in the two models is similar, we assess the cointegrating relationships not to be a major problem in our analysis. This conclusion

27. We allow for a linear trend in the level data and cointegrating relationships that are stationary around a constant mean before we determined the number of ranks.

28. Cumulative IRFs are IRFs where each shock is cumulated over the respective time horizon. For a formal derivation of IRFs for the VECM please consider Lütkepohl and Krätzig (2004) Chapter 4.

is also in line with E. Sims (2013), who finds similar results when comparing VECM and SVAR-model in levels.

9.2 Robustness with Respect to Ordering

As outlined in Section 6.3, the identification of variables, also known as *ordering*, is a fundamental assumption underlying the SVAR-model. In accordance with this understanding, C. A. Sims (1981) highlights the importance of testing different identifications. In order to avoid major biases, testing the robustness with regard to the identification strategy is essential. In the following section we remain with the application of the lower Cholesky decomposition, as the rank of the identification matrix has to be respected. Moreover, we want to enable comparison of results with the initial matrix. In this specific case, C. A. Sims (1981) suggests to try different triangular matrices in the SVAR-model approach. In comparison to the matrix in Section 6.3, we change the order with regard to $R\&D_{REN}$ being contemporaneously prior to $R\&D_{FF}$. In accordance with this change, the ordering implies that $R\&D_{REN}$ is subject to total contemporaneous exogeneity or, in other words, the variable impacts all other variables in the system. This alternative ordering can be motivated by the argument that $R\&D_{REN}$ is increasing in it's priority and size. Due to the energy transition, political attention is devoted to increase the share of renewable energy, while steadily decreasing the share of fossil fuels. This would substantiate the assumption that funds are shifted from traditional to renewable energy sources. Comparing Figure 19 and 20 in Appendix A.4 with the baseline model in Figure 4, 5 and 6 in Chapter 8, we notice consistency in the shape of the response paths of output to shocks in all variables. The major deviation between the models is with regard to the contemporaneous impact between $R\&D_{REN}$ and $R\&D_{FF}$. This observation is anticipated, as for these variables the structural restrictions change and $R\&D_{REN}$ now has a contemporaneous impact on $R\&D_{FF}$ (cf. Figure 19 in Appendix A.4). Due to consistency of the impact through the transmission channels on economic growth, we conclude robust results with regard to the altered identification restrictions.

9.3 Robustness with Respect to Confounding Variable Bias

According to the endogenous growth theory, R&D has a significant impact on total factor productivity and thus economic growth (Romer 1990). By assuming no change in total factor productivity in Chapter 4 and focusing on the analysis of governmental R&D in the energy sector, technical change in other sectors, which receive *R&D* funds, is omitted from the analysis. Due to the high probability of correlation between *R&D* funds in other remaining sectors and the expected attraction of private funds through governmental investments, the analysis has to be tested for its robustness to a confounding variable bias.

For this reason, the variable *total gross domestic expenditure on R&D* in million euro ($R\&D_{Total}$) is extracted for the underlying time period from the OECD data base (OECD 2016). After subtraction of $R\&D_{REN}$ and logarithmic transformation, the variable $R\&D_{Total}$ is substituted for $R\&D_{FF}$ into the model. Including this variable in the model, we account for total, governmental and private, expenditure in *R&D* in Germany. The model specification and diagnostic tests determine a lag selection of $p = 3$ including a trend term, which ensures the stability of the model. Further, no autocorrelation in the residual series is present. In Appendix A.5 the IRFs of variable output are displayed, where $R\&D_{Total}$ is labelled as RD. Here, we notice consistency with the baseline model since the impact of capital, electricity price and $R\&D_{REN}$ remain significant with equal directions of the response. Furthermore, a significant positive impact of total $R\&D$ on economic growth can be observed. This empirical finding is in line with the endogenous growth theory (Romer 1990), which confirms the validity of the underlying model. Overall, accounting for the positive impact of $R\&D_{Total}$, the negative impact of $R\&D_{REN}$ remains significant.

9.4 Robustness with Respect to Model Overspecification

A widely acknowledged risk in the application of SVAR-models with a small sample size is overly exhausting the degrees of freedom resulting in a model overspecification. This can lead to inflated standard errors of the model coefficients and thus biased results (Lütkepohl and Krätzig 2004). The transmission channel and economic theory provide justification for the included variables, however, there is a certain risk of overidentification by including redundant lagged parameter coefficients. In the baseline model, the information criteria have identified an optimal lag length of $p = 3$ and we further observe that a lower number of lags leads to autocorrelation in the residuals. In line with Lütkepohl and Krätzig (2004), this section estimates a SVAR-model with specific inclusion of the first and third lagged value, omitting the second lagged value. This enables a model construction, which estimates (6×6) 36 fewer parameters than the previously defined baseline model. Testing the model for autocorrelation in the residuals series and stability condition, reveals a valid model specification, which permits interpretation of results. Investigating Figure 22 in the Appendix A.6, we see that the impulse of response paths are smaller, however, impacts still remain significant. This reveals the important impact of all lagged variables, which is also economically justified, and we preclude a model overspecification, as results are consistent.

10. Model Extension

Next to the effects of energy R&D on the economy, R&D also impacts consumption in the energy market, as outlined in the transmission channel in Section 2.2. Therefore, it is important to study the impact of R&D on energy consumption to better understand the indirect effect of R&D in the energy sector on economic growth. The authors Wong, Chang and Chia (2013) have investigated the consumption channel of energy R&D for a panel data set, but miss out on country-specific characteristics and the importance of pricing renewable energy consumption. The following analysis is based on a modification of the baseline SVAR-model from Section 6.1. The vector $[R\&D_{FF}, R\&D_{REN}, K, L, P, C_{REN}]'$ is estimated in a SVAR-model to analyse the impact of the investigated energy R&D on renewable energy consumption (C_{REN}). Similarly, a SVAR-model using the vector $[R\&D_{FF}, R\&D_{REN}, K, L, P, C_{FF}]'$ provides insights on the response of fossil fuel consumption (C_{FF}) to shocks in the two energy

R&D investment budgets. Data for renewable energy and fossil fuel consumption intensity is retrieved from the IEA data base for the period 1974-2014 and is given as a percentage of total energy consumption (IEA 2016).

The dummy variables, specified in Chapter 7, remain in the model and are treated as exogenous variables. We find the variable C_{REN} exhibiting a strong time trend and high correlation with the variable capital; thus we incorporate a linear trend variable to ensure passing the eigenvalue stability condition. For both models the AIC determines a lag length selection of $p = 3$. Applying the diagnostic tests specified in Section 7.2, the eigenvalue stability condition confirms stability for both models, as all eigenvalues lie within the unit circle. A Lagrange multiplier test fails to reject the H_0 at a 5% significance level and we conclude that there is no remaining autocorrelation in the error terms. Identical to the approach in Chapter 6, plotting IRFs requires a structural identification. We apply the Cholesky decomposition specified in Section 6.3 to the two vectors defined above. Hereby, we order C_{REN} and C_{FF} as entirely contemporaneously endogenous in the respective model. This is based on the explanation in Section 2.2, that R&D expenditures cause capital expenditure and changes in labour force, which consequently impact the technology stock in the respective sector. The technology improvement, resulting from R&D activities, leads to an alteration of energy consumption.

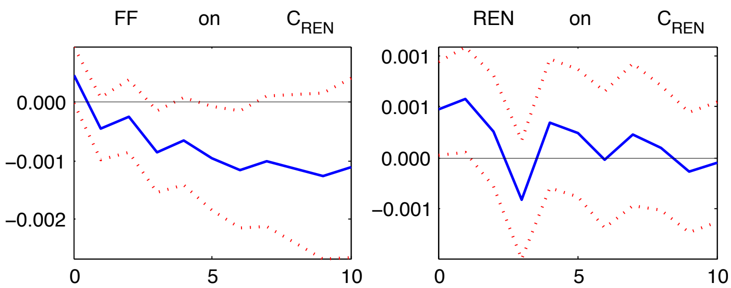
Since we are primarily interested in the impact of $R\&D$ on energy consumption, we will focus on the response paths of the variables C_{FF} and C_{REN} in the following analysis.[29] In Figure 8 we can observe that a structural shock to $R\&D_{REN}$ reveals a contemporaneous positive impact on C_{REN}, which demonstrates that $R\&D_{REN}$ effectively promotes the renewable energy sector. Allocating financial resources to the renewable energy sector immediately increases C_{REN} and thus proves to support the sector. A comparable study on OECD panel data performed by Wong, Chang and Chia (2013b) finds a positive impact of $R\&D_{REN}$ on C_{REN} as well; however this effect is statistically insignificant at the 10% level, which might be explained by insufficient separation of effects due to panel aggregation.

The increase in price, as described in Section 8.1.2, combined with the increase in renewable energy consumption following a shock in $R\&D_{REN}$ may seem counterintuitive at first. Assuming that the production costs are decreasing due to R&D investments as claimed by institutions, such as the Renewable Energy Research Association, the increased consumption of renewable energies by energy providers can be justified. Here, the end-consumer has limited scope in changing the consumption mix, as energy supply is determined by energy providers.[30] German energy end-consumers share the costs of the energy transition through higher electricity prices, but energy demand in Germany is observed to be relatively inelastic to price changes (Boug 2000). Based on this rationale, the observed IRFs can be explained. To derive further conclusions disaggregating the price into its components in upcoming research is essential.

29. The remaining IRFs are displayed in Appendix A.7.

30. The majority of German energy consumers receives so called *grey* electricity, which stems from untraceable sources and can constitute for example of coal or oil but also renewable energies, supported through the feed-in tariffs (Reichmuth 2014).

Additionally, Figure 8 reveals a negative and time deferred impact of a shock in $R\&D_{FF}$ to C_{REN}. An initial positive shock to $R\&D_{FF}$ provides the fossil fuel sector with governmental financial resources dedicated to R&D and helps the sector to advance technology in the future. Fostering the fossil fuel consumption in this way yields an adverse effect on renewable energy consumption. The adverse effect is confirmed by the study of Wong, Chang and Chia (2013b), who find a negative impact of $R\&D_{FF}$ on C_{REN} for OECD countries, among them Germany.

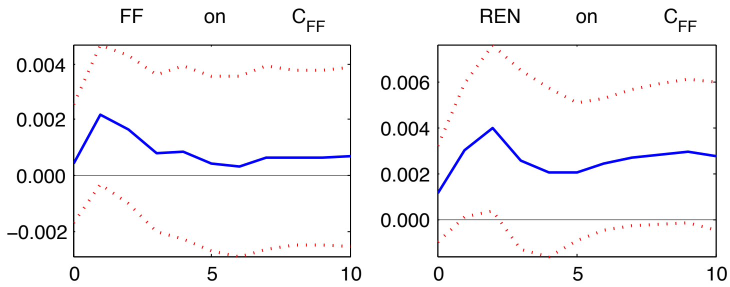


Note: The one standard deviation shocks are in the variables $R\&D_{FF}$ (FF) and $R\&D_{REN}$ (REN). The response path is in the variable renewable energy consumption (C_{REN}). The time horizon on the x-axis is 10 years and the y-axis is given in percentage points. While the blue line is the point estimate, the dotted red lines are the 95% confidence bands.

Figure 8: IRF - Impulse Variable: $R\&D_{FF}$ & $R\&D_{REN}$; Response Variable: C_{REN}

Analysing the response path of C_{FF} in Figure 9, we cannot find evidence for a positive response to a shock in $R\&D_{FF}$. This is against our expectations, as the theory of a substitution effect predicts a consumption increase following a technological change through $R\&D_{FF}$ and a consumption decrease of C_{REN}, which can be observed in Figure 8. The point estimates indicate an increase in C_{FF}, caused by a shock to $R\&D_{FF}$, but due to confidence intervals covering the zero bound, we cannot find evidence for a full substitution effect. In this case an analysis on the disaggregate technologies is required to specify the substitution effect and draw inference from the impulse in $R\&D_{FF}$.

We further find a significant positive impact of $R\&D_{REN}$ on C_{FF}. This observation is not in accordance with the studied literature on panel data, but emphasises the special case of the energy market in Germany instead. Observing a positive response of energy consumption in the fossil fuel sector to a shock in $R\&D_{REN}$, we find evidence for the still existing importance of the fossil fuel industry for the German economy that also has been advocated by industry experts (BGR 2015). Supply of most renewable sources is volatile due to environmental factors and therefore energy security concerns necessitate the existence of fossil fuels until renewable energy sources can independently secure energy supply.



Note: The one standard deviation shocks are in the variables $R\&D_{FF}$ (FF) and $R\&D_{REN}$ (REN). The response path is in the variable renewable energy consumption (C_{FF}). The time horizon on the x-axis is 10 years and the y-axis is given in percentage points. While the blue line is the point estimate, the dotted red lines are the 95% confidence bands.

Figure 9: IRF - Impulse Variable: $R\&D_{FF}$ & $R\&D_{REN}$; Response Variable: C_{FF}

Overall, the empirical analysis of this study finds a significant impact of $R\&D$ investments on the energy consumption, which justifies the use of governmental R&D to change the energy mix in Germany. Furthermore, we note in Figure 8 and 9 that for both sectors, the impulse response in energy consumption to a shock in energy R&D is small. This provides evidence that a shock in energy $R\&D$ marginally impacts the economy's energy consumption and due to inelastic demand, the small magnitude of the observed impulse response paths can be explained.

11. Summary

The assessment of the economic effect stemming from $R\&D$ investments in the renewable and fossil fuel energy sectors reveals critical findings for the German energy policy. This study provides evidence for a negative impact of $R\&D_{REN}$ on economic growth at a period lag between years three and five. Partially, this effect can be explained by two channels: capital and price. A positive shock to $R\&D_{REN}$ yields an initial positive investment effect and a subsequent negative response at a period lag of four and five in capital. After the allocation of governmental funds, capital expenditures are undertaken, which lead to technology improvements and subsequently lower capital requirements. Governmental investments in $R\&D_{REN}$ are followed by crowding out effects of other sources of investment, which result in negative impacts at a later stage.

While a $R\&D_{REN}$ investment reduces technology and innovation costs, it exhibits increasing renewable energy production. Assuming a strong link between energy consumption and production, this is reflected in the positive response of renewable energy consumption to an increase in $R\&D_{REN}$, which is observed in the model extension in Chapter 10.

Due to legislative specifications, an increasing renewable energy production results in higher compensation payments to renewable energy producers. To cover these payments, the government transfers some of the costs to groups, such as the manufacturing industry or private households (BMWi 2016e). In addition to this, the volatile nature of renewable energies and the subsequent higher integration costs further explain the increase in price following a higher consumption triggered by governmental $R\&D_{REN}$ investments (BNetzA 2016). The increase in price can result in a deterioration of "the competitiveness of energy-intensive industries, which leads to a contraction of economic activity" (Bassi, Yudken and Ruth 2009 p.1). This subsequent negative economic impact raises a concern about this form of driving the energy transition. Additionally, it is important to note that the sum of the transmitted impacts through capital and price is smaller than the overall observed negative economic impact of $R\&D_{REN}$. This illustrates that next to the channels price and capital, there are also other mechanisms transmitting the impact from $R\&D_{REN}$ to economic growth.

Further, we find a statistically insignificant impact of a shock to $R\&D_{FF}$ on economic growth over the entire period studied. Nevertheless, a significant positive impact of $R\&D_{FF}$ on labour can be observed after three years. We note that an increase in governmental R&D investments can lead to lagged technology improvements in the fossil fuel sector, which have net employment enhancing effects in the economy. Further, the impact of shocks to $R\&D_{FF}$ on price and capital reveals insignificant impulse response paths. We are not able to differentiate whether this insignificant overall effect is caused by the underlying data of $R\&D_{FF}$, which does not allow for a statistical inference, or $R\&D_{FF}$ has no effect due to a limited effectiveness of $R\&D$ in mature sectors. In order to derive further conclusions, the variable $R\&D_{FF}$ should be disaggregated into its individual fossil fuel technologies in future research.

When comparing the negative economic impact of $R\&D_{REN}$ and the insignificant impact of $R\&D_{FF}$, it is important to note that the externalities of carbon effects of fossil fuel technologies are not incorporated in our model. Scholars, such as Nordhaus (1992), Hope (2006) and Tol (2009), have demonstrated substantial costs originating from carbon emissions. Furthermore, a comparison of both energy sources in the short-term would neglect that investing in renewable energy sources represents a hedge against a rise in electricity prices in the long-term, which will mainly be caused by the expected increase in the cost of fossil fuels (Martin 2012).

Our findings confirm a competitive allocation of energy R&D budgets and the still existing relevance of the fossil fuel energy sector in Germany. A one-unit SD shock in $R\&D_{FF}$ leads to a negative impulse response in $R\&D_{REN}$ and the extended model confirms an adverse effect of $R\&D_{FF}$ on C_{REN}. This finding shows that the importance of $R\&D_{FF}$ should not be undermined as fossil fuels, on the one hand, are still superior to renewable energies with regard to security of supply and, on the other hand, harm the transition towards more renewable sources through their adverse effects on $R\&D_{REN}$ and C_{REN}, as outlined by our analysis.

Contrary, a shock to $R\&D_{REN}$ positively impacts the $R\&D_{FF}$ investment and enhances both C_{REN} and C_{FF}. This illustrates the importance of energy security for Germany, which, due to the volatile supply of renewable energy, requires the preservation of the fossil fuel sector (Renn and Marshall 2016). The empirical results do not provide evidence for an impact of $R\&D_{FF}$ on C_{FF}, which we identify to be possibly caused by measurement errors or inefficient allocation of investment budgets. Generally these observations query the allocation of governmental financial resources to $R\&D$ investments in the investigated energy sectors and show economic side-effects of policies, which are primarily defined for environmental objective.

12. Discussion

12.1 Policy Implications

The energy transition in Germany has a fundamental impact on the country and its economy as it restructures the entire national energy supply. This requires major reforms and highlights why Germany is a suitable case to learn from. The energy transition can be seen as an inter-generational contract, since today's investments in a sustainable energy system permanently reduce costs of renewable energy supply and mitigate environmental risks for the future (Haucap and Kühling 2012). However, bounded governmental intervention and limited participation of the private sector determine the speed of the transition to renewable energies. Thus, it is essential to define the economic implications of the energy transition, to ensure its affordability and to prevent threatening the competitiveness of Germany as an industrial location. While the promotion of renewable energies is necessary for mitigating the climate change, it is in society's interest to achieve this most cost-effectively.

The findings of this study display that renewable energy subsidies, in the form of $R\&D$ investments, have an overall negative impact on economic growth. It is further displayed in our analysis that the negative impact of $R\&D_{REN}$ on economic growth is partially exerted through the channels capital and price. We observe that governmental $R\&D_{REN}$ investments cause contemporaneous capital expenditures, but subsequent crowding out effects and deferred investments have a converse impact. Due to the relevance of capital expenditures in accounting for the forecast error variance in economic growth, it is important for governments to anticipate these contrary effects and time $R\&D_{REN}$ policy initiation adequately. Additionally, $R\&D_{REN}$ investments contribute to an increase in electricity price by raising the renewable energy share. It is specified in the Renewable Energy Sources Act that renewable energy producers receive fixed feed-in tariffs, which act as a premium on energy prices. This form of driving the energy transition counteracts the benefits of reduced production costs caused by $R\&D_{REN}$ investments. While governmental $R\&D_{REN}$ positively contributes to the expansion of renewable energy sources, feed-in tariffs do not reveal to be a sustainable incentive tool to drive the energy transition in Germany. A disadvantage of renewable energy sources is the increase in volatility and the poor compatibility with the current energy grid system. This results in higher integration efforts, which further drives the electricity price. Thus, $R\&D_{REN}$ investments should be targeted to energy technologies that are system compatible. Further, specific policies that contribute to the integration of renewable energies into the energy grid should additionally be considered.

Another option to reduce costs is to improve and particularly evaluate the separate allocation of energy R&D investments. This is important, as for example a substantial amount of investments were historically directed to photovoltaic technology, which inconsistently represents the most expensive renewable energy technology (Wirth 2016). The extensive promotion of photovoltaic technology has led to the installation of more than 40% of the world's entire solar energy capacity in Germany, which determined by yearly sunshine hours, is not the most efficient location (Haucap and Kühling 2012). This depicts the substantial challenge of creating efficient investment incentives that promote interests of the private sector in the energy transition. To most effectively drive the energy transition forward, additional research in the form of an investigation of R&D investments targeted to individual energy technologies is required. This would help to determine at which energy technology governmental R&D can be most effectively targeted with regard to economic and ecological implications.

The empirical analysis of this study finds a significant impact of $R\&D_{REN}$ investments on C_{REN}, which justifies the use of governmental R&D to change the energy mix in Germany. Furthermore, we note that for both sectors the impulse response in energy consumption to a shock in R&D is significant. This provides evidence that a shock in energy $R\&D$ impacts the economy's energy consumption, but the marginal magnitude of the impact accentuates the importance of aligning energy R&D investments with other policies to optimally contribute to Germany's energy transition. Since the impact of $R\&D_{REN}$ on economic growth appears with a lagged impact, German government needs to be aware of the time deferral of R&D investments as a policy tool. Further, our observation of differential impact in sign, time and magnitude on the formation of capital, also reveals the importance of the timing of governmental energy R&D investments.

Moreover, the results indicate an adverse effect on C_{REN} stemming from increasing $R\&D_{FF}$. This shows that if a long-term political strategy is devoted to the transition to renewable energy consumption, continuous R&D investments in the fossil fuel sector are counterproductive. Considering the important factor of energy security, fossil fuel energy supply has to be gradually substituted by renewable energy sources and should not become subject to a drastic politically driven phase-out, as it has been the case for the German nuclear energy sector. This additionally highlights the trade-off between rapid development of renewable energy sources and ensuring a secure energy supply with the support of fossil fuel sources. Since the presented findings do not reveal statistically significant impacts of $R\&D_{FF}$ on fossil fuel consumption and economic growth, a more focused analysis of the fossil fuel sector and its subsidies has to be undertaken to derive policy implications.

Observing a negative impact of $R\&D_{REN}$ on economic growth in contrast to an insignificant impact of $R\&D_{FF}$, one can conclude that if a government solely evaluates a policy based on the inferred economic impact, no R&D investments in the energy sector should be taken. Though, if governments prioritise ecological and energy security targets, the economic impacts, which were observed in this analysis, have to be placed in overall context. Investments in the renewable energy sector exhibit benefits for the energy grid infrastructure and independence from fossil fuels, which can only be observed in the long-term, beyond the scope of this analysis and the specified model. Contrary, support to the fossil fuel sector promotes an energy source which exhibits negative externalities, like carbon emission, whose costs are not incorporated in the model. Thus, a direct comparison between $R\&D_{REN}$ and $R\&D_{FF}$ investments depends on governmental objectives and the considered evaluation criteria.

12.2 Limitations

The application of the VAR methodology is widely applied in the field of Macroeconomics, though several limitations to the underlying results should be discussed. Omitting a confounding variable results in an omitted variable bias and, subsequently, implies inconsistent estimators.[31] Since we base our econometric model on an extension of the Cobb-Douglas production function and in this way control for labour, capital and price, we already account for several omitted variables that may be explained by economic theory. We further include total domestic R&D, which we assess to be a likely confounding variable. As demonstrated in Chapter 9, our model is robust to a potential bias caused by the omission of total R&D and the diagnostic test of autocorrelation in both the SVAR-model and VECM additionally provide no indication for an obvious endogeneity bias, caused by a confounding variable. When specifying a small sample VAR-model, one faces the trade-off between including further variables in the analysis and reducing statistical degrees of freedom, which prohibits the inclusion of a larger number of variables. Due to the foundation of our analysis in the Cobb-Douglas function and the robustness of results in Section 9.3, we do not expect our analysis to be subject to distortions through omitted variables.

The reverse causality in the nature of the underlying variables needs to be incorporated in the model and the underlying SVAR-model accounts for this issue and enables an empirical assessment of the research question. While the model has its strength in allowing for a high degree of (endogenous) interaction between the variables, it requires several identifying restrictions in order to recover its structural shocks. Thus, the outcome of the SVAR-model is sensitive to the choice of identification strategy and its underlying restrictions, which are founded in economic theory, and hence represent a limitation. The presented identification strategy is linked to economic rational and academic research. Additionally, during the interpretation of contemporaneous impacts we pay particular attention to a potential biased result implied by the specified order. Further, we apply a robustness test to mitigate the bias due to a potential misspecified identification. The specification of the SVAR-model also limits the analysis to the interpretation of unexpected policy shocks and prevents drawing conclusions about systematic policy changes (Gottschalk 2001). Nevertheless, historical changes in the energy policy stance have been observed to be partly unexpected. Thus, the analysis of the impact of unexpected policy changes with regard to the energy transition remains important.

In the analysis we examine the relationship between governmental investments in the energy sector and economic growth. While the governmental energy RD&D budget is classified as a proxy of governmental R&D investments in the energy sector, national real GDP has some minor drawbacks. Whereas it is a variable that is commonly under investigation in Economics, which increases the comparability of this study, it remains an extensive vari-

31. "A confounding variable is a variable that affects the response variable and is also related to the explanatory variable" (Utts and Heckard 2014 p.193).

able, which incorporates a large amount of variables and effects within an economy. We have selected the electricity household price as a proxy for the combined energy price, as it incorporates both electricity produced from renewable and fossil fuel resources. Though, we do not account for the individual components of the electricity price, which prevents us from disentangling the underlying changes of the price components. Furthermore, electricity represents next to heat and mobility only one component of energy (Ekardt, Hennig and Unnerstall 2012). Despite the fact that these factors create limitations with regard to interpretations, the household electricity price provides a reasonable projection of price dynamics in the energy market of both sectors. The IEA (2011) specifies that RD&D is ascertained through a questionnaire, which is sent out to national energy ministries. This process can be susceptible to misunderstandings of the respondents or subject to measurement errors (Biemer et al. 2011). An additional limitation is the assumption that RD&D budgets do not differ from actual governmental spending.

Furthermore, specifying the analysis on Germany instead of applying a panel data set, leads to a comparatively small sample size. Though, this study examines the longest time span available, 1974-2014, and used for an evaluation of the economic benefits of governmental subsidies in the German energy market. Governmental budgets are allocated at annual frequency, and in this way, a country-specific analysis is limited with regard to available data. Thereby, larger standard errors and consequently wider confidence intervals are a major disadvantage and provide higher difficulty to derive statistically significant inference. As a consequence of this, we have focused the analysis on deriving conclusions from statistical significant response paths and do not declare the absence of an impact based on statistically insignificant results. A common test for consistency in the estimates of a time series analysis is the evaluation of sub-samples, which is infeasible for this country-specific analysis due to limited sample size. Despite the ensuing limited sample, the choice of a country-specific analysis of Germany allows to study the relationship between R&D investments and economic growth in a focused approach and to specifically account for country-specific characteristics and events in the empirical analysis.

13. Conclusion

Recent international agreements, like for instance the Paris Climate Agreement in 2016, have increased the pressure on governments to reduce their carbon footprints and to steadily increase the use of renewable energy sources. Until now, Germany has been one of the leading countries in the energy transition and exhibits one of the world's largest governmental budgets for supporting the renewable energy sector through general subsidies and R&D investments. Leading the energy transition does not only provide a positive ecological image, but also the opportunity to develop infrastructure and proprietary technology, which will be the backbone of future energy supply. Until 2015, governmental policies accounted to a large degree for the development of the renewable energy share of 29% in Germany (BMWi 2016d). The political objectives set for the energy transition are measured in terms of ecological targets and energy security. However, economic implications are also important to be evaluated for political justification of the allocation of public financial resources.

This study focuses on the impact of renewable and fossil fuel energy R&D investments on economic growth. To assess this impact, the transmission channels through price, capital, labour and energy consumption are incorporated in the model and respective effects are estimated. In a novel empirical approach to Energy Economics, a structural vector autoregressive model is employed to create impulse response functions that provide insights into a variable's response to structural shocks in the system. Further, forecast error variance decompositions are utilised to predict the meaningfulness of shocks with regard to their impact on the variables in the system.

Studying impulse response functions and forecast error variance decompositions enables us to answer the research questions that were defined in Section 3.3. Our findings reveal a negative response of economic growth to shocks in renewable energy R&D and an insignificant response to shocks in fossil fuel energy R&D. The results provide evidence for an impact of renewable energy R&D on economic growth through the channels capital and price. We show a significant impact of fossil fuel energy R&D on labour, but do not find any transmitted effect on economic growth. The assessment of forward error variance decompositions confirms the relevance of the transmitted economic impact of renewable energy R&D through price and capital. The observed significant negative impact occurs at a period lag of three to five years after the initial shock. This clearly exhibits the time deferred characteristic of R&D, which is explained by the protracted process of technology innovation. In combination with an extension of the structural vector autoregressive model, the second research question is answered. We find a significant adverse effect of fossil fuel R&D on renewable energy consumption and R&D. Contrary, we observe a significant positive impact of renewable energy R&D on fossil fuel consumption and R&D. This is a noteworthy finding to illustrate the conflict of interest with regard to governmental investments in the process of the energy transition. To derive further conclusions about the impact of governmental involvement in financing the energy transition, additional Germany specific research is needed. Moreover, this study represents an aggregated investigation of R&D investment. This provides the need for additional sector-specific research to validate the results and potentially derive conclusions not only with regard to the energy resource form, but also the specific technology deployed.

Governmental R&D investments are a meaningful policy tool to foster R&D activities in an energy sector. In this analysis, we cannot find economic benefits from an unexpected increase in energy R&D investments and thus no economic justification for the investments. As the underlying analysis does not incorporate carbon emissions from the fossil fuel sector, this study has to be placed in context with literature on the ecological impact achieved by energy R&D.

Concluding, this study contributes by estimating the economic impact of governmental investments in energy R&D in Germany. It is relevant to evaluate and optimise the allocation of renewable energy R&D, which consequently enhances the German energy transition. Social norms, public opinions and values are in favour of the German energy transition, which facilitates the speed and success of this change. Germany, among other countries transitioning to renewable energies, can act as a role model for a global transition, which is ultimately required to achieve climate and ecological related objectives. Though, if a global consensus in the energy transition is to be reached, this can only be achieved by proving not only ecological but also the economic benefits of the deployment of renewable energies.

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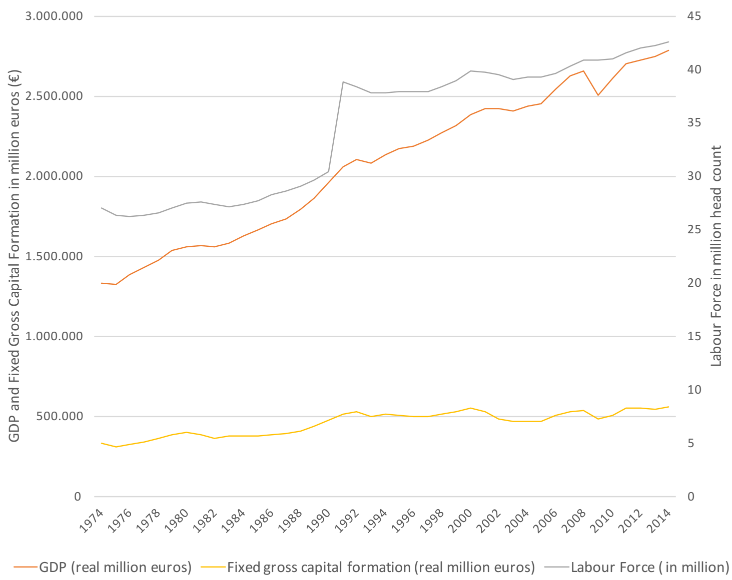
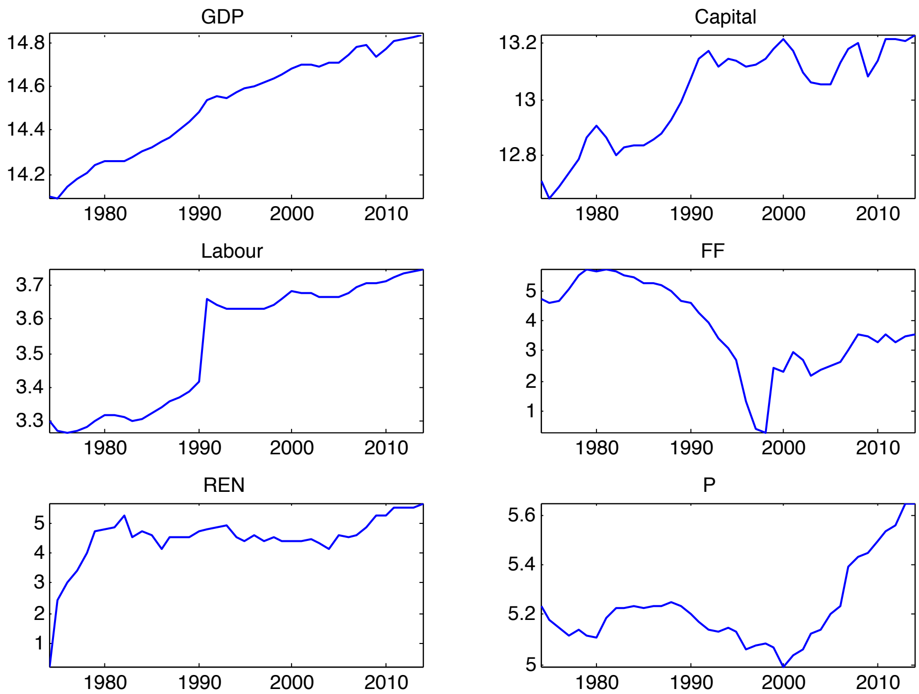
A. Appendix

A.1 Descriptive Statistics



Source: Authors' rendering of data from World Bank (2016)

Figure 10: GDP, Fixed Capital Formation and Labour Force in Germany



Source: Authors' rendering of data from IEA (2016), World Bank (2016) and DStatis (2016)

Figure 11: Input Variables in Logarithmic Form

A.2 Structural Vector Autoregressive Model

A.2.1 Model Specification

Selection-order criteria

Sample: 1977-2014 Number of obs=38

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	280.17				7.80E-14	-13.1669	-12.7069	-11.8741
1	437.93	315.52	36	0	1.40E-16	-19.5755	-18.5635	-16.7312*
2	480.48	85.09	36	0	1.40E-16	-19.92	-18.3561	-15.5244
3	560.50	160.04*	36	0	2.8E-17*	-22.2368*	-20.1209*	-16.2898

Endogenous: log_RDD_FF, log_RDD_REN, log_Capital_fixed, log_Labour, log_P_HH, log_GDP

Exogenous: coalsubsidy, EEG, unification, Energiewende, _cons

Figure 12: SVAR: Information Criteria

A.2.2 Diagnostic Tests

Lagrange-multiplier-test

lag	chi2	df	Prob>chi2
1	35.4477	36	0.49468
2	35.8309	36	0.47658
3	28.1686	36	0.82114
4	33.7203	36	0.57749

H0: no autocorrelation at lag order

Figure 13: SVAR: Lagrange Multiplier Test

A.2.3 Theoretical Derivation of the Impulse Response Function

For calculating the IRFs we return to the standard VAR-model equation:

$$x_t = A_0 + A_1 x_{t-1} + ... + A_p y_{t-p} + e_t \tag{19}$$

One can now rewrite this equation by using backward shift operators (B):

$$\begin{aligned} (I - A_1 B - A_2 B^2 - ... - A_p B^p) x_t &= A_0 + e_t \\ A(B) x_t &= A_0 + e_t \end{aligned} \tag{20}$$

Based on Enders (2010), we note that if a VAR-model is stable, meaning that all roots of the characteristic polynomial are outside the unit circle, we can write any VAR(p) as a MA(∞) representation:

$$x_t = [A(B)]^{-1} \; A_0 + [A(B)]^{-1} \; e_t \tag{21}$$

$$x_t = \mu + \sum_{i=0}^{\infty} \; \theta_i \; e_{t-i} = \mu + \theta(B) \; e_t = \mu + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + ... + \theta_p e_{t-p} \tag{22}$$

where $\theta(B) = [A(B)]^{-1}$. Now analysing IRFs, we are interested in how elements of x_t (for example the k^{th} element being x_t^k) respond to past shocks on the j^{th} element, being e_{t-i}^j. Therefore, derivatives of equation (22) with respect to the mentioned elements are as follows:

$$\frac{\partial \; x_t^k}{\partial \; e_{t-i}^j} = \theta_i^{kj} \tag{23}$$

where i = 0,1,2,...,p. The coefficient θ_i^{kj} is called impact multiplier. Enders (2010) then states that an estimated VAR-model is under-identified and restrictions need to be imposed in order to identify the IRFs. Since we know from Section 6.2, that $e_t = B^{-1}\epsilon_t$, we can substitute this into equation (22):

$$x_t = \mu + \sum_{i=0}^{\infty} \; \theta_i \; B^{-1}\epsilon_{t-i} \tag{24}$$

Imposing the Cholesky decomposition to matrix B^{-1}, as discussed in Section 6.3, constrains the system and enables decomposition of the error terms. This enables us to derive a response path from a structural shock:

$$\frac{\partial \; x_t^k}{\partial \; \epsilon_{t-i}^j} = \theta_i^{kj} B^{-1} \tag{25}$$

A.2.4 Theoretical Derivation of the Forecast Error Variance Decomposition

The FEVD is particularly helpful to decompose the proportion of variance in response of one variable "...due to its own shocks versus shocks to the other variables" (Enders, 2010, p.314). Therefore, the FEVD explains the proportion of variance in the response of x_t^k caused by shocks e_t^j. We can start the derivation of the decomposition with the moving average representation of the VAR-model from equation (24) and create the h-step ahead forecast x_{t+h}, in which $\phi = \theta_i \; B^{-1}$ (Lütkepohl 2004):

$$x_{t+h} = \mu + \sum_{i=0}^{\infty} \; \phi_i \; \epsilon_{t+h-i} \tag{26}$$

Consequently the h-period forecast error ($x_{t+h} - E_t x_{t+h}$) is:

$$x_{t+h} - E_t x_{t+h} = \sum_{i=0}^{h-1} \; \phi_i \; \epsilon_{t+h-i} \tag{27}$$

Denoting the mn^{th} element of ϕ_i by $\Phi_{mn,i}$, the forecast error of the jth component of x_t is:

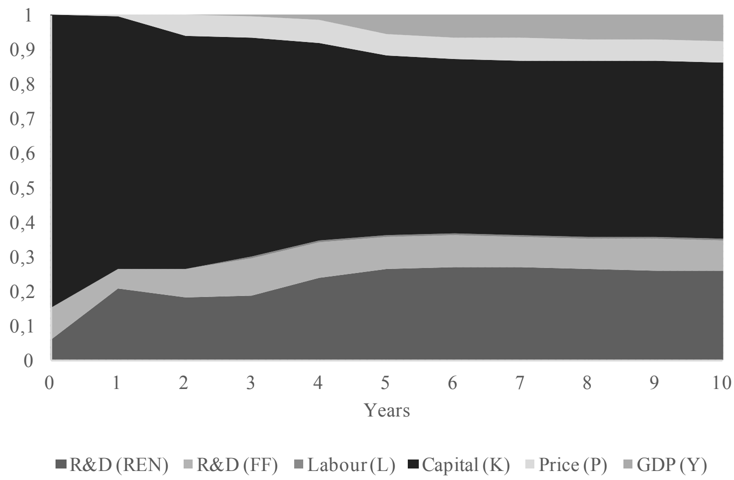
$$x_{j,t+h} - x_{j,t}(h) = \sum_{k=1}^{K} (\Phi_{jk,o}\ \epsilon_{k,t+h} + ... + \Phi_{j,k,h-1}\ \epsilon_{k,t+1}) \tag{28}$$

Taking the mean squared error of the n-period forecast error, one can compute the proportion of each shock attributable to the total variance of the forecast error:

$$E(x_{j,t+h} - x_{j,t}(h))^2 = \sum_{k=1}^{K} (\Phi^2_{jk,0} + ... + \Phi^2_{jk,h-1}) \tag{29}$$

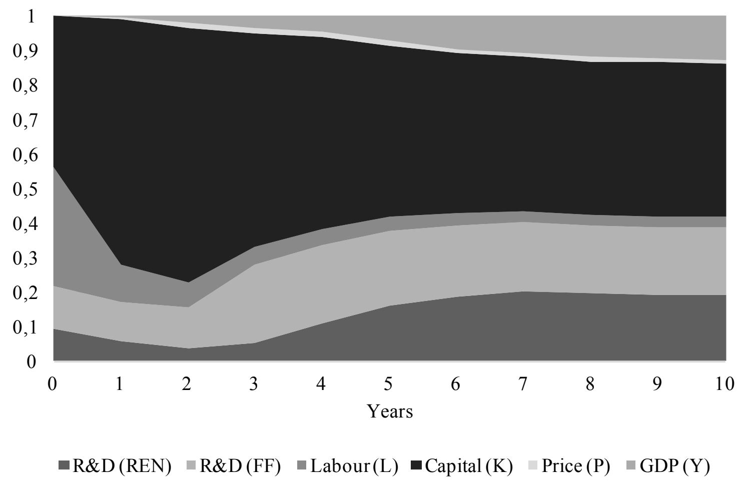
For a more detailed derivation of the FEVD, see Lütkepohl (2005) Chapter 4.

A.2.5 Forecast Error Variance Decompositions



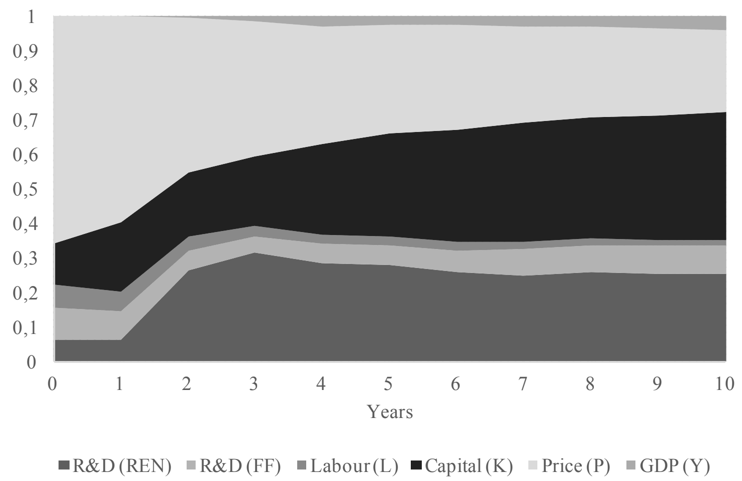
Note: The proportion of movement in the sequence of capital (K) explained by shocks to the other variables and itself.

Figure 14: FEVD: Capital



Note: The proportion of movement in the sequence of labour (L) explained by shocks to the other variables and itself.

Figure 15: FEVD: Labour



Note: The proportion of movement in the sequence of price (P) explained by shocks to the other variables and itself.

Figure 16: FEVD: Price

A.3 Robustness with Respect to Cointegration

A.3.1 Model Specification

Johansen test for Cointegration

Trend: constant — Number of obs = 38

Sample: 1977 - 2014 — Lags=3

maximum rank	parms	LL	eigenvalue	trace statistic	critical value 5%
0	102	394.90403	.	331.1908	94.15
1	113	490.04166	0.99331	140.9155	68.52
2	122	537.40232	0.91731	46.1942*	47.21
3	129	551.14618	0.51488	18.7064	29.68
4	134	559.12882	0.34304	2.7412	15.41
5	137	560.48226	0.06876	0.0343	3.76
6	138	560.4994	0.0009		

Figure 17: Cointegration: Trace Statistic Determining Rank of Cointegration

A.3.2 Diagnostics Tests

First of all, we check for the eigenvalue stability condition because inference in form of the interpretation of IRFs is only possible if this condition is met. Generally, the stability diagnostic test indicates whether "the number of cointegrating relationships is misspecified or the cointegrating relationships, which are assumed to be stationary, are non-stationary" (Enders 2010). We find that all eigenvalues lie within the unit circle, and hence the stability check does not indicate a model misspecification.

Similar to the diagnostic test for the SVAR-model, one has to check for autocorrelation in the error term of the VECM. Here, we cannot reject the H_0 of no remaining serial autocorrelation up to the 4th-order at the 10% significance level in the residual series.

Furthermore, we test whether the residual series from each equation of the VECM are white noise processes. We fail to reject the H_0 hypothesis of a Portmanteau (Q) test for white noise in all cases at the 10% significance level; except for the equation in which $R\&D_{FF}$ is the normalised variable.[32] In this case, we fail to reject the null hypothesis at the 1% significance level. Concluding, we see this condition to be sufficiently met as alternative specifications lead to unstable systems of equations.

The Johansen's methodology assumes that the disturbances in the VECM are independently and identically distributed (Johansen 1995). To check whether this is actually the case, we test the null hypothesis of multivariate normality by applying histogram analysis and the standardised normal probability plot. We conclude that all variables are fairly normally distributed.

32. Portmanteau (Q) test can be used to check whether time series follow a white noise process (Ljung and Box 1978).

Following the statistical theory explained by Lütkepohl and Krätzig (2004) and because our model contains six variables and we find two cointegrating relationships, there can be "at most two shocks with transitory effects and at least six shocks that have permanent effects" (p.168). While transitory shocks cause the impulse responses to converge to the zero line over time, permanent shocks do not. For instance, $R\&D_{REN}$ is reverting towards the zero line, $R\&D_{FF}$, labour, capital and price, on the other hand, are permanent shocks (cf. Appendix A.3.3).

A.3.3 Impulse Response Functions

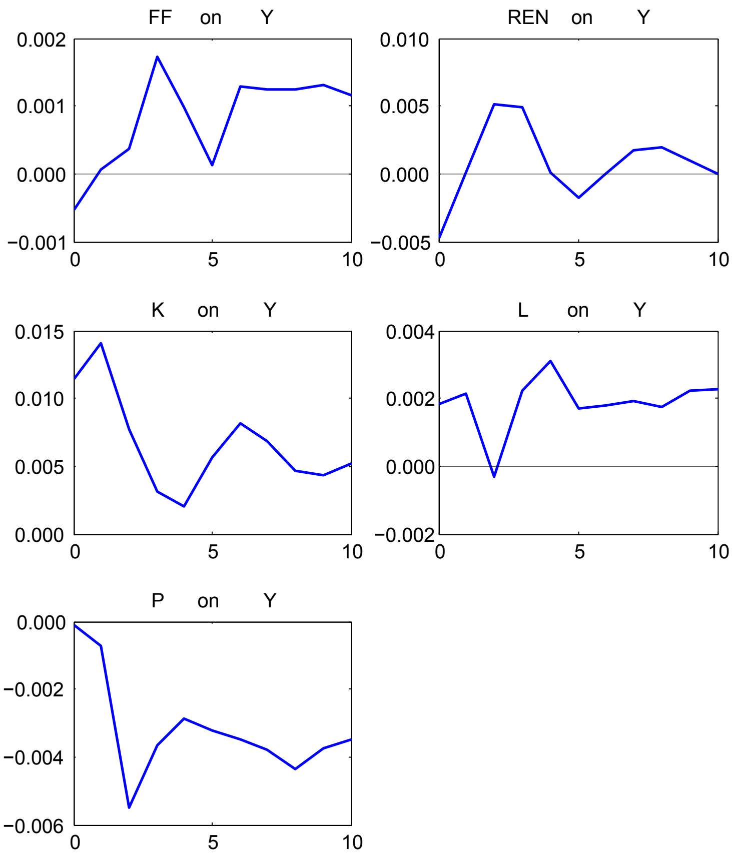


Figure 18: Cointegration: IRF - Response Variable: Y

A.4 Robustness with Respect to Ordering

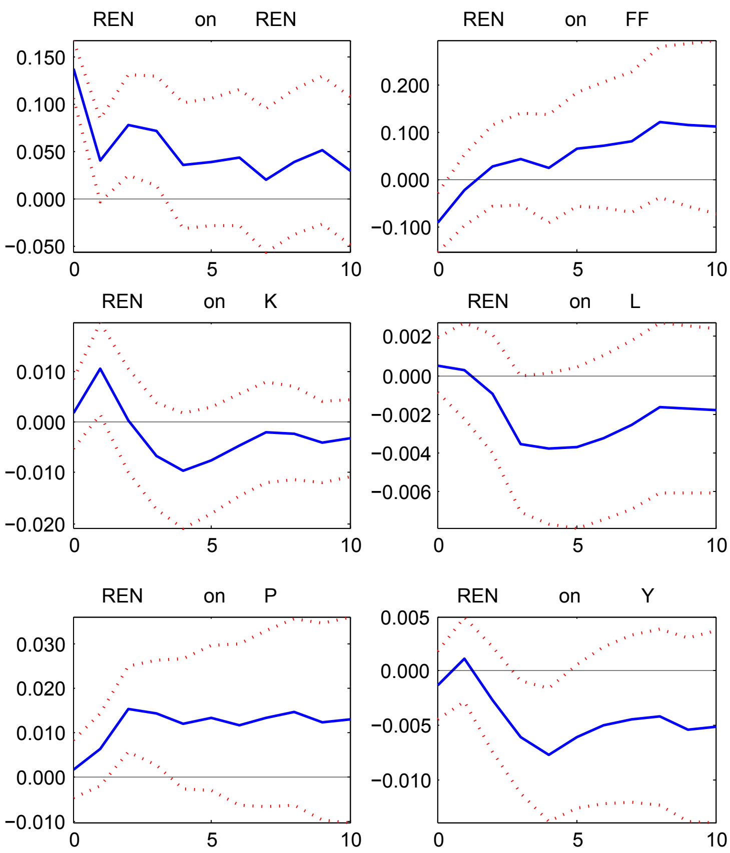


Figure 19: Ordering: IRF - Impulse Variable: $R\&D_{REN}$

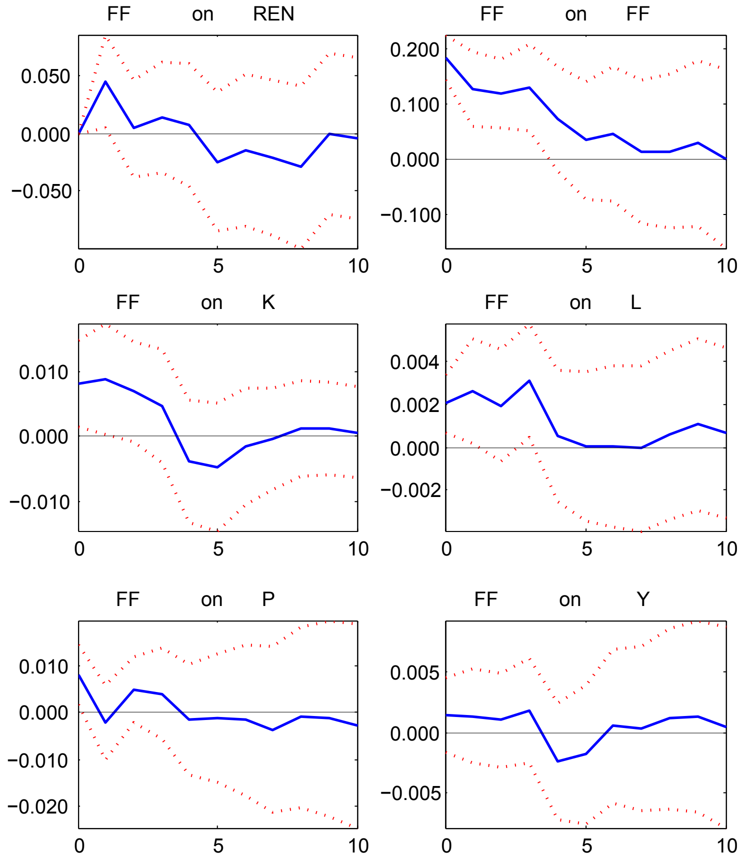


Figure 20: Ordering: IRF - Impulse Variable: $R\&D_{FF}$

A.5 Robustness with Respect to Confounding Variable Bias

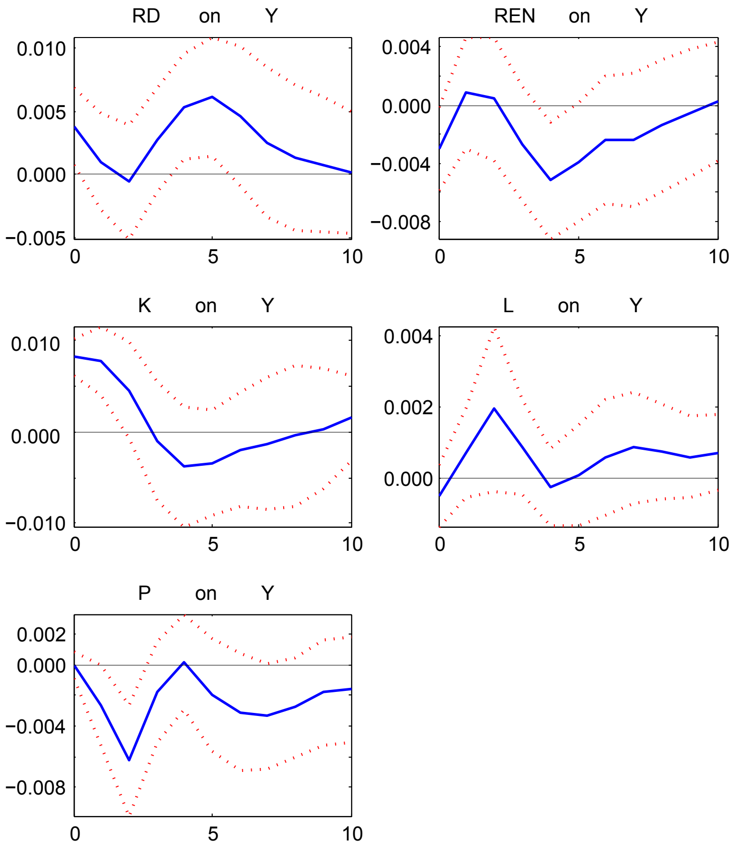


Figure 21: Confounding Variable: IRF - Response Variable: Y

A.6 Robustness with Respect to Overspecification

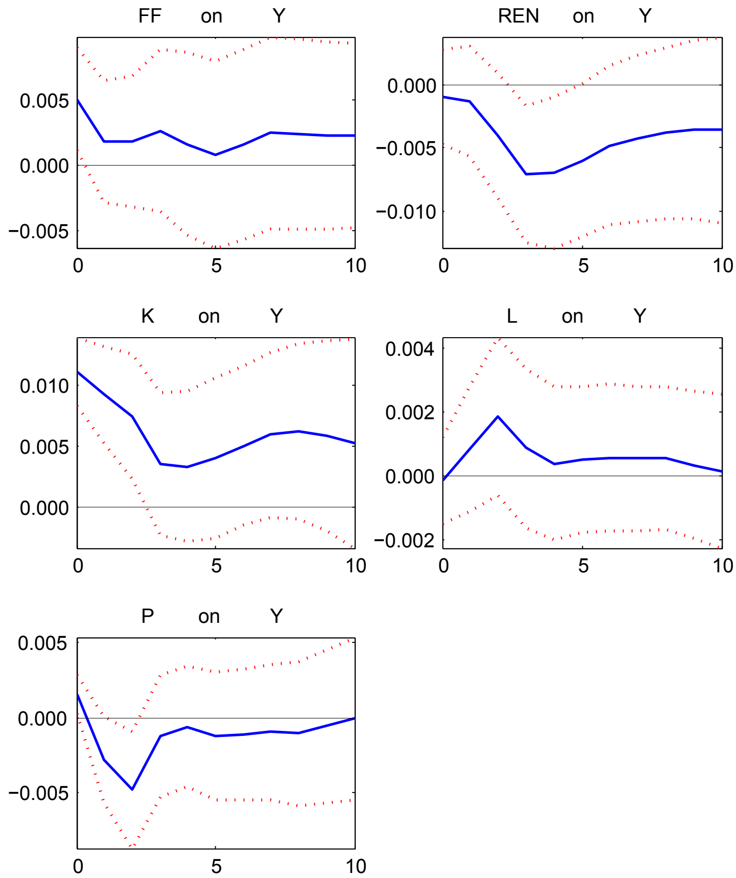


Figure 22: Overspecification: IRF - Response Variable: Y

A.7 Model Extension

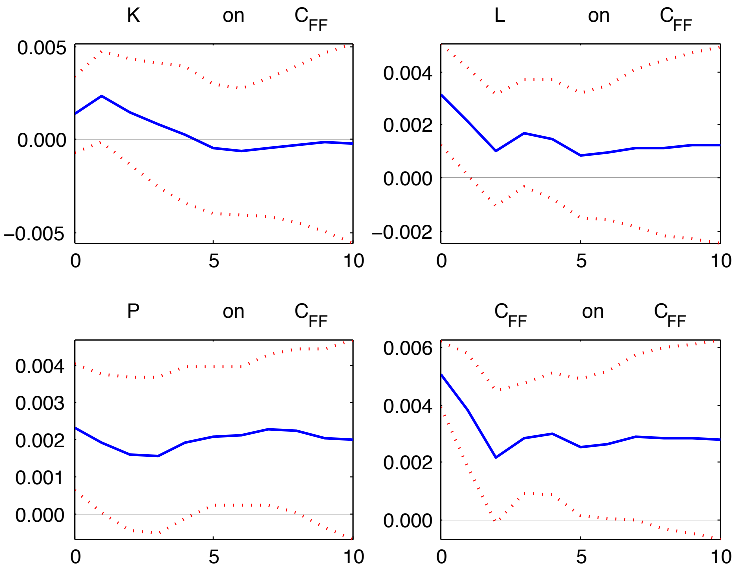


Figure 23: Model Extension: IRF - Response Variable: C_{FF}

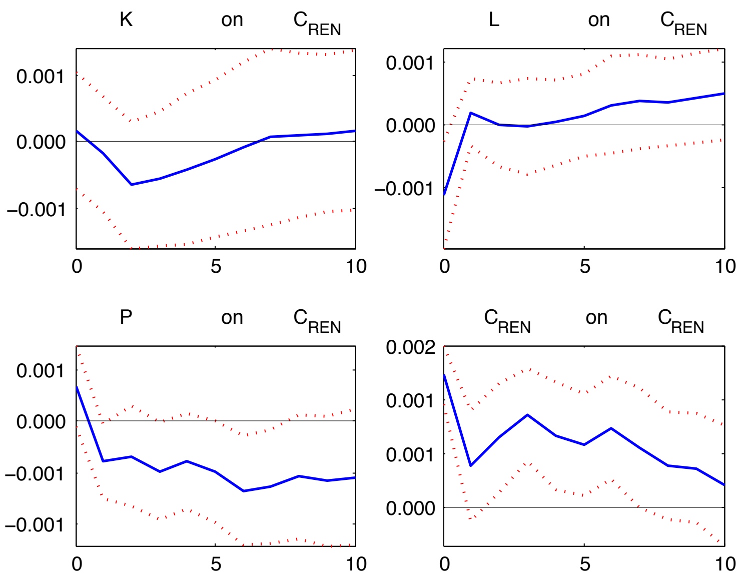


Figure 24: Model Extension: IRF - Response Variable: C_{REN}