RENEWABLE ENERGY; COMPETITION, INNOVATION AND ECONOMIC POLICY

Submitted in partial fulfillment of the requirements for the degree of

Doctor Rerum Politicarum

by

Sherief A. Emam

First Supervisor: Univ.-Prof. Dr. rer. pol. habil. Thomas Grebel, TU Ilmenau
Second Supervisor: Univ.-Prof. Dr. phil. Jens Wolling, TU Ilmenau
Third Supervisor: PD Dr. Holger Graf, Uni Jena

TECHNISCHE UNIVERSITÄT
ILMENAU

Submission date: 11.12.2019
Public defence date: 13.07.2020
urn:nbn:de:gbv:ilm1-2020000225

ABSTRACT

The energy sector enables us to do business, manufacture products as well as enjoy a better quality of life. However, our current energy system depends heavily on fossil fuels. Currently 85% of the world energy consumption stems from fossil fuel sources, which bring two main challenges: the limitation of resources and emissions of green house gases. From an economic perspective, a decline in the supply and non-decreasing consumption will lead to an increase in energy prices. Such an increase should lead to an increase in efficiency and a shift to alternative technologies, such as renewable energies.

The first part of this dissertation tries to explore the energy market mechanism and answer the question whether energy prices lead to an improvement in efficiency levels as well as an increase in innovation activities for renewable energies. Evidence is found, supporting the theory that energy markets are shifting toward more carbon free technologies.

The second part of the dissertations takes up the empirical findings, asking about the inhibiting determinants which accelerate the speed of technical and structural change toward a renewable era. Usually the political agenda is set in advance, but it can be still alternated in the case of two events: cases of natural disasters and intensive media coverage. Results show that accidents, such as nuclear reactor accidents, can highlight the risks of nuclear technologies and lead political leaders to support renewable energy with adequate policies. Additionally, mass media can impact the political agenda setting and promote more supportive policies for renewable energies.

Der Energiesektor ermöglicht es uns, Geschäfte zu machen, Produkte herzustellen und eine bessere Lebensqualität zu genießen. Unser derzeitiges Energiesystem hängt jedoch stark von fossilen Brennstoffen ab. Derzeit stammen 85% des weltweiten Energieverbrauchs aus fossilen Brennstoffen, was zwei große Herausforderungen mit sich bringt. Die Begrenzung von Ressourcen und Emissionen von Treibhausgasen. Aus wirtschaftlicher Sicht sollen ein Rückgang des Angebots und ein nicht abnehmender Verbrauch zu einem Anstieg der Energiepreise führen. Eine solche Erhöhung sollte zu einer Effizienzsteigerung und einer Umstellung auf alternative Technologien, wie beispielsweise erneuerbare Energien, führen.

Der erste Teil dieser Dissertation versucht, den Energiemarktmechanismus zu erforschen und die Frage zu beantworten, ob die Energiepreise zu einer Verbesserung der Effizienz sowie zu einer Steigerung der Innovationsaktivitäten bei erneuerbaren Energien führen. Es werden Beweise gefunden, die die Theorie stützen, dass sich die Energiemärkte in Richtung kohlenstofffreier Technologien verschieben.

Der zweite Teil der Dissertationen greift die empirischen Ergebnisse auf und fragt nach den hemmenden Determinanten, die die Geschwindigkeit des technischen und strukturellen Wandels in Richtung einer erneuerbaren Ära beschleunigen. In der Regel wird die politische Agenda im Voraus festgelegt, kann aber bei zwei Ereignissen noch abgeändert werden: bei Naturkatastrophen und intensiver Medienberichterstattung. Die Ergebnisse zeigen, dass Unfälle, wie z.B. Unfälle in Kernreaktoren, den Nutzen für erneuerbare Energien verdeutlichen können. Darüber hinaus können Massenmedien die Festlegung der politischen Agenda beeinflussen und zu einer unterstützenderen Politik für erneuerbare Energien beitragen.

ACKNOWLEDGEMENT

With immense pleasure and deep sense of gratitude, I wish to express my sincere thanks to my supervisor Prof. Dr. Thomas Grebel, without his motivation and continuous encouragement during all phases of this work, this research would not have been successfully completed. Thank you for being "Doktorvater" with all that the word means.

I am grateful to my second supervisor, Prof. Dr. Jens Wolling for motivating me to carry out my research and providing help and remarks needed.

I express my sincere thanks to my colleagues at both departments (Economic policy and theory). Thank you all for your kind words of support and encouragement. Special thank you Simone Bruhn for the proofreading. I also like to acknowledge the support rendered by Maija Ozola throughout my research.

I wish to extend my profound sense of gratitude to my father and siblings as well as my German family "Eobaldt" for all the patience they had during my research and also providing me with moral support and encouragement whenever required.

Last but not the least, I would like to thank M. Shawky, M. Tabbakh, M. El Hareth, A. Alaa, D. Hammouda, Y. Gawad, S. Fadel, S. Abdelhamid, A. Shetwey and Ola Omar for their constant encouragement and moral support along with patience and understanding.

Place: Ilmenau, Germany

Date: July 28, 2020 **Sherief A. Emam**

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

85% of the current energy production in the world is generated from fossil energy sources. Though fossil energy may still supply us with relatively cheap energy, it comes with two major challenges. The first roots in the fact that fossil energy sources are limited and will be depleted one day. Second, their exploitation generates greenhouse gases such as carbon dioxide or methane as by-products, which eventually contribute to global warming. The well-known consequence is climate change, which threatens our life conditions.

It is in everyone's interest to find solutions to those challenges and limit any undesirable consequences for society. The intention of this dissertation project is to look from an economic viewpoint at the energy markets with a focus on the climate change topic. From a naïve, economic point of view, if markets were perfect, a social welfare optimum would be guaranteed. A change toward renewable energy should emerge endogenously. With dwindling fossil energy sources, energy prices should rise as demand is non-decreasing. The consequence of a price increase is twofold. As it raises competitive pressure, rising prices should force energy suppliers to increase the efficiency in production. In addition, producers will search for alternative energy sources such as renewable energy, since their relative prices go down. Technologies which not used to be competitive will gradually become competitive. This, in turn, should give producers the incentive to invest in new renewable energy technologies.

Against this background, the objective of this dissertation is to shed light on the sluggish change in energy systems. It consists of four papers which can be partitioned into two groups of papers. The first group of papers (paper 1 and 2) investigates the functioning of the market mechanisms. Can rising energy prices lead to higher efficiency levels in energy production? Do they boost innovative activities as well? The empirical answer given to these questions suggests a positive correlation between energy prices and energy efficiency as well as innovative activities, but the evidence is rather weak. Markets seem to induce technical change toward renewables but not to the extent to which society and policy makers hope for. Indeed, new renewable energy production technologies are gaining momentum in terms of installed capacity, but they fall short in fighting climate change.

The second group of papers (paper 3 and 4) takes up on the empirical findings, asking about the inhibiting determinants which slow down the speed of technical and structural change toward a renewable era. Instead of performing policy evaluation studies, which are abundant in literature, we investigate the determinants of the political decision making process when it comes to new policy measures. In paper 3 we try to identify the role of "focusing events" that function as a catalytic moment to pass new renewable policy measures. In a similar vein, paper 4 underlines the role of the media in this process.

For this reason, policy makers do interfere in the energy markets. With a set of policies and measures, they try to boost the implementation and diffusion process of renewable energy technologies. While most studies concentrate on evaluating the effectiveness of these policies and measures, my research focuses on the triggering factors for decision makers, to pass more policies. Usually the political agenda is set in advance, but it can still be alternated in the case of two events: unexpected natural disasters that turn into focus events and intensive media coverage. In the third paper I try to understand the effect of major environmental accidents on the policy making process and whether renewable energy solutions can be introduced as an alternative. Solutions introduced within the first five years after similar accidents are more likely to take place. Media can promote these solutions and signal their importance to policy makers. The media effect and the underlying mechanism that shapes the political agenda are the topics of my last research paper.

Plan of the dissertation

The dissertation is divided into six sections. In section 1, I lay out the motivation, the theoretical framework and the mechanism of perfectly competitive markets.. Afterwards, a short overview of the research papers is presented in sec. 1.5. The research papers are presented in sections 2 to 5. Section 6 concludes the results and discusses the future outlook.

1.2 The energy sector and its challenges

The energy sector enables us to do business, manufacture products as well as enjoy a better quality of life. Since the industrial revolution, the energy produced as well as consumed has been expanding, giving us more opportunities and mobility options that were not possible before. Also, the economy has benefited from the growing energy sector. More energy produced is translated into more products and more trade, hence helping economic growth to flourish (Stern, 2011a; Kammen, 2006).

In 2018, the global primary energy consumption grew by 2.9% - the fastest growth seen since 2010 (Dudley et al., 2019). 80% of this energy consumed stemmed from fossil fuels. Crude oil is the main energy source with around 40 percent of the fossil energy generated, followed by coal and natural gas at 33 and 29 percent, respectively (Ritchie and Roser, 2019b). While some countries like the EU and OECD countries try to substitute fossil fuels, their shares have been declining since the 1980s, see fig.(1.1, green and blue lines). Developing countries such as China and India as well as the US have been increasing their shares and dependencies on fossil fuels as a response to their growing demand for energy, as illustrated in fig.(1.1, red and orange lines). All three countries combined account for around two thirds of the growth in 2018. IEA's world energy outlook (2018b) projects that the dependency for low and middle income countries as well as Asian and pacific ones on fossil fuels as primary energy sources will last at least until 2030.

There is no doubt that fossil fuels are a major energy supply contributor in the world energy market; however, the global reliance on them brings two associated challenges. The first is linked to the uncertainty surrounding the availability of these sources in the future, especially because of their finite, non-renewable nature and the fact that they are diminishing. To determine when fossil fuel production peaks, declines and depletes depends on proven reserves, exploration and consumption rates (Abas et al., 2015). However, there has been an academic debate around this topic with no concurrence to date (Cheney and Hawkes, 2007; Shafiee and Topal, 2009). The first group believes that the global oil, gas and coal reserves are actually steadily increasing, due to new discoveries (Helm, 2016, 2015). An example can be the case of the US, where new discoveries of shale gas changed the US position from being a net oil importer to a net exporter (Tan et al., 2018). This group believes that no immediate depletion threat is in sight (Abas et al., 2015; Dudley et al., 2015). The second group of studies does support the theory that fossil fuel supply has peaked already and speculates by using the depletion rate curves and current consumption pattern that an end is in sight (Deffeyes,

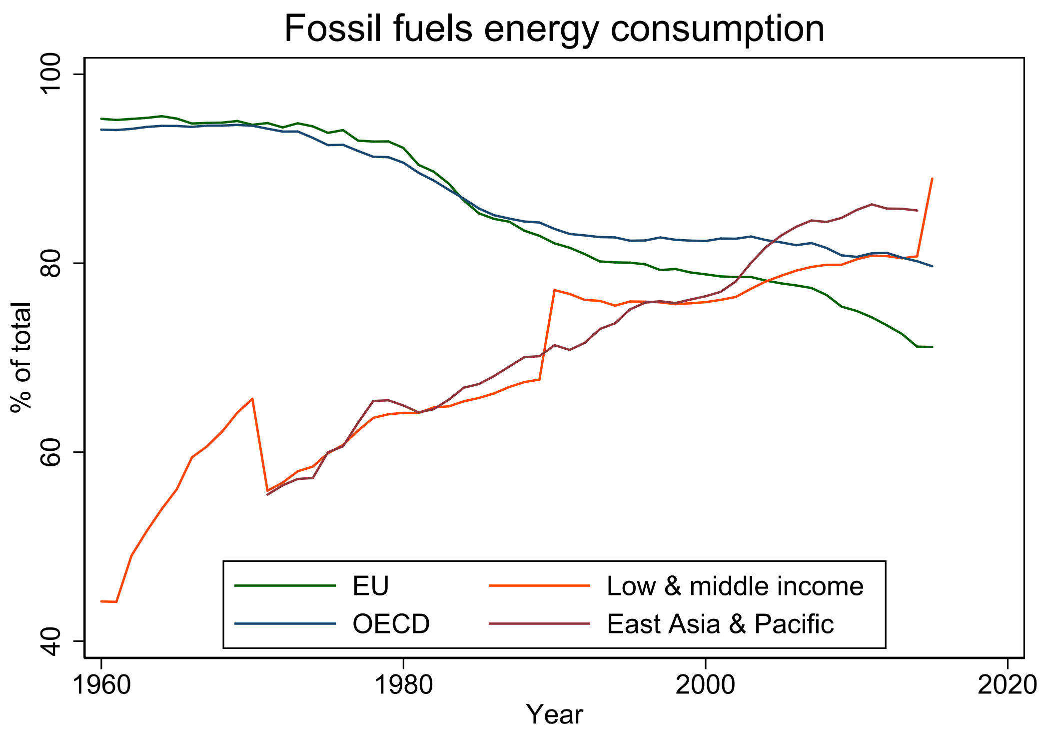


Figure 1.1 Share of fossil Fuel consumption. Own diagram. Data source: IEA (2018b)

2008; Simmons, 2007). This group estimates that current reserves will only last between 40 to maximum 200 years (Shafiee and Topal, 2009). Despite the debate and the disagreement among researchers, both groups still do agree, however, on one fact, namely that global resources will eventually run out.

The second side effect from using fossil fuels is its negative impact on the environment. They contribute the largest share of the generated greenhouse gases (GHGs)[1] emissions, in particular carbon dioxide (CO_2) and methane (IEA, 2013; Bauer et al., 2015). Around 72% of the GHG emissions in 2017 are related to the usage or production of energy. And since the discovery of oil in the 1850s, CO_2 concentrations have doubled compared to the pre-industrial levels (Ritchie and Roser, 2019b). They increased from 210ppm to a historical record of 411ppm in August 2019, as seen in Fig.1.2. This concentration is the highest in the last 650,000 years and is expected to continue rising.

The idea itself that GHG are emitted in the atmosphere is not harmful. On the contrary, the existence of GHGs is vital for our livelihood. They do play an important role in warming the Earth surface's temperature. Without GHG the

[1]Greenhouse gases refer to the sum of seven gases that have direct effects on climate change: carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), chlorofluorocarbons (CFCs), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF6) and nitrogen trifluoride (NF3) (OECD, 2019).

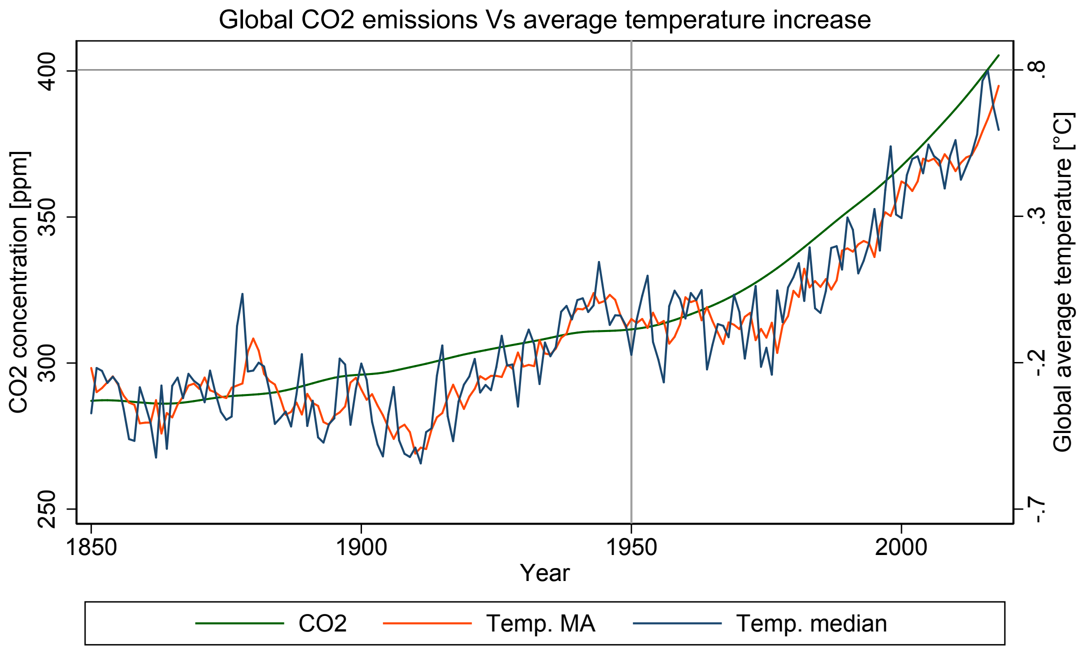


Figure 1.2 Global CO_2 emissions measured in parts per million [ppm] versus the median average temperature change and its moving average in degrees Celsius. (°C). Own diagram. Data source: Ritchie and Roser (2019a)

surface temperature would have dropped to -18°C, according to Ma (1998), and the likelihood that life could exist on earth would vanish. GHG concentration in the atmosphere can also be naturally regulated and absorbed through the carbon cycle. Plants, oceans and soil absorb GHG. The problem however, started around 1950, when the amount of emissions began to exceed nature's capacity to absorb them (IEA, 2018b). During the past five decades, nature could only absorb between 25% to 30% of the CO_2 emissions (Le Quéré et al., 2009; Schimel, 1995). This imbalance between the emissions and nature's capacity to absorb them tends to excessively warm the planet in the long run. This phenomenon is known as "global warming", where the average global temperature increases. Fig.1.2 shows, along with the CO_2 concentration in the atmosphere, the average median temperature trend. When the emissions started to exceed the natural capacity, the average temperature started steadily increasing. Along with the increase in energy demands and the excessive usage of coal fired power plants in 2018, the average temperature median reached its maximum level at 0.83°C relative to pre-industrial temperatures. If the situation continues uncontrolled, the global average temperature could rise by between 1.1 to 6.5°C (IPCC, 2013). Such an increase in CO_2 concentrations and subsequent increase in average temperature will not just cause global warming, but will have several further consequences, which are generally summarized under the term "climate change".

1.3 Climate change

Climate change will not only have an impact on the environment, and the ecosystem, but will by far threaten public health and livelihood (Smith et al., 2001). All these consequences combined will be reflected in the end in the economic performances of the countries. Although the main research idea of this dissertation is to understand the mechanisms of the energy market and not to investigate or quantify the effects of climate change, highlighting the consequences of climate change justifies the main idea and the content of this dissertation.

If global warming continues, environmental changes will take place. Examples will be rising sea-levels along with increased intensity and frequency of extreme weather events, such as days with very high or very low temperatures, extreme floods, tropical cyclones and storms (Allen et al., 2019; Weitzman, 2015; Barnett and Adger, 2003a; Smith et al., 2001). Currently the Amazon rain forest has been burning at a record speed and the dry season is one of the reasons for accelerating the fire. Finally, droughts and desertification will also be direct outcomes of climate change (Gough, 2013). These changes on the global environment will reflect as well on the ecosystem and raise the probability of species losses and extinction.

In addition to the above mentioned effects, it is our health which is at stake. Climate change will get hold of public health and food security (Costello et al., 2009; Smith et al., 2001). The IPCC (2013) report expects an increase in related illnesses in many regions and especially in developing countries. Examples include higher likelihood of injury, disease, and death due to more intense heat waves and fires. In addition, risks from food- and water-borne diseases will increase. Droughts, floods and desertification will lead to a shrinkage in the available land for agriculture and cultivation of staple food will become more costly and difficult (Smith et al., 2001, 938). This will lead directly to under-nutrition threats (Costello et al., 2009).

From an economic prospective, risks of under-nutrition, diseases and increase in the mean temperature will have a direct impact on the capacity of workers and their productivity (Day et al., 2019; IPCC, 2013). Since labour productivity is a key element of any economic success, economists devote great attention to understanding, measuring and enhancing it (Bosworth and Collins, 2008; Jorgenson et al., 2008; Van Ark et al., 2008). Any decrease in labo ur productivity will negatively affect the economic performance and lead to a decrease in the income within and between nations (Lemoine and Kapnick, 2016; Bretschger and Valente, 2011; Eboli et al., 2010; Fankhauser and Tol, 2005; Hallegatte, 2005). The International Labour organisation published a report in 2019 about the impact of heat stress on labour productivity and concluded that climate change will cause losses in productivity capacity reaching 2.2%. The percentage might look small, but it is equivalent to 80 millions full time jobs or to 2400 billions US dollars. As a conclusion, the potential impact of climate change is therefore an important economic concern (Day et al., 2019).

Perhaps, quantifying the consequences and aggregating them can throw some light on the total cost of climate change. However, researchers are in disagreement about the exact estimated cost. Tol (2014), in his research, reviewed 27 published studies that estimated the total economic impact of climate change and came to the conclusion that an increase in the average temperature by 2.5° will cause individuals on average to loose around 1.3% of their income. It is also estimated that the overall costs and risks of climate change can reach up to 5% of the global GDP (Nordhaus, 2007; Stern, 2007).

Unfortunately, regardless of all the above mentioned consequences, global emissions are still on the rise (IEA, 2018b) and have been increasing at an annual rate of 3% since 2000[2]. However, to reduce carbon emissions and to avoid the consequences, actions must be taken in two directions: increasing the energy efficiency and adopting new technologies. For these reasons, governments have been involved and have set mitigation actions (Fisher et al., 2007).

Since the energy sector is the greatest emitter of GHGs and responsible alone for 72% of the total GHG emissions, governments intervene, taking corrective actions to reduce these emissions. Government intervention with adequate policies may help decelerating the emissions in general by setting incentives to increase the efficiency and supporting the market adopting new technologies like renewables. Government intervention can induce efficiency by setting uniform standards and regulations for firms and specifying technologies like filters for industries to use (Popp et al., 2010; Jaffe and Stavins, 1995; Hepburn, 2010). These kinds of policies are known as "Command and Control" policies and can limit the amount of emissions but, on the other hand, determining exact technologies for firms can decrease their incentive to move beyond the current standards, deterring investments in innovation and leading to a technology freeze (Kemp, 2000; Heaton Jr and Banks, 1997). For these reasons, governments pass "Market based" policies, which tend to *induce* rather than *command*. These policies encourage companies to be efficient by creating financial incentives for them. Market based policies try to strengthen the market signal, i.e. energy prices, rather than setting standards. They do so by adding a price tag, known as the social cost of carbon, to the energy generated from fossil fuels. If the energy generated from fossil fuels is more costy, market participants will change their behaviours and search for alternative technologies

[2]Mainly dominated by Asia's growing economy (IEA, 2018)

(Markandya, 2009; Abolhosseini and Heshmati, 2014)[3]. Economic theories help to explain why market participants react to changes in prices and change their behaviour.

1.4 Economic framework

From a naïve, economic point of view, if markets were perfect, a social welfare optimum would be guaranteed. This idea was explained first by Adam Smith in his work "The wealth of nations". He argued that, if individuals (suppliers and consumers) behave like '**homo oeconomicus**'[4], who pursue rationally their self-interest under conditions of justice, the good of the whole society will be promoted. The interaction between profit maximizing producers and utility maximizing consumers will lead the market to reach a maximum social welfare and will lead to economic prosperity (Pol, 2013). This mechanism will take place when prices for goods or services are freely set implicitly by supply and demand, both reacting in turn to the prices. Smith then concluded that, without business or consumers being given any protection, market activities will be beneficial to the whole society.

With dwindling fossil energy sources, the additional price tag, imposed by the state intervention and non-decreasing energy demand, energy prices are rising as a response. Figure (1.3,blue line) illustrates the historical development of the averaged price of oil, gas and coal. To simplify and implicitly show the increasing trend in energy prices over the years, a linear fit (Fig.1.3,red line) is calculated with 95% confidence bands. An increase in the relative price for energy will provide incentives for both consumers and energy producers to change their behaviour. Consumers, for example, will try to adapt by decreasing their energy consumption. They, for example, could reduce the usage of energy-consuming household devices.[5] In the long run, however, they will search for alternatives to substitute the energy intensive devices with more efficient ones (Newell et al., 1999). On the producers' side, the results are similar even if the incentives are different. An increase in raw material prices, either because of a decrease in the supply or because of the additional social carbon cost, will increase the competition pressure on energy producers, and rising prices will force suppliers to reallocate and selectively utilize the most energy-efficient capital among the existing vintages (Gamtessa and Olani, 2016). In the long run, producers will search for alternative energy sources such as renewable energy, since their relative prices go down. Thus technologies which used to be noncompetitive become gradually competitive. This,

[3] see also: (Milliman and Prince, 1989; Orr, 1976; Wenders, 1975; Smith, 1972; Zerbe, 1970)

[4] The term was formulated later on by John Stuart Mill's work on political economy.

[5] such as air conditioners

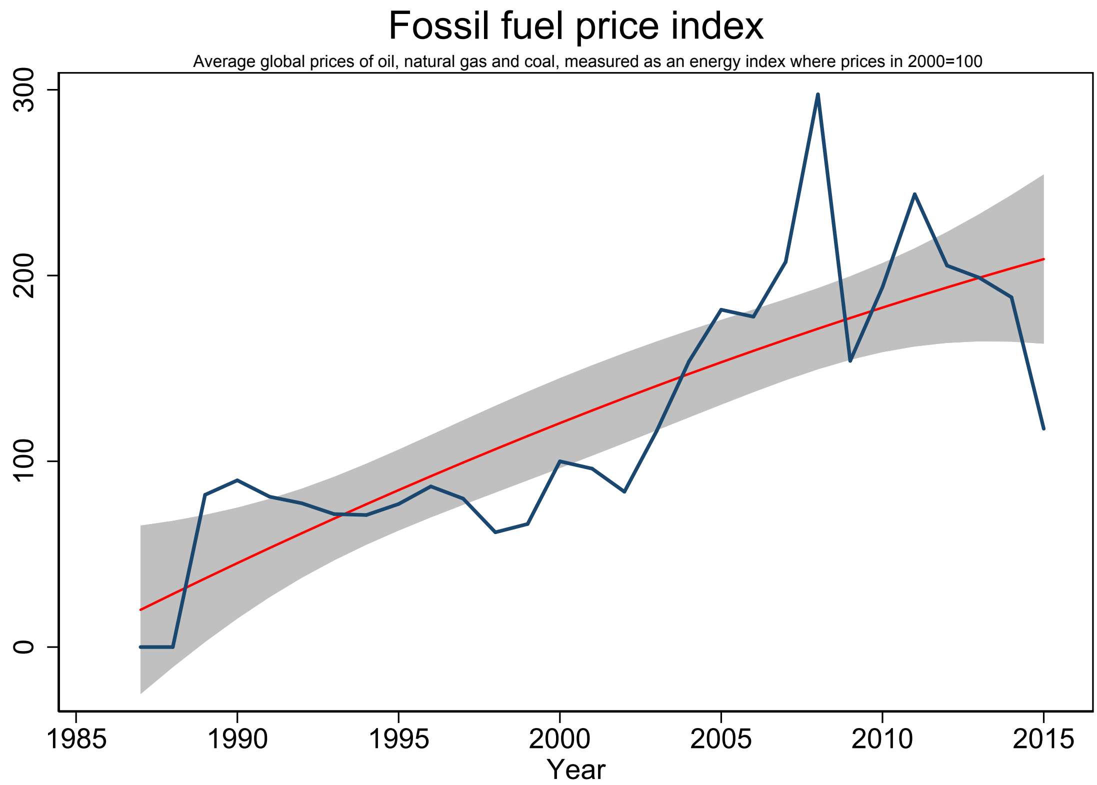


Figure 1.3 Averaged energy prices in blue. Linear fit is in red with confident limits of 95% (gray). Own graph. Data source: Ritchie and Roser (2019b)

in turn, should give producers the incentive to invest in new technologies, and a change toward renewable energy should emerge endogenously. Hicks (1932), in his publication "The theory of wages", labelled this mechanism as the "induced innovation hypothesis", where he stated:

> "A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind – directed at economizing the use of a factor which has become relatively expensive"[6] (Hicks, 1932, p. 124).

According to Hicks, an increase in the relatively expensive production factor, like energy prices, will not only lead to changes in input proportions: **energy efficiency**, but will also affect the pace and direction of the **technological change** (Brugger and Gehrke, 2017).

Against this background, the aim of this dissertation is to understand the functionality of the energy markets and whether prices can endogenously lead to

[6]Hicks back then did not differentiate between using the word "invention" and "innovation" as later specified by Schumpeter and got adopted later by authors. Hicks, however, use the two terms in a synonym sense encompassing both invention and innovation, as used today (Jaffe et al., 2003).

the aforementioned changes, namely induce energy efficiency and technological changes, as explained by Hicks. The first group of papers (paper 1 and 2) of this dissertation is trying to answer this question. Do rising energy prices lead to higher efficiency levels in energy production? Do they boost innovative activities as well?

1.5 Research papers

1.5.1 Part I:

Paper I

The first step to understand market mechanism, as discussed in section 1.4, is to investigate the link between rising energy prices and the resulting effect on the energy efficiency. Research done in this area is numerous but mainly concentrated on a specific industrial sector or country specific studies, like the energy sector, the automobile and steel industry as well specific products like air conditioning, refrigerators.

In the energy sector, for example, Rose and Joskow (1988) and his colleagues investigated the effect of increasing fuel prices as a production cost factor for electric utilities in the US and collected data for 144 plants for the time period between 1950 and 1980. Their conclusion was that electricity producers respond to an increase in fuel prices by adopting fuel saving technologies. Nevertheless, Rose and Joskow notice that company size and their organization structure play an important role in the adoption of new technologies, where large and investor owned companies adopt technologies earlier than small and publically owned plants. A more recent study was done by Gamtessa and Olani (2016). They employed panel vector auto regressions as well as co-integration and error correction techniques to study the link between increasing energy prices and whether they can lead to more efficiency. They included 33 different industries in Canada and concluded that a one percent rise in energy prices will reflect positively on energy efficiency by 0.23%, both in the short-run and in the long-run. Similar studies, from the automobile and steel industry, concluded a direct correlation between an increase in energy prices and an upgrade in energy efficiency (Ohta and Griliches, 1976; Goodman, 1983; Atkinson and Halvorsen, 1984; Wilcox, 1984; Ohta and Griliches, 1986; Boyd and Karlson, 1993).

The difference between the above mentioned research and the research presented here, is that we concentrate on the macro scale, rather than a specific market sector. We aggregate the data from all sectors to calculate a country specific efficiency index. Using DEA analysis, we calculate the efficiency index, where the production system is described by inputs (energy and labor), good output (GDP) and bad output (CO_2). In addition, we also calculate a Malmquist index for all of the 34 OECD countries over the period of 1990 to 2015. For each year, every country get an efficiency score depending on its distance to the frontier. The two efficiency indices are later used to measure energy efficiency and technological change. Explanatory variables are energy prices, stock of knowledge, competition in the energy market and governmental policies. In addition to the explanatory variables, we control for the size of the country and the total energy production.

As for the empirical analyses, we started our models with a typical OLS regression and extended the calculations later to use an ARDL technique called Dynamic Heterogeneous Panel Models (DHPM). With the help of this technique we can differentiate between the short- and the long-run effects of energy prices on energy efficiencies.

The results show evidence that energy prices positively correlate with energy efficiency. In all 16 models, energy prices positively correlate with the efficiency indices. Using the Dynamic Heterogeneous Panel Models, we distinguish between the short- and long-run effect. Energy prices positively affected the efficiency scores in both the short- and the long-run.

Paper II

In the context that the energy market can efficiently allocate enough resources to enable technological change (Induced innovation theory) toward low-carbon technologies, we introduce the second research paper entitled: "Rising Energy Prices and Advances in Renewable Energy Technologies". We raise the following research question:

> Research question: Do rising oil prices induce technological progress in renewable energies?

Researches have tried to answer similar questions before. Prominent research efforts in this field are, for example, the works done by Johnstone et al. (2010b) and Popp (2002), where they tried to understand the effect of both energy prices and environmental policies on the innovation activities in the renewable energy field. Popp (2002) collected patent data from 1970 to 1994 to estimate the effect of energy prices on innovation activities. In addition to the sum of registered patents, he included a quality index as well, by using patent citations as an indicator for the quality of innovation. He concluded that both energy prices and the quality of the stock of knowledge have strong positive effects on innovation activities. Johnstone et al. (2010a) collected data for 25 countries over the period between

1978 and 2003 and used electricity prices as a proxy for energy prices. Beside the innovation index, Johnstone controlled for public policies by counting active renewable energy policies. He could find that public policies have a significant role in determining patent applications and that renewable energy technologies respond differently to the type of policy. However, he found no link between energy prices and the overall patent activities in renewable energy in general but only on solar cells patent activities.

A more recent study was conducted by Nesta et al. (2014). Nesta and his colleagues extended Johnston's and Popp's work and added a market liberalization index to measure market competitiveness. They also control for patent quality and not just the aggregated number of registered patents. They came to the conclusion that environmental policies are more effective in liberalized markets to foster green innovation, especially regarding high quality patents. Energy prices, however, did not prompt any technological change (patenting activities). Similar results to Nesta et al. (2014); Johnstone et al. (2010b) were also reported by Nicolli and Vona (2016). They extended the work of Nesta et al. and examined in depth the role of competition, policies and energy prices on the innovation activities in different renewable energy technologies. They came to the conclusion that both energy prices and the entry barriers index have a positive impact on the total innovation activities in the renewable energy domain. However, with respect to single technologies, energy prices have an effect only on solar, wind and biofuel technologies.

Because the results of different researchers are inconsistent, we decided to conduct a cross country analysis in order to answer the research question. For this purpose, we collected data for 36 OECD countries covering a time span from 1970 to 2010. As an independent variable, we count patents for wind energy as an indicator for innovation activities. Data are collected from the European Patent Office Worldwide Patent Statistics Database PATSTAT (EPO, 2015). We alternatively use oil prices as a proxy for energy prices and expect that an increase in the price of energy would induce innovation incentives in renewable energy technologies (Popp, 2002; Johnstone et al., 2010b; Nesta et al., 2014). In addition, we control for country size, research and development funding, financial development and electrical consumption. We apply 11 models in-total, starting with OLS, binomial regression and continuing with pooled mean group (PMG), mean group (MG) and dynamic fixed effects (DFE) as dynamic heterogeneous models.

Our results show a positive effect of energy prices on innovation activities measured in the number of registered patents. When differentiating between the short-run and the long-run, energy prices had a significant effect only on the long-run. Therefore, we conclude that energy prices can, in the long run, direct the market participants towards new low carbon technologies and induce a technological change towards renewable energies.

Conclusion of part I

The outcome from the first two research papers has shown that increasing energy prices can induce higher levels of efficiency in energy production. Besides energy efficiency, innovation activities are induced as well. Their is evidence that the number of patents registered rises after energy prices go up. These are the answers for the two main questions raised before and they conclude that energy markets seem to function as theoretically expected.

If the results can reflect the real market mechanism, then global emissions should be reducing and adopting and diffusing renewable energies should be observable. Unfortunately, global emissions are still on the rise (IEA, 2018b) and have been increasing at an annual rate of 3% since 2000.[7] Regarding the renewable energy adoption and diffusion, the global renewable energy consumption can be seen as a proxy. At the first glance, the current consumption of renewable energies is six times more the values in 1970, see figure 1.4. While it can be concluded that renewable energy technologies (REN) have been adopted and well diffused in the energy market, by having a closer look at the shares of renewable energies rather than seeing only the absolute values, the data provide another insight. In contrast to the rapid increase in the absolute values of renewable energy consumption, the shares have just increased by 2% since 1970. This observation is similar in the OECD countries, where the shares of REN have increased from 6.2% in 1997 to just 10.7% in 2017 (IEA 2019). An increase that did not exceed 5% over a period of 20 years.

Conclusively and based on these two observations, the problem in reducing emission and the adopting more renewable energy technologies, might not be the direction of the energy market but rather its speed. The market is shifting in the right direction but not at the needed pace. For these reasons, governments have been involved in the energy market and have set mitigation actions (Fisher et al., 2007). Government intervention with adequate policies may help decelerating the emissions in general by setting incentives to increase the efficiency and supporting the market adopting new technologies like renewables.

[7] Mainly dominated by Asia's growing economy (IEA, 2018)

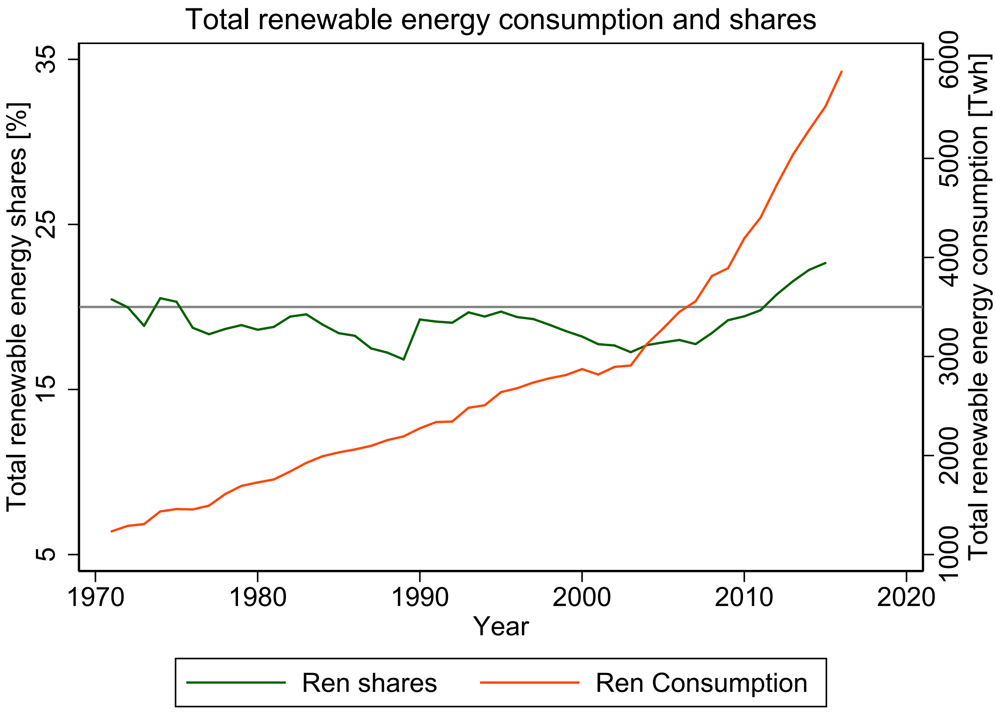


Figure 1.4 Renewable energy consumption [Twh] in red and their shares of global electricity production [%] in green. Own Diagram. Source: Ritchie and Roser (2019c)

Motivation part II

Government intervention can induce efficiency by setting uniform standards and regulations for firms and specifying technologies like filters for industries to use (Popp et al., 2010; Jaffe and Stavins, 1995; Hepburn, 2010). These kinds of policies are known as "Command and Control" policies and can limit the amount of emissions but, on the other hand, determining exact technologies for firms can decrease their incentive to move beyond the current standards, deterring investments in innovation and leading to a technology freeze (Kemp, 2000; Heaton Jr and Banks, 1997). For these reasons, governments pass "Market based" policies, which tend to induce rather than command. These policies encourage companies to be efficient by creating financial incentives for them. Market based policies try to strengthen the market signal, i.e. energy prices, rather than setting standards. They do so by adding a price tag, known as the social cost of carbon, to the energy generated from fossil fuels (Markandya, 2009; Abolhosseini and Heshmati, 2014).[8] Studies like (Nesta et al., 2014; Johnstone et al., 2010a) have raised the importance of proper policies in accelerating the rates of development, adoption and diffusion of renewable energies. Policies have proven to be effective and the

[8]see also: (Milliman and Prince, 1989; Orr, 1976; Wenders, 1975; Smith, 1972; Zerbe, 1970)

2°C target can still be met if more stringent policies were to be adopted (Alcamo et al., 2013, p. 11).

Instead of pursuing further evaluation studies of policy measures, which are abundant in literature, I decided to pursue my dissertation by asking about the inhibiting determinants which induce changes toward a more renewable era. My research focuses on the triggering factors for decision makers to pass more policies. The political agenda is usually set in advance, however it can be altered in the case of two events: natural disasters, that turn into focusing events and intensified media coverage. In the first paper concerning this question (and the third paper of my dissertation), I try to understand the effect of major environmental accidents on the policy making process and whether renewable energy solutions can be introduced as an alternative. In a similar vein, the second paper (the fourth and final paper of the dissertation) underlines the role of the media to promote solutions and raises the question whether media can help setting the political agenda within the renewable energy domain.

1.5.2 Part II

Paper III

Disruptive moments like major accidents in nuclear reactors, such as Fukushima and Chernobyl reinforce society's disapproval against polluting technologies. They give policymakers the chance to form coalitions and gain political momentum to introduce alternatives. Policies previously excluded from the political agenda are brought back for discussion and appear enforceable. In other words, we ask whether these accidents function as a catalyst, i. e. as a focusing event (Kozluk and Zipperer, 2015; Nohrstedt, 2005) for policy making. The Advocacy Coalition Framework (ACF) is a theoretical framework, which explains the link and the momentum of external shocks, i.e. nuclear accidents to the consequential policy initiatives arising from it. Within this context, we propose the following hypothesis:

> Hypothesis: *Nuclear accidents should have a positive effect on green energy policies.*

Based on the data of 34 OECD countries, we disentangle the effect of disruptive exogenous shocks on countries' policy activity. Starting with OLS regressions, we run several robustness checks by using a pre-sample mean approach, an ARDL technique called Dynamic Heterogeneous Panel Models (DHPM), which allows for the distinction between long- and short-run effects. The results corroborate the hypothesis that unexpected, disruptive events have a positive impact on the actual number of renewable energy policies. The fade-out time for shocks is about seven years, leaving a positive long-term effect.

However, for crises to have the expected changes in policymakers behaviours, mass media has to cover the topic. By reporting intensively about an accident like Fukushima, or alternative technologies, policy makers can signalize the importance of these topics. They can understand and reevaluate the costs and benefits of different technologies (Cohen, 1963; McCombs and Shaw, 1972). Therefore, studying the role of mass media in the environmental policy making process is of interest.

Paper IV

Traditionally, such a study of mass media has been viewed through the lens of communication and political sciences. Yet more economists have turned their attention to mass media, especially because of its strong influence on the policy making process (McCluskey and Swinnen, 2010). Comprehensive studies on why political actors react to media coverage might be still missing, but multiple reasons for media responsiveness have been suggested (Mathias Kepplinger, 2007; Walgrave and Van Aelst, 2006). The straightforward answer is driven by the previous research paper and it is the association of media coverage with public opinion (Walgrave and Van Aelst, 2006; Protess, 1992). Mass media can put pressure on politicians to respond and take positions.

In this research paper, I am trying to understand and highlight the role the mass media plays to draw public attention to climate change issues. Such an attention can reflect on the actions of policymakers to increase their support for renewable energies and pass supportive policies. Because of the multiple reasons how media can influence politicians and force them to take actions, the following hypothesis is suggested.

> Hypothesis 1: *Media coverage can promote the introduction of more environmental policies*

I built a data set for four OECD countries: Germany, Austria, United Kingdom and the United States, covering the period from 1985 until 2013. Media coverage is measured in the number of published articles. I run several regression models such as OLS, negative binomial regression and pooled mean group estimation. The results shed light on the positive and consistent influence of mass media on the policy making process. An increase in the number of publications about environmental topics is translated into more policies. Mass media can interfere in the environmental political agenda and raise the importance of the climate change topic. In return, policymakers react accordingly and pass more supportive policies. This effect is persistent only in the short run, which adheres well with the attention cycle theory, introduced by .

Additional results can be derived from paper III and IV. Intuitively, it can be concluded that there is a pattern in which policymakers can be pushed by external catalysts to adopt the climate change topic. It seems that, when disasters happen or mass media intensively report about environmental topics, policymakers sense the seriousness of the topic and act accordingly to pass more supportive policies.

Chapter 2

Can rising energy prices lead to higher efficiency levels in energy production?

Authors: Sherief Emam, Thomas Grebel

Fossil fuels are the primary energy source and their role is essential for economic performance and growth. However, the GHGs emissions have been increasing steadily, which lead to global warming and climate change. To mitigate the effects, governments have been intervening in the energy market to increase its efficiency and induce technological change.

In this paper, we investigate if an increase in energy prices can lead to better energy efficiency and direct technological change toward renewable energies. For this purpose, we calculate country specific efficiency and technological change indices for 31 OECD countries, over a period of 25 years using DEA model. We could find evidence that an increase in energy prices can induce energy efficiency and lead to a long-run technological change. In addition to that, public policies and competition have positive roles, promoting renewable energies.

2.1 Introduction

Fossil fuels are the major energy source for modern economies and that they deliver us relatively cheap energy. Fossil fuels continue to play a dominant role in the world energy consumption. According to Dudley et al. (2019), global primary energy grew by 2.9% in 2018 and around 80% of the world primary energy consumption originated from fossil fuel sources. A big change in this pattern is not expected as reported by the IEA's world energy outlook (2018b), where it forecasts that the dependency on fossil fuels as a primary energy source will last least until 2030.

However, the dependency on fossil fuels brings two main challenges. The first is linked to the fact that fossil fuels are limited and discussions about actual reserves and their availability have been taking place. Although there is no concurrence between researchers to date about the exact time frame, most researchers do agree that fossil fuel resources are limited and will end (Abas et al., 2015; Cheney and

Hawkes, 2007; Shafiee and Topal, 2009). The second challenge from using fossil fuels is the negative impact on the environment. Fossil fuels are the main source for generating green house gases (GHGs)[1] (IEA, 2013; Bauer et al., 2015). Around 72% of the GHGs emissions in 2017 are related to the usage or production of energy. And since the discovery of oil in 1850s, CO2 concentrations have doubled compared to the pre-industrial levels (Ritchie and Roser, 2019b).

Emissions can in general be absorbed and regulated by nature. Carbon sinks like oceans, plants and soil can regulate the CO_2 concentration in the atmosphere; however, the capacity is limited. During the past five decades, nature could only absorb between 25% to 30% of the CO_2 emissions (Le Quéré et al., 2009; Schimel, 1995). This imbalance between the emissions and nature's capacity to absorb them tend to excessively warm the planet and lead to global warming and climate change on the long run.

Climate change and its dangers have long been known, and they do not only have an impact on the environment and the ecosystem, but they also threaten public health and livelihood (Smith et al., 2001). Examples are rising sea-levels, along with increased intensity and frequency of extreme weather events, such as days with very high or very low temperatures, extreme floods, tropical cyclones, and storms (Allen et al., 2019; Weitzman, 2015; Barnett and Adger, 2003a; Smith et al., 2001). In addition, it is our health which is at stake. Climate change will get hold of public health and food security (Costello et al., 2009; Smith et al., 2001). In addition, The IPCC (2013) reports expect an increase in illness in many regions and especially in developing countries. From an economic perspective, an increase in the mean temperature will have a direct impact on the capacity of workers and their productivity (Day et al., 2019; IPCC, 2013). 80 million jobs are at risk with climate change, as the international Labour organisation has reported (ILO, 2019). An overall cost of mitigating climate change is difficult to quantify; however, Tol (2014) in his research reviewed 27 published studies that estimated the total economic impact of climate change and came to a conclusion that an increase in the average temperature by 2.5° will cause individuals on average to lose around 1.3% of their income. It is also estimated that the overall cost and risks of climate change can amount to 5% of the global GDP (Nordhaus, 2007; Stern, 2007).

Unfortunately regardless of all the above mentioned consequences, global emissions are still on the rise (IEA, 2018b) and in 2018 alone carbon emissions grew by 2%, the fastest for seven years (Dudley et al., 2019). Governments are involved

[1] Greenhouse gases refer to the sum of seven gases that have direct effects on climate change: carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), chlorofluorocarbons (CFCs), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF6) and nitrogen trifluoride (NF3) (OECD, 2019).

and have set mitigating actions to limit the emissions. Government intervention with adequate policies might provide a solution to decrease the level of emissions in general, by increasing the efficiency and supporting the market adopting new technologies like renewables. The first step is to set uniform standards or regulations for firms and specify technologies for industries to use (Popp et al., 2010; Jaffe and Stavins, 1995; Hepburn, 2010). The second set of policies are market based policies with the aim to strengthen the market signal, the energy prices. They achieve that either by adding a price tag in form of taxes (social cost of carbon) to the energy generated from fossil fuels, or by subsidizing new technologies like renewables. If the energy generated from fossil fuels gets more costly, market participants will be encouraged to change their behaviors and search for alternative technologies (Markandya, 2009; Abolhosseini and Heshmati, 2014).[2]

From a simplified economic point of view, if markets were perfect, a social welfare optimum would be guaranteed and an increase in the relative price for energy will provide two incentives for energy producers to change their behavior. In competitive markets, rising prices should force energy suppliers to increase their efficiency in production to avoid losing their market shares (Gamtessa and Olani, 2016; Newell et al., 1999). In the same vine, an increase in the relative price will induce innovation activities. According to Hicks (1932, p.124), an increase in the relatively expensive production factor, like energy prices, will not only lead energy producers to change their inputs proportions: energy efficiency, but will also reflect on the pace and direction of technological change. Producers will search for alternative energy sources such as renewable energy, since their relative prices go down. Technologies which used to not be competitive become gradually competitive. This, in turn, should give producers the incentive to invest in new renewable energy technologies.

Against this background, we raise the following research question: can energy prices in competitive markets under government intervention induce energy efficiency and lead to technological change towards carbon free technologies? The novelty of our research lies in using a non-parametric approach, Data Envelopment Analysis (DEA), to calculate efficiency scores and implement the Malmquist index to measure discontinuous and localized technological change for 30 OECD countries, over a 25 years period.

Our main findings are the following. First and foremost, we find that energy prices have a positive effect on improving the energy efficiencies. This effect is more consistence when technological heterogeneities between countries are taken into account. Public policies introduced by governments have a positive outcome as well on increasing energy efficiency. Technology changes react similarly to

[2] see also: (Milliman and Prince, 1989; Orr, 1976; Wenders, 1975; Smith, 1972; Zerbe, 1970)

increasing energy prices on both the short as well as the long run.

The paper is organised in the following order. In section 2.2, we will list the related work and our research questions, followed by the empirical protocol in section 2.3, where we will discuss the basic DEA model and drive our adapted model. In section 2.4 we will illustrate the results of our regressions, and finally, the discussion and conclusion will be presented in section 2.5.

2.2 Related work and research questions

In the energy sector, Rose and Joskow (1988) and his colleges investigated the effect of increasing fuel prices as a production cost factor for electric utilities in the US and collected data for 144 plant for the time period between 1950 and 1980. Their conclusion was that electricity producers respond to an increase in fuel prices by adopting fuel saving technologies. Nevertheless Rose and Joskow notice that company size and their organization structure play an important role in the adoption of new technologies, where large and investor owned companies adopt technologies earlier than small and public owned plants. A more recent study was done by Gamtessa and Olani (2016). They conducted a broad vector panel analysis to study the effect increasing energy prices exert on energy efficiency. They included 33 different industries in Canada and concluded that a one percentage rise in energy prices will reflect positively on energy efficiency by 0.23% both in the short-run and in the long-run.

Similar results were also reported from the automobile industry: an increase in energy efficiency was linked as well to rising oil prices (Ohta and Griliches, 1976; Goodman, 1983; Atkinson and Halvorsen, 1984; Wilcox, 1984; Ohta and Griliches, 1986). In the iron and steel industry, Boyd and Karlson (1993) investigated the US steel industry and collected data for 30 years to monitor the effect of crude oil prices on replacing steel furnaces with basic oxygen to more efficient electric arc furnaces. The price for energy had an effect but was marginal, and non-price parameters were more significant. They conclude that the adoption of the new technology was not price induced but a part of a major technical change in the industry. Jaffe and Stavins (1995) found evidence for adoption of thermal insulation technologies as a response to energy prices but stated that the magnitude is small compared to other variables effect. Similar results to the marginal effect of energy prices on the demanded quantity between 1970s and 1980s was also found by Linn (2008).

Finally, Newell et al. (1999) investigated the air conditioning market. He compiled a database for 735 room air conditioner models between the period of 1958 and 1993. He used a relative price index for electricity to test the inducement mechanism. For the regulatory index, Newell used the National Appliance Energy Conservation Act of 1987 as a policy index, where he differentiated its effect from passing the act till enforcement to measure the different effect through time. He concluded that an increase in the energy prices changed the offered model's pattern. However, he also noticed that the induced effect by energy prices was particularly stronger after regulations (government intervention) were introduced.

In the field of price induced innovation, research has tried to investigate this topic before. Prominent research done in this field is, for example, the works done by Johnstone et al. (2010b) and Popp (2002), where they tried to understand the effect of both energy prices and environmental policies on the innovation activities in the renewable energy field. Popp (2002) collected patent data from 1970 to 1994 to estimate the effect of energy prices on innovation activities. In addition to the sum of registered patents, he included a quality index as well, by using patent citations as an indicator for the quality of innovation. He concluded that both energy prices and the quality of the stock of knowledge have strongly positive effects on innovation activities. Johnstone et al. (2010a) collected data for 25 countries over the period between 1978 and 2003 and used electricity prices as a proxy for energy prices. Beside the innovation index, Johnstone controlled for public policies by counting active renewable energy policies. He could find that public policies have a significant role in determining patent applications and that renewable energy technologies respond differently to the type of policy. However, he found no link between energy prices and the overall patent activities in renewable energy in general but only on solar cells' patent activities.

Nesta et al. (2014) extended Johnstons and Popps work and added a market liberalization index to measure markets competitiveness. They also control for patent quality and not just the aggregated number of registered patents. They came to the conclusion that environmental policies are more effective in liberalized markets to foster green innovation, especially high quality patents. Energy prices, however, did not have influence on promoting any technological change (patenting activities). Similar results to Johnstone et al. (2010a) were also reported by Nicolli and Vona (2016). They extended the work of Nesta et al. and examined in depth the role of competition, policies and energy prices on the innovation activities in different renewable energy technologies. They came to the conclusion that both energy prices and entry barriers index have a positive impact on the total innovation activities in renewable energy domain. However, with respect to single technologies, energy prices have an effect only on mature technologies, like solar, wind and biofuel technologies.

Based on the mentioned studies, we are raising the following research questions:

- Research Question 1: Do increasing energy prices induce energy efficiency and technological progress in renewable energies?

- Research Question 2: What are the effects of state intervention and competition in improving energy efficiency and boosting technological change?

2.2.1 Measuring Heterogeneity with Data Envelopment Analysis

In this section, we briefly introduce the Data envelopment analysis (DEA). We follow closely the approach by Sueyoshi and Goto (2012, 2011). DEA is a mathematical method based on linear programming techniques with the purpose to evaluate relative efficiencies of entities, which are called "Decision Making Units" (DMU). In our case the "Decision Making Units" are the OECD countries. Typically, in DEA the resources are referred to as "inputs" and outcomes as "outputs", where each DMU can be of a unique combination of inputs and outputs in order to maximize its relative efficiency. The calculated efficiency score is the ratio of the total weighed output to the total weighed input, and hence it determines how a DMU is efficient compared to a frontier of efficiency. (Mardani et al., 2017; Zhu, 2014; Grebel, 2018).

There are two main approaches while using DEA: "input" and "output" oriented approaches. Input oriented approachs ask how much inputs should be reduced to achieve the given output values, in order for the DMU to be technically efficient. The output oriented approach, on the other hand, measures the value with which the output has to be increased at a given set of inputs. In our research, we are interested in reducing the consumption of fossil fuels (inputs), while maintaining the GDP levels (output), and therefore we will base our calculations using the input oriented approach. An additional assumption has to be met before we can measure the potential reduction in inputs, namely the returns to scale (increasing, decreasing, or constant). A constant returns on scale (CCR) means that outputs will increase proportionally to inputs. If DMUs are homogeneous in sense of size and technology used, then a constant returns on scale can be assumed; however, this is not our case. We compare 31 OECD countries together and they vary in size, GDP and technology usage, and therefore we expect heterogeneity between the DMUs. In this case a variable returns on scale (BCC) should be applied (Oh et al., 2009; Grebel, 2018).

To simplify the DEA idea, we assume that there is only one input x, one output y and $n = 6$ observations i.e. j DMUs with $j = \{\mathrm{A}, \mathrm{B}, \mathrm{C}, \ldots, \mathrm{F}\}$. The two lines in figure (2.1) illustrate both best practice frontiers for the constant returns to scale (CCR) and the variable returns to scale (BCC). Only the DMU B has the best output-input ratio under the assumption of CRS. No other DMU achieves higher productivity of factor x compared to B. While under the assumption of variable return on scale, the DMU A and B are technically efficient. DMU C and E are not located on the frontier line and they are technically inefficient. For DMU E to become technically efficient, the *input-oriented* form of the VRS model gauges E relative to point E*. In another words, DMU E needs to reduce its inputs by a fraction (1-θ_xE) to reach the frontier. (Grebel, 2018).

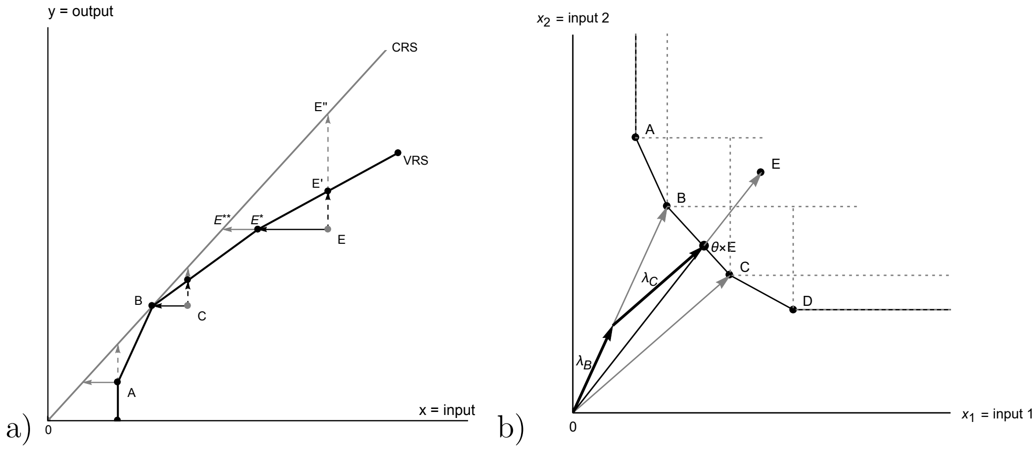


Figure 2.1 Best-practice frontier. Source: Grebel (2018)

2.2.2 Technological change

Measuring technological change (TC) is an intangible concept, and so there is no unique way to measure it. TC is defined as an endogenous, localized (Atkinson and Stiglitz, 1969) and heterogeneous process. It could be understood as well as a continuous and incremental process, or even as a disruptive process (Dosi, 1982; Rosenberg, 1976; Dosi, 1982; Nelson and Winter, 1982; Rosenberg, 1982; Freeman, 1982; Mokyr, 1990; Grebel, 2018).

Based on the aforementioned description of technological change, measuring it using a parametric approach and assuming an explicit functional form might seem inappropriate. Conversely, using a non-parametric approach can offer more generic results and features like measuring the discontinuous shifts in technical change.

In this contribution, we use dynamic DEA approach to measure the technical change. We follow the same approach applied by (Färe et al., 1992) and use the input-based Malmquist productivity index introduced by (Caves et al., 1982). Figure (2.2), illustrates the concept with two CCR frontiers at time t_0 and t_1. Following the earlier example, E is the only inefficient DMU, where E_{t_0} stands for the productivity situation of E at time t_0 and E_{t_1} for the situation at t_1 (Grebel, 2018).

Equation (2.1), explains how to mathematically measure the technology change. It consists of two parts, the efficiency and technical shift. The ratio between the

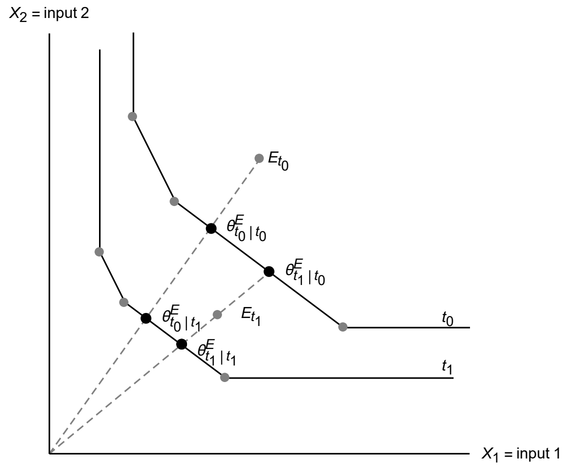


Figure 2.2 Technological Change – a shift of the best-practice frontier. Source: Grebel (2018)

two efficiencies of E delivers the change in efficiency ($\mathrm{EC}_{t_0|t_1}$) from t_0 to t_1, when compared to their corresponding frontier. This explains the first part of equation (2.1). The second part is the technical shift $\mathrm{TC}_{t_0|t_1}$ of the frontier from t_0 to t_1 (Grebel, 2018). Malmquist (1953)

$$\mathrm{MQ}_{t_0|t_1} = \underbrace{\frac{\theta_{t_1|t_1}}{\theta_{t_0|t_0}}}_{\mathrm{EC}_{t_0|t_1}} \times \underbrace{\sqrt{\frac{\theta_{t_0|t_0}}{\theta_{t_0|t_1}} \times \frac{\theta_{t_1|t_0}}{\theta_{t_1|t_1}}}}_{\mathrm{TC}_{t_0|t_1}} \tag{2.1}$$

If the EC value is greater (less) than one, an improvement (deterioration) in efficiency can be concluded. In the same manner, if TC is greater (smaller) than one, technical change is progressive (regressive). A value of 1 for TC means no change has occurred. ncy. Multiplying both indexes leads to the Malmquist productivity index as stated by Färe et al. (1992) (Grebel, 2018).

2.3 Empirical protocol

In this section, we describe our econometric protocol and the data with which we proxy the efficiency improvement for the OECD countries. We test the effect of an increase in the price, on efficiency index and technological changes in 30 countries. For that, we perform panel data regressions such as LSDV. Moreover, a heterogeneous dynamic panel regression will allow us to monitor whether there is a difference between the short- and longrun effects.

2.3.1 Data and methodology

Overall, we collected an unbalanced panel data set of 30 OECD countries (DMUs) from 1990 to 2015. From these, the information used to build the DEA indices are collected from the the International Energy Agency (IEA) database, as well as energy prices and renewable energy policies (REP). The competition variable (product market regulation) index as well as patent data are retrieved from the OECD database. GDP per capita as well as the total renewable energy generated stems also come from the IEA.

As dependent variables, we calculate two efficiency indices based on the input oriented theory. We build two indicators, one for constant return to scale (CCR) and the second is for variable returns to scale (BCC). For measuring the technological change over time, we calculate the Malmquist index. As output we pick the gross domestic product in 2005 bn. US$ purchasing power parity. As inputs we use population (POP – in millions), total primary energy supply (TPES – in terajoule: production + imports - exports ± stock changes) and finally carbon dioxide emissions (CO2 – in tons of CO_2). Although carbon dioxide is an output, we employ it as an input. The DEA model minimizes all inputs per unit output. As CO_2 is to be minimized per unit output, it can technically be treated as an input (Seiford and Zhu, 2002; Chung et al., 1997; Førsund, 2009; Sueyoshi and Goto, 2011). Hence, the simplified production process consists of three inputs, POP, TPES, and CO2 that transform into GDP.[3]

We calculated the Malmquist index in a more generic way, based on the variable returns to scale. Figure (2.3,orange line) shows the values distribution and the histogram of the calculated index before and after the transformation to the data. The index has a high density of values around the value 1 and the value changes are relatively small; however, these small changes in the efficiency values have an important economic meaning. Therefore, we exponentially transformed the index to explore these small differences and label it for further analysis as $e\mathsf{MQ}-\mathsf{BCC}$ index, see figure (2.3,green line).

Explanatory variables

Energy prices: diminishing fossil fuel sources will increase energy prices. This, in turn, should increase the incentive for energy producers to improve their energy efficiency and in the long run search for alternatives. The energy prices index

[3]Capital and labor are the traditional input factors. This is why we use those. Instead of capital input, however, we use TPES, which can be considered an instrument for capital input. As a proxy for labor input we use population. With carbon dioxide we add an environmental variable which countries should economize on. This examplifies how to take environmental aspects into account in DEA.

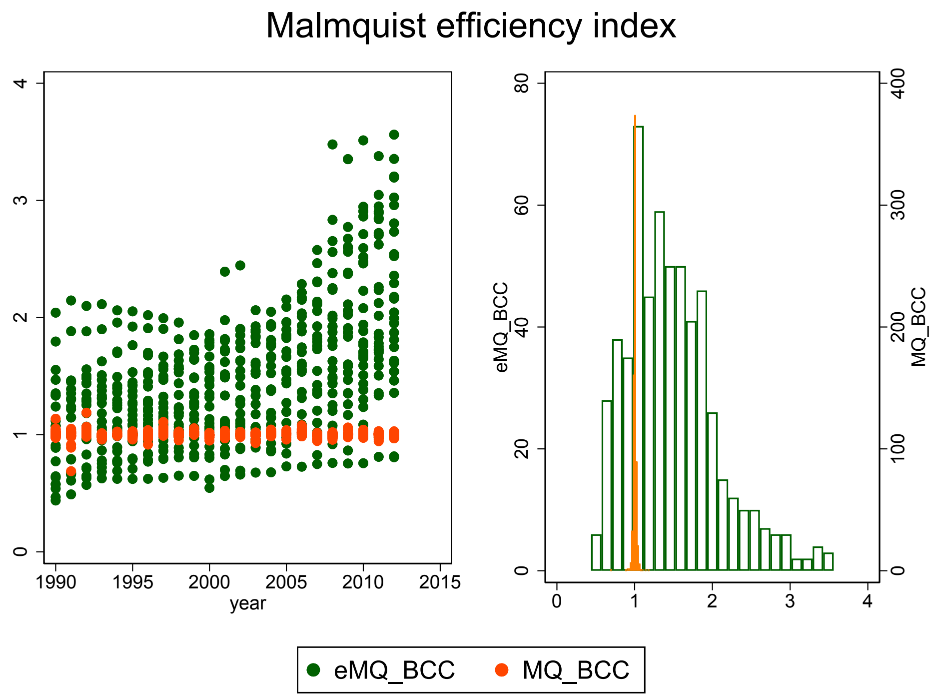


Figure 2.3 Transformation of the Malmquist index.

is calculated based on data on end-user electricity prices in both residential and industrial sectors. The calculated price index was constructed by weighing the prices by the consumption in both residential and industrial sector, respectively, similar to Johnstone et al. (2010b); Popp et al. (2010) or Nesta et al. (2014). We expect a positive effect of increasing energy prices on energy efficiency and technological change.

Renewable energy policies (REP): states have been intervening in the energy market, trying to boost their efficiency and induce a technological change. Therefore, we include the number of policies in force during a given year. As in Johnstone et al. (2010a); Nesta et al. (2014), and Dasgupta et al. (2001), we build a policy index by counting the number of active renewable energy policies by country and year. The effectiveness period of each policy can be derived from the reported information about the year of adoption and expiration date. Each policy from these takes the value of zero, and only during the effectiveness period does the value change to one. The aggregated index includes different kinds of policies such as *economic instruments*, *regulatory instruments*, *policy support* and *information and education*. By doing this we might be losing information about singular effect and scope of each policy type; nevertheless, it allows us to track the activity level of policymakers.

Competition: To measure the level of competition in the energy sector, we use the "Product Market Regulation" (PMR) index, developed at the OECD. It combines information about multiple features, such as the number and market shares of the largest energy suppliers; the higher the number and low market concentration levels, the more competitive the market is. Secondly, we view public ownership/state control (such as price control and ownership), vertical integration, and finally entry barriers and market regulations[4] (regulations of third party access to the grid). The combined index ranges from 0 to 6, where high values indicate a high level of regulation and hence a low level of competition. Therefore we expect a negative correlation sign between the PMR index and energy efficiency; the higher the level of competition, the more efficient energy producers will be.

Green knowledge: Innovation, accumulated Learning and scientific results and evidences can lead to technological change, as discussed by Sabatier and Jenkins-Smith (1999). The more scientific knowledge a country has, the more alternatives they will have to enable the swift change to other technologies than fossil fuels (Weible et al., 2011). Therefore, we include patent counts per country for each year as an indicator for innovation activities. They can be seen as proxy for the scientific and technical information available.

Despite several empirical and conceptual caveats (Griliches, 1990), patents have been widely used in quantitative empirical studies in environment domains as an indicator for innovation (Lanjouw and Mody, 1996; Brunnermeier and Cohen, 2003; Costantini and Crespi, 2013). Just counting the annual number of patents in green technologies does not reflect the actual stock of knowledge of a country. The Stock of Knowledge, by nature, is difficult to measure. Accumulating patent counts instead would ignore the fact that knowledge wears off over time (Popp, 2002). Therefore, we use the perpetual inventory method (PIM) as suggested and applied by (Meinen et al., 1998; Hall, 1993; Hall et al., 2000; Nesta and Saviotti, 2006). The number of patents (Pat_t at time t) is counted while depreciating past patent counts. Correspondingly, the stock of green knowledge (GK) is calculated as $\mathrm{GK}_{it} = (1-\delta)\mathrm{GK}_{t-1} + \mathrm{P}at_t$.[5] The patent data originates from PATSTAT[6]. For patents identification purposes, we used the OECD Indicator of Environmental Technologies (OECD, 2012). We expect that countries with high level of green knowledge, will positively lead to a technological change toward renewables sources.

GDP and *population*: are the simplest measures used to account for the economic growth, the size of the country. To decrease the correlation between these two variables, we prefer to calculate *GDP per capita* as a combined variable. By including this variable we expect that the bigger and richer a country, the better

[4] For a more detailed information and different weighting for features, please refer to (Conway et al., 2005)

[5] The annual depreciation rate δ is assumed to be 15%

[6] We used the 2015 version of the EPO database PATSTAT EPO (2015).

the level of efficiency and technological change.

Total renewable energy generation: To control for the energy sector structure and energy mix, we include the total energy generated from renewable sources. We expect that the higher the integration capacity of renewable energies in a country energy mix, the higher the energy efficiency levels and the faster technological change will be.

Table (2.1) collects the summary statistics of variables.

VARIABLES	Obs	Mean	Std Dev.	Min	Max
CCR_in	754	0.181	0.241	0.00142	1
BCC_in	754	0.861	0.0958	0.636	1
eMQ_BCC	574	1.483	0.585	0.439	3.561
Energy price	642	0.873	0.231	0	1.490
REP	884	0.116	0.141	0	1.010
PMR	795	3.841	1.665	0.872	6
GDP per Capita	772	3.198	0.401	1.872	3.917
Ren. energy generation	789	2.839	1.591	0.001	6.270
Green Knowledge	782	3.971	2.22	0	8.671

Table 2.1 Summary statistics

2.3.2 Basic Econometric Specification

To test whether energy prices can induce energy efficiency in OECD countries and lead to a technological change, we state the following basic econometric specification, where we start with a least square dummy variable (LSDV) regression, expressed in equation (5.1).

$$\mathrm{Ef}_{it} = \beta_0 + \boldsymbol{\phi}_{1t}\mathrm{EP}_{it} + \boldsymbol{\phi}_{2t}\mathrm{REP}_{it} + \boldsymbol{\phi}_{3t}\mathrm{PMR}_{it} + \boldsymbol{\psi}\mathbf{X}_{it} + \epsilon_{it} \tag{2.2}$$

with $i = 1, 2, .., n$ as number of countries, $t = 1, 2, .., \mathrm{T}$ as time span, and Ef_{it} as the dependent variable, which will vary between (constant returns to scale (CCR), variable returns to scale (BCC) and technological change (eMQ_BCC)). β_0 is the constant term, EP is the energy price variable, REP represents the renewable energy polices and PMR is the competition index. $\phi_{1..3t}$ represent the explanatory variables coefficients respectively, while ψ is the coefficient matrix for the control variables $\mathbf{X}$. Finally, an error term is assumed with ϵ_{it}.

Using models like the suggested LSDV model is proper for micro panels with small time series (T) and a large number of cross section observations (N). Such panel structure usually rely on either fixed effects, random effects, static fixed effect (SFE), or a combination of those (Arellano and Bond, 1991), to estimate the coefficients. However, as Pesaran and Smith (1995) point out, with large T, such traditional estimators may generate inconsistent results, because they assume homogeneous slopes among panel units.[7] To make sure the results are robust, we will apply, in additional to the LSDV model, a dynamic heterogeneous panel model. The latter will be explained in the following:

2.3.3 Estimators for heterogeneous slopes

In general, the assumption of homogeneous slope parameters does not hold in dynamic panel data with large T and large N (Phillips and Moon, 2000; Im et al., 2003). With T increasing, more attention has to be paid to issues like serial correlation, as shocks, whether temporary or persistent, may lead to biased estimation results. Pesaran and Smith (1995), show that GMM estimation in a dynamic panel model has inconsistent long-term coefficients when actual slopes are heterogeneous. For these reasons, we apply the pooled mean group model (PMG) introduced by Pesaran and Smith (1995) and Blackburne and Frank (2007).

Dynamic Heterogeneous Panel Models (DHPM) are based on an autoregressive distributed lag model, which includes an error correction, and allows addressing endogeneity issues. In a nutshell, it estimates a short-run dynamic to which the system returns after an exogenous shock, and additionally, it estimates long-run effects. It allows, in the short-run, coefficients, convergence adjustment speed (the coefficient of error correction term), and the error variances to differ across countries. However, it assumes homogeneity of slope parameters across countries on the long-run (Blackburne and Frank (2007)).

The DHPM estimator can be calculated as mean group (MG), dynamic fixed-effects (DFE) models or a combination of both. Whereas the MG model averages the slope coefficients of separate regressions by panel-unit, the DFE model is similar to the one-way fixed effects or least square dummy variable (LSDV) approach allowing for heterogeneous intercepts but homogeneous slope coefficients. In contrast to the fixed-effects model, the DFE approach also distinguishes between short-run and long-run effects. There are various reasons to assume common long-run coefficients across OECD countries, because they have access to common technologies and very similar policies trends. Popp et al. (2011), for example, put forward that the Kyoto protocol played a fundamental role in accelerating the development of renewable energy installed capacities, where all member countries are exposed to the same international pressure for more environmental regulations. Nesta et al. (2014) identify a positive effect between the introduction of the Kyoto protocol and renewable energy policies.

Conversely, assuming the speed of convergence across countries to be similar is

[7] Compare Pesaran et al. (1999).

rather implausible, as countries' institutional frames differ. Together with the fact that our data set is a large T, large N data set, the DFE is comparable to the LSDV model (eq. 5.1, with heterogeneous intercepts assumed. The mathematical background of the DHPM models is described in the following:

Dynamic Heterogeneous Panel Models

The general model of the dynamic heterogeneous panel estimation, which will be presented here, is discussed by (Blackburne and Frank, 2007; Freeman, 2000; Pesaran et al., 1999).

General Model

The general model assumes that the input data on time period $t = 1, 2, ..., T$ and across section groups $i = 1, 2, ..., N$ can be estimated by an autoregressive distributive lag model ARDL$(p, q, .., q_k)$:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} X_{i,t-j} + \mu_i + \epsilon_{it} \tag{2.3}$$

where X_{it} is the $(k \times 1)$-vector of explanatory variables, λ_{ij} a scalar of constants, δ_{it} the $k \times 1$ coefficient vectors, μ_i the group specific effect and, ϵ_{it} the group specific effect. As T is large enough, each group can be estimated separately. The variables in equation (5.2) are cointegrated of level $I(1)$ and the error term is an $I(0)$ process for all i, therefore, the error correction equation can be reparameterized:

$$\triangle y_{it} = \phi_i (y_{i,t-1} - \beta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \triangle y_{i,t-1} + \sum_{j=0}^{q-1} \delta'^*_{ij} \triangle X_{i,t-1} + \mu_i + \epsilon_{it} \tag{2.4}$$

for $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$. The error correction speed of adjustment parameter is expressed as in the following:

$$\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}), \tag{2.5}$$

$$\beta'_i = \sum_{j=0}^{q} \delta_{ij}, \tag{2.6}$$

$$\lambda^*_{ij} = -\textstyle\sum_{m=j+1}^{p} \lambda_{im} \quad j = 1, 2, ..., p-1 \tag{2.7}$$

and

$$\delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im} \quad j = 1,2,...,q-1 \tag{2.8}$$

assuming that the ARDL model in equation (5.2) is stable in that the roots of $\sum_{j=1}^{p} \lambda_{ij} z^j = 1$ for $i = 1,2,...,\mathrm{N}$ lie outside the unit circle, ensuring that the error correcting speed of adjustment term $\phi_i < 0$. This implies that there is a long-run relationship between the dependent variable y_{it} and the regressors x_{it} . It is calculated as:

$$y_{it} = -(\beta'_i/\phi_i)x_{it} + \eta_{it} \tag{2.9}$$

Adapted Model

When adapting the general model to our case, we obtain the following long run function:

$$\mathrm{Y}_{it} = \theta_{0t} + \theta_{1t}\mathrm{EP}_t + \theta_{2t}\mathrm{REP}_t + \theta_{3t}\mathrm{PMR}_t + \mathbf{B}_{\boldsymbol{i}}\mathbf{X}_{it} + \mu_i + \epsilon_{it} \tag{2.10}$$

where $i = 1,2,..,\mathrm{N}$ is the number of countries, $t = 1,2,..,\mathrm{T}$ the time span, and y_{it} the respective dependent variables (constant returns to scale, variable returns to scale (BCC) and technological shift (eMQBCC). $\mathbf{X}_{it}$ stands for the control variables and $\mathbf{B}_{\boldsymbol{i}}$ are their corresponding coefficients. According to a cointegration test, the data is cointegrated $\mathrm{I}(1)$ and the error term is an $\mathrm{I}(0)$ process for all i. This transforms the ARDL(1,1,1) dynamic panel specification of equation (5.9) into our basic regression equation:

$$\begin{aligned}\Delta\mathrm{Y}_{it} = {} & \phi_i(\theta_{0i} + \theta_{1i}\mathrm{EP}_{it} + \theta_{2i}\mathrm{REP}_t + \theta_{3i}\mathrm{PMR}_t + \mathbf{B}_{\boldsymbol{i}}\mathbf{X}_{it}) \\ & + \delta_{11i}\Delta\mathrm{EP}_{it} + \delta_{21i}\Delta\mathrm{REP}_t + \delta_{31i}\Delta\mathrm{PMR}_t + \delta_{41i}\Delta\mathbf{B}\,\mathbf{X}_{it} + \epsilon_{it}\end{aligned} \tag{2.11}$$

where $\theta_{0i} = \frac{\mu_i}{1-\lambda_i}$, $\theta_{it} = \frac{\delta_{i0i}+\delta_{i1i}}{1-\lambda_i}$, and $\phi_i = -(1-\lambda_i)$. The error correction speed of adjustment parameter is ϕ_i. $\theta_{1i}, \theta_{2i}, ..., \theta_{\mathrm{N}i}$ are the long-run coefficients.

2.4 Empirical results

We begin by presenting the result from the LSDV model, presented in equation (5.1). Beforehand, we performed a unit root and cointegration test. The unit-root test is executed using the augmented Dickey-Fuller test. The null hypothesis of the panel containing a unit root can be rejected with a p-value of 0.006 for all values except the CCR variable, therefore we calculated and use the exponential form in our calculations. All regressions and tests are performed using STATA 15.

Table (2.2) shows our first results. We apply fixed effect LSDV regression[8] with a time trend. In models (1-4) we use the efficiency score calculated by means of the CCR model as a dependent variable. In the first model, we regress only energy prices on efficiency score. The results show a significant positive effect of energy prices on the energy efficiency. In further models, we started adding variables sequentially. In models (2 and 3), we added renewable energy policies and competition variable. Energy prices kept their effect, and the effect of REP on energy efficiency is additionally strongly positive. The competition variable is also significant and has a negative sign, as expected. State intervention in the energy market as well as market liberalization can lead to a better efficiency. In model 4, we added further control variables (GDP.p.c, share of renewable energy capacities and stock of green knowledge). As a result, both energy prices and PMR lost their significance and only renewable energy policies kept their significance level in addition to the GDP per capita variable.

In models (4-8) we repeat the same sequence and same regression specifications, but use the variable returns to scale (BCC) as a dependent variable. The BCC variable is used to account for the technological heterogeneity between countries. At the first glance, the results seem similar to the previous models, where energy prices correlate positively with the efficiency variable, even when additional variables are added. Both REP and competition variables have the expected effects on the BCC variable. REP kept a positive sign through all the models and PMR, on the other hand, has a negative sign, meaning that competitive markets can boost the efficiency levels in the market. In model 8, add all the control variables. In contrast to model 4, where energy prices lost their effect, the sign and significance level of energy prices on the BCC variable did not change. In addition, both renewable energy policies indicator and competition variable have held their significance and signs.

Table (2.3) shows the results to test the second hypothesis, if energy prices can lead to technological change. The dependent variable is the Malmquist index explained in section 2.3.3, which is exponentially transformed. As for the regression specification, we apply a LSDV regression, with year dummies and standard error robustness check through all the models (9-13). The results show a strong and significant correlation between energy prices and the technological change variable. In models (2 and 3) we added both the policy and competition indices sequentially. Only the competition index is negatively significant. Following this, we add an interaction term between both indices to test the effect of increasing policies in competitive markets. The variable is significant, showing that policies might be not significant in general, but only in more liberalized markets. In model 5, we

[8]The Hausmann tests suggests to use a fixed-effect model.

VARIABLES	(1) eCCR	(2) eCCR	(3) eCCR	(4) eCCR	(5) BCC	(6) BCC	(7) BCC	(8) BCC
Energy price	0.063**	0.068**	0.070**	0.044	0.128***	0.119***	0.120***	0.099***
	(0.028)	(0.029)	(0.029)	(0.029)	(0.013)	(0.013)	(0.013)	(0.014)
REP (lagged)		0.134***	0.139***	0.166***		0.030*	0.035*	0.032*
		(0.038)	(0.039)	(0.037)		(0.018)	(0.018)	(0.018)
Product Market Regulations			-0.006*	0.001			-0.005***	-0.004**
			(0.004)	(0.004)			(0.002)	(0.002)
GDP per Capita				0.257***				0.010
				(0.031)				(0.015)
Share of Ren. cap.				0.273***				0.181***
				(0.090)				(0.043)
GK				-0.010				0.003
				(0.008)				(0.004)
Constant	4.902***	6.633***	7.076***	9.269	3.188***	3.785***	5.630***	5.791***
	(0.586)	(0.726)	(1.006)	(5.485)	(0.569)	(0.714)	(0.982)	(1.748)
Observations	594	594	594	592	594	594	594	592
Number of ctry	31	31	31	31	31	31	31	31
R2 adj. within	0.155	0.177	0.178	0.306	0.193	0.196	0.206	0.229
R2 adj. between	0.0129	0.279	0.291	0.00199	0.0111	0.0245	0.0438	0.210
R2 adj. overall	0.00133	0.105	0.120	0.00588	0.0380	0.0546	0.0712	0.184

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.2 Energy efficiency LSDV regression results. Dep. variable for models (1-4) is eCCR and 1-8 BCC.

add the control variables, where only energy prices kept their significant level and sign. In addition to that, the stock of green knowledge plays a positive role in inducing technological change.

Dept. Variable: eMQ–BCC

	(9)	(10)	(11)	(12)	(13)
Energy price	2.828***	2.825***	2.808***	2.793***	2.774***
	(0.116)	(0.113)	(0.110)	(0.109)	(0.132)
REP		-0.160	-0.164	0.051	0.025
		(0.158)	(0.153)	(0.159)	(0.149)
PMR			-0.020**	-0.015*	-0.015
			(0.008)	(0.008)	(0.009)
REPxPMR				-0.095*	-0.080
				(0.049)	(0.050)
GDP per Capita					-0.086
					(0.091)
GK					0.035*
					(0.017)
Ren cap					0.154
					(0.303)
Constant	-0.924***	-0.921***	-0.795***	-0.809***	-0.692**
	(0.089)	(0.088)	(0.093)	(0.092)	(0.297)
Observations	574	574	574	574	572
R-squared	0.973	0.973	0.974	0.974	0.975
Number of ctry	31	31	31	31	31
Year dummies	Yes	Yes	Yes	Yes	Yes
Robustness check	Yes	Yes	Yes	Yes	Yes
R2 adj. within	0.973	0.973	0.974	0.974	0.975
R2 adj. between	0.987	0.986	0.987	0.987	0.976
R2 adj. overall	0.976	0.975	0.975	0.975	0.970

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3 LSDV regression. Dept. variable Malmquist index index.

Our last results are presented in table (2.4). We apply the dynamic fixed effects model, presented in section 3.5. In the first two models, we use the eCCR variable, followed by the BCC and finally the eMQ-BCC variable. All regressions have the same specifications. The advantage of using this model is the ability to distinguish between short- and long-run effects and the additional error correction term that captures serial correlations between the variables.

The results for the constant returns to scale show no effect of energy prices neither in the short nor the long run. On the other hand, the effect of energy prices appears significant, when the technological heterogeneity between countries

	Variables	14 eCCR	15 eCCR	16 BCC	17 BCC	18 eMQ-BCC	19 eMQ-BCC
Long run	Energy price	-0.020	-0.125	0.212***	0.243***	2.350***	2.412***
		(0.115)	(0.189)	(0.043)	(0.063)	(0.155)	(0.148)
	REP	0.273	0.235	-0.053	-0.049	-0.073	-0.067
		(0.314)	(0.290)	(0.056)	(0.054)	(0.185)	(0.181)
	PMR	0.024	0.041	0.006	0.006	0.003	-0.007
		(0.018)	(0.032)	(0.005)	(0.006)	(0.006)	(0.010)
	GDP.p.c		0.176		0.011		-0.148
			(0.129)		(0.058)		(0.127)
	Ren. cap.		0.350		-0.259		0.066
			(0.283)		(0.256)		(0.352)
	GK		0.021		-0.003		-0.003
			(0.052)		(0.018)		(0.022)
short run	Error term	0.044*	0.046	0.177***	0.168***	0.191***	0.202***
		(0.026)	(0.029)	(0.037)	(0.039)	(0.027)	(0.028)
	Energy price	0.007	0.005	0.023	0.025	2.681***	2.686***
		(0.014)	(0.014)	(0.020)	(0.018)	(0.159)	(0.159)
	REP,	0.013	0.015	0.009	0.010	0.053	0.043
		(0.018)	(0.018)	(0.025)	(0.025)	(0.040)	(0.036)
	PMR,	0.001	0.002	0.001	0.001	-0.001	-0.001
		(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
	Constant	-0.055*	-0.024	-0.117***	-0.114**	0.114***	0.030
		(0.034)	(0.036)	(0.028)	(0.045)	(0.038)	(0.091)
	Esigma	0.0281	0.0283	0.0239	0.0265	0.0358	0.0381

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.4 Dynamic fixed effect models.

is taken into consideration. Models (3 and 4) show these results. Energy prices have a positive effect on energy efficiency on the long-run. The last two models (5 and 6) we introduce to run the regression against the Malmquist index, measuring shift in the technological frontier. The results show a significant positive effect of increasing energy prices on inducing technological change both in the short-run and the long-run. Also, the error correction term is significant, meaning serial correlation between the variables is captured. Additional information from the error correction term can be concluded, namely the length of the shock after a change in energy prices. An increase in energy prices will induce technological change for 5 years, before its effect fades away. However, the effect of energy prices can fade away, but the system will have gained from a positive effect on the technological change frontier.

2.5 Discussion and conclusion

In our research paper, we raised the question whether an increase in energy prices can lead to a better energy efficiency between countries and accelerate a technological change toward renewable energies. The decrease in the supply of fossil fuels and the additional taxes introduced after state intervention, to mitigate the effects of climate change, both lead energy prices to go up. According to fundamental economic theories, if energy prices increase and markets are competitive, energy producers will try to increase their efficiency levels, in order to not lose their market shares. Also, simultaneously alternative technologies that seemed too expensive in the past will be more attractive and more investment will be put into new technologies.

To answer this question and model the effect on the efficiency levels and technological change, we collected a dataset for 31 OECD countries between 1990 and 2015. To build our dependent variables we used data envelopment analysis and we calculated two efficiency scores. The first depends on the assumption that countries have the same technologies and have a constant returns to scales. The second efficiency score assumes heterogeneity between countries technologies and assumes variable returns to scale. An additional outcome from the calculated efficiency scores is the Malmquist index, which measures the shift of the technological frontier. Based on this index we can measure the technological change.

Overall, we observe an elevation in the energy efficiency levels across the OECD countries after energy prices rise. The results using constant returns to scale are inconsistent, which indicates that countries apply different technologies. On the other hand, the effect on the dependent variable BCC, which accounts for the technological heterogeneity between countries, has been consistently positive through all the models. The role of policies and competition can not be neglected. renewable energy policies and competition both have a positive effect on energy efficiency. The dynamic panel regressions as well point toward a long-run positive correlation between energy prices and energy efficiency when heterogeneity is taken into consideration.

With regard to inducing technological change, energy prices have a positive significant effect through all the models. Additionally the Dynamic Heterogenous Panel Models show a positive effect on both the short-run and the long-run. In addition to energy prices, competition does play a positive role in inducing technological change. State intervention does have a positive effect on inducing technological change in more competitive liberalized markets. These findings are similar to those reported by (Nesta et al., 2014).

Our results are in line with previous studies that concluded that an increase in energy prices can boost energy efficiency levels. Additionally this increase can lead to technological change. These findings might be different than the results documented by (Johnstone et al., 2010a; Nesta et al., 2014), however coherent with the results from (Popp, 2002; Nicolli and Vona, 2016).

In summary, we can conclude that energy prices can lead to better energy efficiency, when heterogeneity between countries is taken into consideration and in the long-run induce technological change. Renewable energy policies play a critical role in supporting the shift when markets are liberated and competition is taking place.

In future research, we can introduce attempts to measure technological change based on innovation activities,i.e. patent counts. Nesta et al. (2014) used patents data as an indicator for technological change. In additional to that, we can distinguish the types of policies and monitor their singular effects. In a similar vein, we can determine empirically the interaction between those policies and market liberalization steps.

Chapter 3

Rising Energy Prices and Advances in Renewable Energy Technologies

Authors: Sherief Emam, Thomas Grebel

In this paper we investigate the impact of rising energy prices on technological progress in the market for renewable energies. We use patent data of OECD countries from 1970 to 2010 and test the impact of oil prices on the innovative success of countries; R & D, investment activities, electricity consumption , etc. are used as control variables. We compare several models such as Pooled Mean Group (PMG), Mean Group (MG), Count data (CD) and Dynamic fixed effects (DFE) models to distinguish short and long-term effects. The preliminary results show that increasing energy prices seem to encourage innovation in renewable energy technologies.

3.1 Introduction

This paper tries to provide evidence for the relationship between rising energy prices and technological progress in the market for renewable energies. The technology push and the demand pull approach, respectively, argue why we observe technological advances in industries (Di Stefano et al., 2012; Schmookler, 1966; Mowery and Rosenberg, 1979; Rosenberg and Nathan, 1982). The technology push argument claims that it is the advances in sciences that may induce the rate and direction of technological change in contrast to the demand pull approach which finds the drivers of technological change in yet unsatisfied consumer needs. Both arguments received critique. The demand pull approach would be too broad as a concept to be useful. It would be inadequate to explain discontinuous change as the most important source of progress. Firms would not have sufficient capabilities to identify consumer needs, nor would they have the chance to choose from a ready-made stock of technological solutions to come to grips with consumer needs. It neglects the role of technological opportunities. The technology-push argument has been strongly criticized as it ignores the role of prices as an incentive to invest in new technologies. With respect to technology policies, as Nemet (2009) points out, a consensus has evolved that both types of instruments – demand-pull and technology-push policies – should be pursued as market conditions (to which the demand-pull argument relates to), and technological opportunities (the basis for the technology push argument) have to coincide in order to lead to technological progress. On these grounds, we will focus on the demand pull argument and try to find out whether increasing oil prices (changing market conditions), as indicators for a steadily increasing demand for energy and the general perception of dwindling fossil energy resources, make countries increase their innovative activities in order to boost technological progress in alternative renewable energy technologies. Our work draws to a large extent on Nesta et al. (2014), Johnstone et al. (2010b) and Nemet (2009).

As in Johnstone et al. (2010b) and Nesta et al. (2014), we apply negative binomial regression and extend our empirical exercise with estimators allowing for non-stationary heterogeneous panels suggested by Blackburne and Frank (2007), which also allows, besides traditional fixed-effects estimation, the estimation of the *mean-group* estimator (MG) (Pesaran et al., 1999) and the *pooled mean-group* estimator (PMG) put forward by Pesaran and Smith (1995). Thus we try to differentiate long-run and short-run effects.

In section 3.2 we refer to related work on the determinants of the technological progress in renewable energies. Section 3.3 presents the construction of our data and the methodological specifications we use. Results delivered by negative binomial count data models will be discussed in section 3.4. These results will be compared with the results of dynamic heterogeneous panel estimation in section 3.5. Section 3.6 primarily discusses shortcomings/caveats and conclusions.

3.2 Related Work and Research Question

Economic growth hinges on the disposability of energy. As Stern (2011b) points out, energy scarcity is a main constraint for economic growth. The industrial revolution impressively showed that the invention of new technologies that drove economic growth was based on the usage of fossil fuels. This was key to substitute human labor for automated labor and thus enhance economic growth. Ever since the world economy has been growing, the consumption of fossil fuels has been also growing. A side effect of the steady increase in demand for fossil fuels has been rising energy prices. Standard textbook economics tells us about the consequences of increasing (relative) prices: all market participants will adapt their behavior. If fossil fuels become more expensive relative to non-energy goods, (1) the demand for energy should go down, as consumers adapt their behavior. They try to substitute energy-intensive goods for non-energy goods. Quite similarly, (2) the supply side will change its behavior as well. Producers will try to innovate on energy-efficient products and technologies. They try to find less expensive substitutes (Newell et al., 1999). Last but not least, (3) policy makers will participate in this process, too. Legitimizing their interventions by market failure, they carry out reforms to foster renewable energy sources and, at the same time, try to fight negative externalities such as greenhouse gas emissions or the potential risks involved in nuclear waste as a by-product of electricity production. Hence, renewable energies should be attractive for all market participants: policy makers, consumers and suppliers. Renewable energies make us believe that they can be supplied at almost zero marginal costs and no negative externalities. All that remains to be done is to develop and employ such new energy sources and to build the required infrastructure.

In traditional theory, markets should do the job, and as Newell et al. (1999) concludes, rising energy prices should eventually lead to increasing innovative activities. We want to empirically answer the following research question:

Research Question: Can rising oil prices induce technological progress in renewable energies?

Meanwhile, this topic of technological progress in renewable energies and its determinants has been investigated intensively. Johnstone et al. (2010b) and Nesta et al. (2014) give an excellent overview of this strand of literature. By and large, there are two fundamental options to boost technological progress – and this we can already conclude from Newell et al. (1999): either leave it to the market (Nesta et al., 2014; Sanyal and Ghosh, 2012) or try to induce innovation by policy intervention (Nesta et al., 2014; Acemoglu et al., 2012; Johnstone et al., 2010b). In many countries, market liberalization has intensified competition. Along with an increasing demand for renewable energy sources, due to a growing consumer awareness of environmental issues, innovative activity has risen. Many countries also carried out policy reforms to stimulate the innovation and adoption of renewable energy technologies (Johnstone et al., 2010b; International Energy Agency, 2004). However, it is not obvious to which extent rising energy prices actually contribute to increasing innovative activities. If we can shed light on this, we will, at the same time, gain insights in the question of how well the price mechanism and the market for energy works as a whole.

3.3 Data

As dependent variable to measure innovative activity in renewable energy technology, we collected patent statistics from the European Patent Office Worldwide Patent Statistics Database PATSTAT (EPO,2012) and focused on patents related to wind power technologies. Oil prices were retrieved from the Federal Reserves Economic Data (FRED) database. As further controls we included GDP, financial development funding, and electricity consumption all downloaded from the World Bank database. Research and development data stem from the OECD database. The time span of annual data covered ranges from 1970 to 2010.

Variable	Label	Source	Unit
PatNumb	# of patents	PATSTAT 2012	counts
GDP	gross domestic product	World Bank DB	In Millions $
Fdev	financial development	World Bank DB	% of GDP
R & D	research and development funding	OECD database	bn.$
OilPrice	oil price	Dow Jones & Company	Ind $
ElecConsump	Electrical Consumption	World Bank DB	MWh

Table 3.1 Data properties and sources.

A higher GDP stands for a country's potential to generate technological progress in general. Industrialized countries manage to patent far more than less developed ones. As a further control we introduce financial development, which gives indications on the investment activity within a country. Financial development can be measured in various ways. The ratio of broad Money (M2) to GDP, for example, expresses the overall size of the financial intermediary of the country. Or, it can be expressed in terms of domestic credit to private sector to GDP (Hamdi et al., 2013; Fernandez and Galetovic, 1994; Calderón and Liu, 2003; Khan and Semlali, 2000). Due to missing data in the M2 indicator, we calculate financial development as the ratio of domestic credit of the private sector to GDP.

	Mean	Std. Dev.	Min.	Max.	N
PatNumb	414	28.14	57.85	0	393
GDP	11.555	1.467	8.023	15.186	504
Fdev	87.047	43.39	20.749	227.753	501
R & D	1.647	1.552	0.015	10.497	417
OilPrice	24.477	15.358	3.4	72.400	504
ElecConsump	0.878	0.545	0.142	2.559	504

Table 3.2 Descriptive statistics.

An increase in credit offered for the private sector should lead to an increase in patents counts. R & D is included as a major input factor in generating technological progress. Hence, a positive impact of R & D on patent counts should be expected. With the consumption of electricity, patenting activities should also increase, as producers try to escape the shortage in its supply. Table (3.1) depicts the sources and units of our data.

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	PatNumb	1.00					
(2)	OilPrice	0.34	1.00				
(3)	GDP	0.60	0.17	1.00			
(4)	RD	-0.07	0.27	-0.15	1.00		
(5)	Fdev	0.60	0.36	0.58	0.00	1.00	
(6)	ElecConsump	-0.08	0.07	0.03	0.14	-0.02	1.00

Table 3.3 Cross-correlation table

Descriptive statistics can be found in table (3.2). With respect to patents, we confined the analysis to all OECD countries patents on wind power. Table (3.3) shows the pairwise correlations between dependent variables and all covariates. We also performed a multicollinearity test the variance inflated factor (VIF) and did not find multicollinearity among regressors.

In the following, negative binomial regressions provide first preliminary results with respect to our research question, whether oil prices have an effect on innovative activities among in respective countries.

3.4 Negative Binomial Regressions

Since the dependent variable is count data, we use negative binomial regression. Additionally, because of over dispersion, this model has to be preferred to a Poisson model. We introduce variables sequentially to see whether there are changes in the signs of estimated coefficients, when further covariates are considered. All covariates are instrumented by their one year lag. All models in this table are fixed-effects models taking a full set of year dummies into account. Model (1) in table (3.4) is a univariate regression of *PatNumb* on *OilPrice*. The correlation suggests a positive relationship between rising oil prices and patent counts. With *GDP* as a first control, *OilPrice* remains positive and significant, and so does *GDP*. Model (3) takes additional control variables into account; that is, *R & D*, *Fdev*, and *ElectConsump*. The coefficients of OilPrice and GDP change little; they are positive and the correlation is significant to the 1% level.

Dependent Variable: PatNumb (model: 1-3) log(PatNumb) (model: 4-5)

	(1)	(2)	(3)	(4)	(5)
OilPrice	0.038**	0.030***	0.025***	0.917***	-0.607
	(0.016)	(0.006)	(0.006)	(0.350)	(0.531)
GDP		0.003***	0.002***	0.397*	-0.186
		(0.000)	(0.000)	(0.228)	(0.424)
RD		0.017	-0.002	-0.139	0.491***
		(0.025)	(0.024)	(0.098)	(0.148)
Fdev			0.005***	0.333***	0.047
			(0.001)	(0.119)	(0.244)
ElectConsump			-0.113	-1.029	-5.207*
			(0.237)	(1.039)	(2.829)
Constant	0.192	0.641*	0.599	-2.730***	1.792***
	(1.063)	(0.366)	(0.372)	(0.674)	(0.278)
Observations	408	377	375	375	364
Number of country1	14	14	14	14	14
LL	-1288	-1128	-1110	-255.4	-248.4

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4 Regression 1: Neg. Bin (1-3), Panel fixed effects (4-5)

From the three variables introduced, only *Fdev* has a significant, positive effect on the number of patents generated in a country. *R & D* and *Fdev*, however, are insignificant. To calculate the elasticity, all variables are logged in model (4). The fixed-effect model applied here does not change the basic relationship between the dependent variable and the independent variables. Model (5) differs from model (4) in this regard that all logged variables are in differences; in other words, model (5) regresses the logged growth rates. The interesting observation in this model is that all variables which are significant in the previous models become insignificant, whereas *R & D* and *ElecConsump* all of a sudden have a significant effect, a positive effect with respect to *R & D* and a negative effect with respect to *ElecConsump*. A change in R & D funding has a positive effect on patent counts, the absolute amount of R & D does not. The same holds for *ElecConsump*. A positive change in electricity consumption explains a decreases in patent counts; the absolute value, however, does not.

We are aware that these results are very rudimentary. But what we can infer is that there are differences in the time patterns. An increase in R & D funding as a short-term impulse may induce patenting activities, and a short-term positive change in electricity consumption seems to reduce patent counts. This can be explained as following. R & D funding is directed to support research and development and a positive result in the number of patents is a direct outcome, while an increase in electricity consumption can exert budget restrictions on Firms and hence, lead to budget allocations and a decrease in the private funding for R & D activities. Models (1) to (3) suggest that there might be a positive long-term relationship between oil prices, GDP and patent counts. As most of these variables are co-integrated, a robust conclusion cannot be drawn from these results. Furthermore, spurious regression and endogeneity problems qualify these results even more. In order to face those problems, we apply dynamic heterogeneous panel models, which offer alternative estimators in addition to the traditional fixed-effects estimator, i.e. the pooled mean-group estimator by Pesaran and Smith (1995) and the mean-group estimator by Pesaran et al. (1999) (Blackburne and Frank, 2007).

3.4.1 Estimators for heterogeneous slopes

So far the two introduced models do not handle macro panel problems. Micro panels, i.e. small T and large N, usually rely on either fixed- or random-effects estimators or a combination of both including instrumental variable estimators such as the Generalized Method Of Moments (GMM) put forward by Arellano and Bond (1991). It requires pooling individual groups and allows for different intercepts across groups.

As a rule, macro panels do not fulfill the assumption of homogeneous slope parameters (Phillips and Moon, 2000; Im et al., 2003). In contrast to micro panels, the issue of non-stationarity plays a more important role. When T becomes large, it is necessary to pay more attention to serial correlation, when shocks, whether temporary or persistent, bias estimation results. Traditional nonstationary panels with a short time span T have different characteristics (Phillips and Moon, 2000). Analyzing panel data with large T in this paper, we draw on techniques introduced by Pesaran and Smith (1995) and Blackburne and Frank (2007), which allow estimating nonstationary dynamic panels heterogeneous parameters across groups: the mean-group (MG), pooled mean group (PMG), and dynamic fixed effects (DFE) estimators.

The MG estimator depends on estimating N time series regressions and averaging the coefficient (Pesaran and Smith, 1995). PMG is based on a combination of pooling and averaging coefficients (Pesaran et al., 1999). The dynamic fixed-effects estimator (DFE) is similar to the PMG estimator. Both restrict the coefficients of the cointegrating vector to be equal across all panels. The fixed-effects model additionally restricts the speed of the adjustment coefficient to be equal to the short-run coefficients.

3.4.2 Dynamic Heterogeneous Panel Models

In this subsection, we introduce the general model of dynamic heterogenous panel estimation as presented by (Blackburne and Frank, 2007) and then adapt this model to our example.

General Model

In the general model it is assumed that the input data on time period , $t = 1, 2, ..., \mathrm{T}$, and cross section groups, $i = 1, 2, ..., \mathrm{N}$, can be estimated by an autoregressive distributive lag (ARDL) model $(p, q, .., q_k)$ as in the following:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} \mathrm{X}_{i,t-j} + \mu_i + \epsilon_{it} \tag{3.1}$$

where X_{it} is the $(k \times 1)$-vector of explanatory variables, μ_i the group specific effect, λ_{it} the $k \times 1$ coefficient vectors and λ_{ij} a scalar of constants. As T is large enough, each group can be estimated separately and the variables equation (5.2) are conintegrated with I(1), then the error term is an $\mathrm{I}(0)$ process for all i, thus the error correction equation can be reparameterized:

$$\triangle y_{it} = \phi_i y_{i,t-1} - \beta'_i \mathrm{X}_{it} + \sum_{j=1}^{p-1} \lambda^*_{ij} \triangle y_{i,t-1} + \sum_{j=0}^{q-1} \delta'^*_{ij} \triangle \mathrm{X}_{i,t-1} + \mu_i + \epsilon_{it} \tag{3.2}$$

for $i = 1,2,...,\mathrm{N}$ and $t = 1,2,...,\mathrm{T}$ where the error correction speed of adjustment is the parameter expressed by:

$$\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}), \tag{3.3}$$

$$\beta_i = \sum_{j=0}^{q} \delta_{ij}, \tag{3.4}$$

$$\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im} \quad j = 1,2,...,p \tag{3.5}$$

and

$$\delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im} \quad j = 1,2,...,q-1 \tag{3.6}$$

assuming that the ARDL model in equation (5.2) is stable, where the roots of

$$\sum_{j=1}^{p} \lambda_{ij} z^j = 1 \qquad i = 1,2,...,\mathrm{N} \tag{3.7}$$

lie outside the unit circle, ensuring that the error correcting speed of adjustment term $\phi_i < 0$. This indicates that there is a long-run relationship between dependent variable y_{it} and controllers x_{it} and is defined by

$$y_{it} = -(\beta'_i/\phi_i)x_{it} + \eta_{it} \tag{3.8}$$

Adapted Model

Adapting the general model from above to our case renders the long-run function:

$$\begin{aligned} patnum_{it} = \theta_{0t} + \theta_{1t}\mathrm{GDP}_{it} + \theta_{2t}\mathrm{O}il\mathrm{P}rice_{it} + \theta_{3t}\mathrm{RD}_{it} + \theta_{4t}\mathrm{F}dev_{it} \\ + \theta_{5t}\mathrm{E}lect\mathrm{C}onsump_{it} + \mu_i + \epsilon_{it} \end{aligned} \tag{3.9}$$

where $i = 1,2,..,\mathrm{N}$ is the number countries in our panel. $t = 1,2,..,\mathrm{T}$ the time span of the panel, and $patnum_{it}$ the real number of patents per country i in period t.

The variables are cointegrated with $\mathrm{I}(1)$ and cointergrated. Hence, the ARDL(1,1,1) dynamic panel specification of 5.9 is

$$\begin{aligned}\triangle PatNumb_{it} = \phi_i(&PatNumb_{it-1} - \theta_{0i} + \theta_{1i}GDP_{it} + \theta_{2i}OilPrice_{it} + \\ &\theta_{3i}RD_{it} + \theta_{4i}Fdev_{it} + \theta_{5i}ElectConsump_{it}) \\ &+ \delta_{11i}\triangle GDP_{it} + \delta_{21i}\triangle OilPrice_{it} + \delta_{31i}\triangle RD_{it} + \delta_{41i}\triangle Fdev_{it} \\ &+ \delta_{51i}\triangle ElectConsump_{it} + \epsilon_{it} \qquad (3.10)\end{aligned}$$

where $\phi_i = -(1-\lambda_i)$, $\theta_{0i} = \frac{\mu_i}{1-\lambda_i}$, $\theta_{it} = \frac{\delta_{i0i}+\delta_{i1i}}{1-\lambda_i}$, and $\phi_i = -(1-\lambda_i)$. The error correction speed of adjustment parameter is ϕ_i. The long-run coefficients $\theta_{1i}, \theta_{2i}, ..., \theta_{Ni}$ are of primary interest.

3.5 Dynamic Heterogeneous Estimators

The regressions in this section refer to the heterogeneous panel techniques discussed above. All three estimators, PMG, MG and DFE, are applied in order to investigate short-run and long-run effects. The preliminary findings, depicted in table (3.4), give some indications to possible short-run and long-run effects. Therefore, we consider R & D and electricity consumption to also have short-run effects on innovative activities. In table (3.5) all three model results are reported with two model versions each.

In models (6-11), we introduced R & D and $ElectConsump$ as short-term variables and also as variables for the long-run. Persistent R & D investments should, in the long-run, increase the country stock of knowledge captured in new technologies and human capital. Further long-term explanatory variables are GDP, $Fdev$ and $OilPrice$, the latter as the variable of our interest. Note that these variables are the same as in our negative binomial regressions above. The two model versions of each estimation approach differ only in the (non-)inclusion of $ElectConsump$. Comparing all six models, we observe that the error correction coefficient (ec) is positive and significant in all models. This suggests that the time series components are serially correlated. In model (6-9) R & D seems to have a short-term effect on patent counts.[1] Electricity consumption has no significant explanatory power. Looking at the long-run coefficients, $OilPrice$ has a positive effect on patent counts, a preliminary result which is in line with our research hypothesis that it should have such an effect on innovative activities. In models (8) and (9), this effect vanishes; that is, it becomes insignificant. GDP has a negative long-run effect on patenting in renewable energy in all six models. A

[1] We used a five-year forward window of patent counts to take into account that the time span between innovative activities and the resulting actualization of innovation can take several years. Compare e.g. Nesta (2008).

Dependent Variable: PatNumb

		(6) PMG	(7) PMG	(8) MG	(9) MG	(10) DFE	(11) DFE
short run	ec	1.018***	1.018***	0.875***	0.824***	1.045***	1.045***
		(0.073)	(0.072)	(0.114)	(0.124)	(0.011)	(0.011)
	D.RD	5.784**	5.605**	18.555**	14.736**	-0.696	-0.836
		(2.475)	(2.468)	(7.812)	(6.446)	(2.238)	(2.249)
	D.Elect. Consump	131.473	133.617	-477.713	-485.562	-15.419	-13.202
		(108.852)	(109.555)	(499.072)	(488.092)	(75.411)	(75.550)
long run	OilPrice	0.177***	0.168**	-0.468	-1.116	0.546**	0.557**
		(0.065)	(0.066)	(0.835)	(1.122)	(0.256)	(0.256)
	GDP2	-0.084***	-0.079***	-2.285	-2.283	-0.181***	-0.184***
		(0.016)	(0.016)	(1.746)	(1.575)	(0.021)	(0.022)
	RD	2.127***	2.031***	34.015	40.263	-2.041	-1.818
		(0.434)	(0.471)	(22.485)	(32.712)	(1.528)	(1.560)
	Fdev	0.036*	0.043*	-0.880	-1.242	-0.237***	-0.258***
		(0.020)	(0.023)	(1.413)	(2.512)	(0.071)	(0.076)
	Elect. Consump		-4.498***		-274.220		12.671
			(1.364)		(223.733)		(17.875)
	Constant	3.234	0.309	-78.869	-137.879	-31.176***	-21.790
		(6.235)	(6.131)	(66.371)	(106.134)	(8.684)	(15.849)
	Observations	286	286	286	286	286	286

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5 Regression 2: Pooled-Mean-Group (PMG) (6-7), Mean-Group (8-9) and Dynamic Fixed-Effects (10-11)

possible explanation could be that economic growth is uncoupled from the progress in renewable energy technologies. To recall, we only consider wind power patents so far, which gives us a rather blurred picture of the role of renewable energy technologies. The sign of its coefficient is consistently negative. The reported long-run effects of R & D investments deliver only in model (6) and (7) a positive significant effect. In all other models it is insignificant. The sign of financial development ($Fdev$) is ambiguous. In model (6) and (7), $Fdev$, i.e. the share of credits to the private sector as a percentage of GDP, appears as a positive driver of patenting in this field. In model (8) and (9) this effect is insignificant, and in model (10) and (11) we observe flipped and significant signs. Electricity consumption (model 7) has a significant and negative long-run effect on patent counts. When comparing model (6) and (7), we observe that introducing $ElecConsump$ does not change a lot with regard to the other coefficients. So far, this can be interpreted as an indication for these two models' robustness.

There is no need for denying that the results in Table (3.5) are mixed. This calls for further research efforts on our side. One step to differentiate and choose the most suitable model is to run the Hausman test. It suggests that the PMG estimator, models (6-7) are to be preferred over the MG and DFE estimator. This is good news with regard to the effect of $\mathtt{O}il\mathtt{P}rice$, R & D and $\mathtt{F}dev$. All three are positive, which is consistent with the results in the negative binomial regressions above.

3.6 Discussion, Caveats and Conclusion

From an econometric stance, more tests have to be performed to understand the characteristics of the panel time series. This hopefully sheds more light on the inconsistencies identified. A further option is to compare the models with other models such as a pre-sample mean count data specification used in Nesta et al. (2014). It is conceivable that this could explain the negative sign of the long-run effects of GDP. Moreover, the paper by Nesta et al. (2014) also gives good advice on further factors that have an impact on innovative activities in the field of renewable energies. For example, weighting patent counts by patent family or by their triadic relationship to adjust for patent quality makes a difference. Industry dynamics play an important role, too. Many countries have liberalized their energy markets in recent years. This has increased market competition, and the ongoing technological progress in renewable energies driven by small start-up firms change the industry dynamics (Klepper, 1997, 1996; Abernathy and Utterback, 1978). This scrapes off some of the market power of large incumbent firms. Another aspect is the role of global warming that has risen consumer awareness to environmental issues. The demand for renewable energies has been steadily increasing Nesta et al. (2014). Even households become energy producers, as is the case in Denmark, where the majority of wind power plants are owned by households Hadjilambrinos (2000). From the viewpoint of policy making, policy reforms adapt the institutional frame of energy markets to the new needs. Consumers are drawn in to participate in energy production. An example for having introduced such demand side policies is the US (Loiter and Norberg-Bohm, 1999). Finally, the interplay between industrial change and policy reforms needs attention in our work, too. Nesta et al. (2014) provide evidence for such kind of endogeneity issues.

For the time being, it remains our positive attitude that we will find convincing evidence of the oil price impact on countries' innovative activities in renewable energies.

Chapter 4

Do we need disasters to adopt more environmental policies?

Authors: Sherief Emam, Thomas Grebel and Ana-Despina Tudor

Background

In this paper, we try to shed light on the question whether natural disasters, such as nuclear accidents, have an impact on policy makers' activity in passing new green energy policies. Disruptive moments like exogenous shocks reinforce society's disapproval against polluting technologies and should open a window of opportunities to eventually initiate a change toward green energy.

Methods

Based on the data of 34 OECD countries, we disentangle the effect of disruptive exogenous shocks on countries' policy activity. Starting with OLS regressions, we run several robustness checks by using a pre-sample mean approach, an ARDL technique called Dynamic Heterogeneous Panel Models (DHPM), which allows for the distinction between long- and short-run effects.

Results

The results corroborate the hypothesis that unexpected, disruptive events have a positive impact on the actual number of renewable energy policies. The fade-out time for shocks is about seven years, leaving a positive long-term effect.

Conclusion

Exogenous events such as nuclear disasters act as "focusing event" and seem to offer policy makers a window of opportunities to initiate conducive policy measures toward a cleaner economy. Furthermore, a country's capacity in green technologies is key to a pervasive diffusion of green technologies.

4.1 Introduction

The dangers of climate change have long been known. Global warming along with a rising sea-level, increased intensity and frequency of extreme weather events (Allen et al., 2019; Weitzman, 2015; Barnett and Adger, 2003b) threaten our livelihood. Apart from the negative effect on economic development, beyond and above all, it is our health which is at stake. Rising temperatures will make life impossible in many regions that are already struggling with heat. The cultivation of staple food becomes more costly and difficult (Costello et al., 2009). In spite of all the damaging consequences, global emissions are still on the rise (IEA, 2018a).

The reasons for this political sclerosis are threefold. Firstly, it is difficult for the public to understand climate change. Already the time dimension causes problems in doing so. A single hot summer day does not prove climate change, a persistent increase in average temperature however does, although 2 degrees Celsius might sound little (Nordhaus, 2007). Secondly, climate change is delocalized, meaning that the polluters are not necessarily those directly affected. Atoll countries, for example, despite little domestic emissions suffer from a declining habitat due to climate change (Barnett and Adger, 2003b), whereas the effects on industrialized countries emitting a multiple of greenhouse gases are less immediate and therefore less obvious to the public. This makes it difficult for the broad public to discern the injured from the injuring party. So it thirdly is little surprising that the awareness of having to act against climate change is little pronounced in the public eye (Hamilton et al., 2018; Marquart-Pyatt, 2012, 2008, 2007). The public reacts if it can "see" or "feel" the obvious consequences of a pressing problem. It seems that only after some natural disaster (i.e., hurricanes or heatwaves) the public becomes aware of the possible dangerous consequences of climate change. As it has been observed in previous studies, people search the Internet for keywords such as "climate change" or "global warming" (Herrnstadt and Muehlegger, 2014).

This phenomenon is even more obvious in the case of nuclear energy production. The danger of nuclear technology has been known ever since its discovery. Exposure to nuclear radiations can lead to environmental distraction (Alexakhin et al., 2006), food insecurities (Fesenko et al., 2007) as well as health complications (Yasumura et al., 2013; Havenaar, 1996). On the other hand, energy produced by nuclear technology is stable and relatively low in price. Therefore, public awareness and beliefs about possible consequences are heterogeneous across countries and fluctuating over time (Millner and Ollivier, 2016; Pajo, 2015). For instance, Bisconti (2018) analysed long-term public opinion data and concluded that the larger portion of the US public takes a neutral position concerning nuclear energy. For example, 64% of the population neither strongly favor nor oppose nuclear energy. However, changes in public opinion can be observed as an immediate consequence of sudden nuclear accidents, where generic support for nuclear energy decreases. Such decrease in support was reported in a cross-country public opinion survey (WIN-Gallup). In April 2011, after the accident of Fukushima, an average of 8% loss in nuclear energy support was measured in 47 countries (Bisconti, 2018). Taking this into consideration, it is plausible that accidents would raise public concern and, in turn, result in changes on the political level as a search for alternative solutions.

Hence, an unexpected crisis, such as nuclear accidents, can help accelerate the political process. Policies previously excluded from the political agenda, suddenly are brought back and appear enforceable. According to the policy literature (Birkland, 1998), these events become so-called "focusing events". They make citizens as well as politicians alert to the risks of nuclear power production or climate change. In the aftermath of the nuclear accident in Fukushima, Germany took drastic decisions concerning the phase-out of nuclear energy. As a response to decreasing public support for nuclear power, the government decided to shut down seven reactors temporarily and to accelerate the phase-out of nuclear energy production . Similar reactions took place in other countries, where governments rethought their energy production strategy and decided to withdraw from nuclear power production. For instance, Switzerland voted for a phase-out by 2034 (Glaser, 2011). In Japan, after the Fukushima accidents, the government shifted its energy consumption to fossil fuels resources (Taghizadeh-Hesary et al., 2017).

The main interest in policy research is to investigate the challenges of their implementation or ex-post – the evaluation of policy effectiveness (Gerhartz-Muro et al., 2018; Yang et al., 2015; Hoppe et al., 2014). Scholars investigate the challenges when implementing policy measures (Beveridge and Kern, 2013), however, the vast majority of studies address policy effectiveness questions. To wit, whether policies positively affect green innovation (Nesta et al., 2014; Johnstone et al., 2010b; Popp, 2002; Jaffe et al., 2003), the potential of policies to reduce carbon dioxide emissions (Fischer and Newell, 2008), or whether they contribute to economic growth (Kozluk and Zipperer, 2015; Lund, 2009).

To our knowledge, there is little work on the possible determinants triggering respective green policies. We raise the question if external shocks can work as incentives for decision makers to pass new renewable energy policies. In other words, we ask whether these accidents function as a catalyst, i. e. as a focusing event (Kozluk and Zipperer, 2015; Nohrstedt, 2005) for policy making. The strand of literature, to which we intend to contribute, is the so-called Advocacy Coalition Framework (ACF) as put forward by Jenkins-Smith and Sabatier (1994). This concept offers a general frame explaining the basic mechanisms of shifts in policy making.[1] As, for instance, Nohrstedt (2005) points out, the ACF links the momentum of external shocks (i.e. nuclear accidents) to the consequential policy initiatives arising from it. Complementary to the abundance of micro studies in the literature, we add a quantitative cross-country comparison quantifying the results of a crisis to policy change on the theoretical grounds of the ACF.

The data we use is gathered from various data sources. From the International Energy Agency, we collected about 60 different supply and demand side policies in renewable energy of 34 OECD countries.[2] For identifying nuclear accidents as possible focusing events triggering new renewable energy policies, we perform several regression models such as ordinary least square regressions, followed by count data models; to distinguish between short-run and long-run effects, we perform dynamic heterogeneous panel model (DHPM) estimation. Thus we retrieve a proxy for the fade-out time of shocks. The proxy will be implemented in further robustness checks. Additionally, several controls are included in the models, such as energy prices, power production capacities as well as shares of renewable energy production.

The results suggest a significantly positive effect of nuclear disasters on the enactment of renewable energy policies. The shock, according to our calculations, fades out after about seven years, indicating that the "window of opportunity" for policy makers lasts about seven years. Finally, evidence for an increase in R & D as well as diffusion policies after both Fukushima and Ibaraki are found; however, no effect was found for either of the policies after Chernobyl.

We may conclude that severe external shocks, such as nuclear accidents, redirect policy makers' attention. Such shocks function as "focusing events" which finally have policy makers reconsider their policy agenda. They are catalytic moments that help (political) actors form coalitions to eventually bring about policy change and introduce supportive policies such as policies promoting renewable energy technologies.

Moreover, as longing for further external shocks cannot be a serious policy implication, it remains to pose the question whether there is a comparably effective policy momentum to create the same effect as external shocks. This question, however, cannot and is not to be answer with this research setting.

The rest of the paper is organized as in the following. In Section (4.2), we discuss the concept of the Advocacy Coalition Framework (ACF) and our adaptation of the ACF for empirical testing. Section (4.3.1) delivers descriptive statistics, lays out our general empirical approach, and discusses the econometric specification

[1] See also Schlager (1995); Sotirov and Memmler (2012); Sabatier (1998, 1987); Henry et al. (2014); Kübler (2001); John (2003).

[2] The data have also been used in studies by Nesta et al. (2014); Johnstone et al. (2010a); Popp (2002); Fischer and Newell (2008).

of models. Results are presented in Section (4.4) including robustness checks, endogeneity issues and the differentiation between long- and short-run effects. A discussion and conclusion round off the paper in Section (5.5).

4.2 Background

4.2.1 Crises, Focusing Events, and the Advocacy Coalition Framework (ACF)

Nuclear accidents mark moments of crisis, they manifest "... a combination of severe threats, high uncertainty, and the need for urgent decision making" (McConnell, 2008, p. 557).[3] In policy change literature, crises are often considered as "focusing events". Birkland (1997) distinguishes three categories: (1) *normal* events which can be expected to happen but are unpredictable such as earthquakes, hurricanes, or nuclear disasters; (2) *new* events which refer to unprecedented events as induced by technological change, or the usage of new products; and (3) *common events under uncommon circumstances*. This type of events refers to events which occur on a fairly regular basis, but cannot be predicted where and when it happens. School shootings would be one those examples (Birkland and Warnement, 2013).

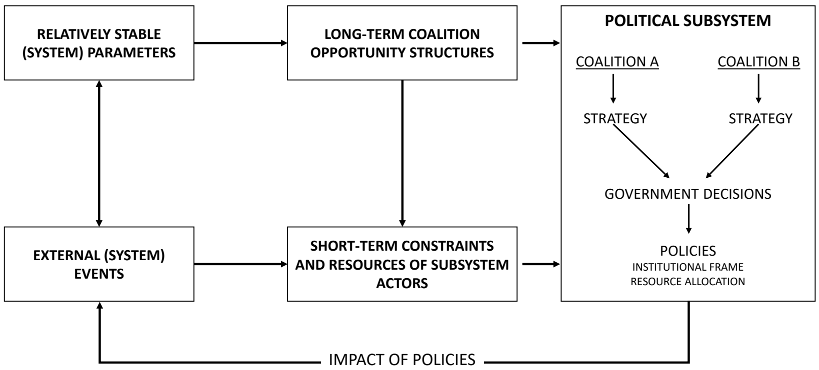
With respect to policy making, the bigger the accident, the more attention is paid to the underlying political issue. Nuclear disasters, although labelled *normal* event, are major events and unpredictable. Once an accident occurs, as Nohrstedt and Weible (2010) point out, the emerging crisis becomes a *focusing event*, which has political actors focus on the issue and become aware of the potential consequences of such accident. This moment opens up an opportunity to come to a democratic consensus and make a change. Therefore, such events are frequently considered causal drivers for major or non-incremental policy changes.

The underlying mechanism how such kind of events lead to policy change can be described with the so-called Advocacy Coalition Framework (ACF) as suggested by Sabatier and Jenkins-Smith (1999). It is a general framework explaining the basic mechanism how shifts in policy making occur, while linking the momentum of crisis to the consequential policy initiatives arising from it (Nohrstedt, 2005).

Figure (4.1) sketches the basic concept in a simplified version. According to Sabatier and Weible (2014, p. 191), (1) policy making takes place among spe-

[3]There are many terms in the literature which relate to the concept of "crisis." These concepts refer to different situations in academic discourse, however, they are clearly related (Boin and 'T Hart, 2007). They can be defined as a situation of large-scale public dissatisfaction, where communities perceive an urgent threat to core values of life or even fear stemming from an unusual degree of social unrest or economic problems or even threats to national security (Keeler (1993); Flanagan (1973); Rosenthal et al. (2001)). Both crises and disasters deal with events that belong in the "un-ness" category: unexpected, undesirable and often unmanageable situations Hewitt (1983).

cialists (macro perspective) who are influenced by many factors of the political as well as the socio-economic system; (2) actors decide within lines of certain political and social context, even if once taken decisions may not necessarily be perfectly rational (micro perspective)[4] and (3) actors need to form *advocacy coalitions* in order to have a say in the political process (meso perspective).[5] As a consequence, subgroups emerge which share common expertise, interests, and beliefs. It is the coalitions that take influence on the decision-making process within a given political subsystem, which eventually results in the specific design of the institutional frame or the (re-)distribution of resource.[6]



Source: Adapted from Sabatier and Weible (2014)

Figure 4.1 Advocacy Coalition Framework

The emergence and the development of political subsystems are determined by the *opportunity structure* constituted by actors, subgroups, and the prevailing participation pattern. The more diverse beliefs or attitudes, the more difficult to form coalitions. Some coalitions may remain uninfluential because of their *(short-term) resource constraints*, or they may simply lack the funds to make themselves be heard in the political process.

Whether a policy change is actually initiated or not, depends on various factors. The political proximity as well as the geographic proximity play a decisive role (Keeler, 1993; Flanagan, 1973; Rosenthal et al., 2001). The closer political

[4]This micro concept is taken from social psychology and is in contrast to rational choice theory. The concept refrains from the orthodox economic approach of methodological individualism. Decision making is not performed in isolation as if actors behave purely rationally. Conversely, the ACF follows the normative grounds of March and Olsen (1996), who argue that decisions are made in accordance with the "logic of appropriateness" and the "logic of consequences"; decision makers follow rules and intend to maximize good consequences. Compare Sabatier and Weible (2014, p. 194). This also explains the inertia in the political system; it is not sufficient when individuals change their mind. It needs the majority of a group to come to new beliefs and convictions. Only if the majority shares new common attitudes, beliefs, or interests, a change in the coalition's strategy can occur.

[5]With regard to an endogenous concept of change, rule-based behavior, and meso economics, see also Dopfer and Potts (2008), Dopfer (2004), and Dopfer et al. (2004), respectively.

[6]It shall be stressed that coalitions are not confined to political parties rather than any kind of participant in the political process such as interest group leaders, journalist, or researchers.

parties' proximity, the simpler a consensus to achieve. The more geographically concentrated the point of interest, the less difficult the opinion-forming process. Also, the political system itself may represent an inhibiting factor, since the inert institutional setting of a political system, may create a "... policy equilibrium, that cannot be changed from within." (Nohrstedt and Weible, 2010, p. 3). Hence, an external shock can help destruct the political equilibrium and initiate a policy change (Nohrstedt and Weible, 2010). Whether the effect of a crisis is long lasting or not, depends on the severity of the crisis: the bigger the cause, the bigger the impact (Keeler, 1993; Flanagan, 1973; Rosenthal et al., 2001). But it is also conceivable that small events have a large and enduring political consequence (Pierson, 2000). Further complexity is added by the fact that not all system parameters are stable over time. Some are rather stable, such as the constitutional structure, the social structure, or the socio-cultural values within society, others may change substantially, such as the public opinion or the socio-economic conditions. The wholistic approach of the Advocacy Coaltion Framework (ACF) captures all these factors that take impact on the participating subsystems within the political decision-making process.

4.2.2 A Simplified ACF for Empirical Testing

For the purpose of this paper, we will not elaborate any further on the ACF as such. Instead, we intend to use the concept to describe the country-specific context in which external shocks, i. e. nuclear disasters, may have an impact on the political process. To date, most empirical studies focus on case studies.[7] Instead, we want to perform a quantitative study evaluating the impact of external shocks on political activity in 34 OECD countries. For this reason, the ACF has to be simplified even further. The perspective of case studies using the ACF model are quite detailed and differentiate many micro-level parameters which cannot be identified when it comes to country comparisons. To our knowledge, there is no available data set, which would contain all required variables for a detailed description of the underlying mechanisms.[8] As we deal with annual data, we concentrate on system elements trackable on a yearly basis.

On these grounds, we reduce the ACF to an even simpler representation in Figure (4.2). Three building blocks remain in our version of the ACF. The (1) *Relatively Stable Parameters*, as in the original version, reflect the substratum of the *Long-term Coalition Opportunity Structure*, with which we will proxy the persistence

[7]Compare appendix in Sabatier and Weible (2014) for further information.

[8]Not only would we need to identify possible proxies for each element, including their interdependencies, we would also need to have data of higher frequency, since many changes in the political process may occur within days, weeks, or months.

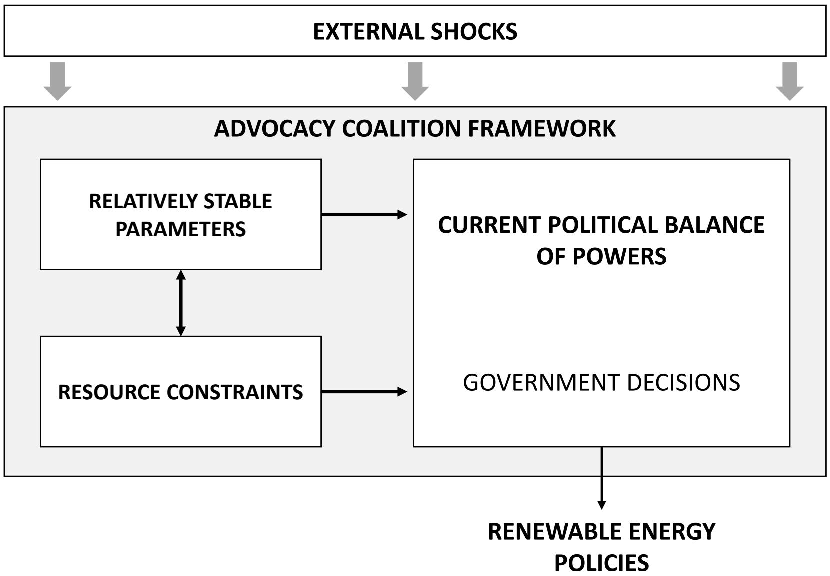


Figure 4.2 Simplified Advocacy Coalition Framework

of the political system of a country, (2) the representation of the country-specific political subsystem, labelled *Current Political Balance of Power*, which is held responsible for decisions made on policy measures, and (3) the resource constraints referring to a country's temporary socio-economic context in which policy making occurs.[9]

Based on the country-specific ACF, we can now look at the effects external shocks have on political activity. Nuclear disasters are major events with great impact on the policy due to their gravity and breadth, as they affect political, environmental, and societal levels. The nuclear events in the last decades, which represent severe external shocks, are the accidents in Chernobyl, Ibraraki, and Fukushima. Their severity can be measured by the International Nuclear Event Scale (INES) introduced by the International Atomic Energy Agency (IAEA) in 1990. The classification ranges from 0 to 7, where 0 means that a nuclear incident has no significant effects on safety and 7 reflects an accident with a "major release of radioactive material with widespread health and environmental effects requiring implementation of planned and extended countermeasures." (IAEA, 2016, p. 3). The accident in Chernobyl in 1986 was rated 7, the accident in the year 1999 in Ibaraki rated 4, and the Fukushima accident 7.[10] In other words, these three accidents can be considered as focusing events, with the potential to trigger a

[9]This is quite different from the understanding of *short-term resource constraints* in the original ACF. In the latter, the constraints relate to the actors of political subgroups. Since this micro-level information is not available across all countries, we interpret resource constraints as the constraints given by a country's economic context.

[10]According to the INES scale, an incident rated 4 or above is considered a severe accident (IAEA, 2016).

policy change. It is expected that they open up an opportunity to bring renewable energy back on the policy agenda and that they not only gain increased attention but turn into actual measures. This is what Baumgartner and Jones (1991) point out: after disasters the agenda experiences a rapid growth, which in the case of nuclear accidents should accordingly translate into an increase in renewable energy policies. Nohrstedt (2008, 2005) investigating the impact of nuclear accidents on nuclear energy policies provide corresponding evidence for the Swedish case. This leads us to the hypothesis that, along the lines of our simplified ACF, the focusing event of a nuclear accident should eventually lead the political system to increase green energy initiatives.

Though a crisis may be a "little push" to catch public attention (Jenkins-Smith and Sabatier, 1994; Kingdon, 2003), an event on its own does not make policy change. Event attributes, as Birkland (1997) and Birkland and Warnement (2013) argue, are important in policy change, the crucial element, however, is the "polictical climate". An event-driven policy change takes place, when problems are matched with feasible solutions together with political concordance (Kingdon, 2003). He refers to this moment as a "window of opportunity". Likewise, Zahariadis (2014) argues that policy windows are a result of problems, i.e crises. Also, windows of opportunity do not open eternally. It depends on the severity of a crisis and the size of a mandate (Keeler, 1993). Therefore, we will also test the hypothesis, whether a timely limit in the "windows of opportunity" can be detected.

Last not least, the historicity of events needs to be considered. A policy change toward green technologies requires the existence of feasible technologies. Without available innovations/inventions, their diffusion is impossible. Nowadays, renewable energy technologies are far more advanced than at the time of the nuclear accident in Chernobyl. This implies that also the kind of policies should have changed over time. While policies supporting research and development should have been prevalent in the 1980's, diffusion-oriented policies should have gradually become more important over the years. This hypothesis we also test in this paper.

4.3 Empirical Protocol

In this section, we describe our econometric protocol and the data with which we proxy the building blocks of our simplified ACF above. We test the effect of external shocks, i. e. nuclear disasters, on political activity in countries. For that, we perform panel data regressions such as two-way fixed effects, pre-sample mean, and count data regressions. Moreover, a heterogeneous dynamic panel regression shall help identify the time of shocks to fade out. This information will be used as a proxy for the timely limit of the windows of opportunity with which we will recalculate previous panel regressions. In addition, the distinction between types of policies will shed light on the change in policy making over time, as diffusion-oriented policies should gain importance while the role of R & D-oriented policies should decline.

4.3.1 Data

The data we collected is an unbalanced panel data set of 34 OECD countries from 1980 to 2015. Thereof, the information about renewable energy policies (REP) stems from the International Energy Agency (IEA). The data on the *Relatively Stable Parameters* we took from Scartascini et al. (2018). Economic indicators to proxy *Resource Constraints* were retrieved from the OECD database. Energy prices and further information about countries' energy production system also come from the IEA.

As dependent variable throughout all regressions, we use the number of renewable energy policies in force during a given year. As in Johnstone et al. (2010a); Nesta et al. (2014), and Dasgupta et al. (2001), we build a policy index by counting the number of effective renewable energy policies by country, see Figure 4.3. The time span of effectiveness can be derived from the reported information about the year of adoption and expiration of the renewable energy policy. The aggregated index covers all available types of renewable energy policies.[11] The drawback of this variable is that it does not compare on a cardinal basis, nor does it provide any information about the actual scope of a policy. In addition, the aggregation across different types of renewable energy policies in a single index incurs a loss of information in terms of policy-specific individual effects (Johnstone et al., 2010a). Nevertheless, it allows us to track the activity level of policy makers.

Whether natural disasters matter, certainly depends on their magnitude. The extent of nuclear disasters is classified according to the International Nuclear Event Scale (INES) introduced by the International Atomic Energy Agency (IAEA) in 1990.[12] The classification ranges from 0 to 7, where 0 means that a nuclear incident has no significant effects on safety and 7 reflects an accident with a "[m]ajor release of radioactive material with widespread health and environmental effects requiring implementation of planned and extended countermeasures."(International Atomic Energy Agency, 2008, p. 3).

Concerning the three accidents we chose for our analysis, they all are considered

[11] The IEA also reports different kinds of policies such as policies considered *economic instruments*, *regulatory instruments*, *policy support* and *information and education*.
[12] See International Atomic Energy Agency (2008).

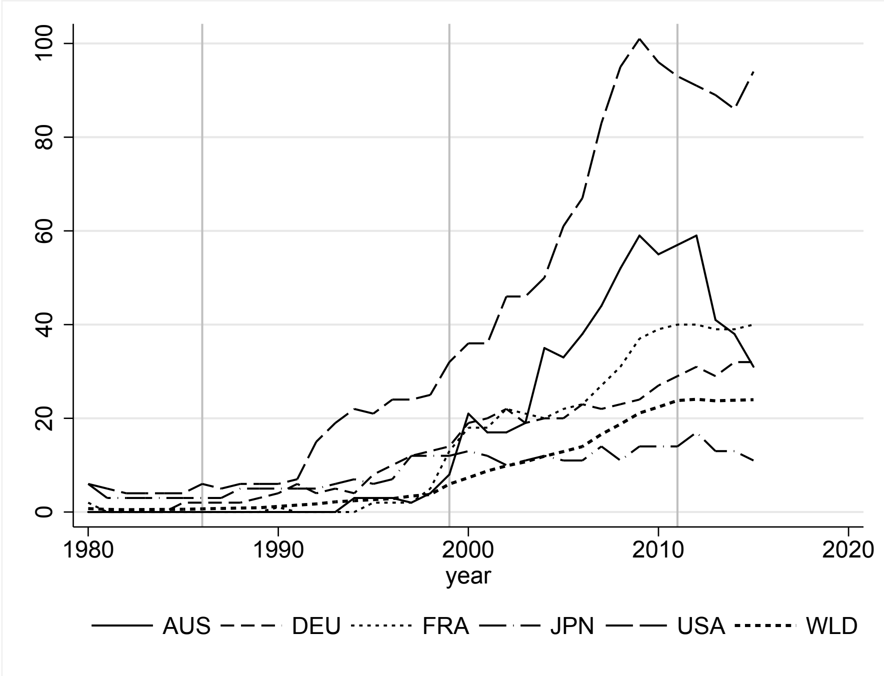


Figure 4.3 Accumulated Renewable energy policies Index. Vertical lines indicate the nuclear accidents. Source: own calculations from IEA data.

major accidents with an INES level of at least 4. The accident in Chernobyl in 1986 was rated 7, the accident in the year 1999 in Ibaraki Tokaimura rated 4, and the Fukushima accident 7. In other words, these three accidents can be considered as focusing events, which eventually may impact the political decision-making process.

ACF model parameters:

To proxy the *Relatively Stable Parameters* of the ACF, we select the variable *Established Democracies* from the Database of Political Institutions 2017 (Scartascini et al., 2018). It counts the number of years when a country has been democratic. In the case of countries that have been democratic even before 1980, this variable represents a monotonously increasing line with slope one.

A further indicator of this database that we use, is the variable *Autonomous Region*. This variable indicates, whether a region can make autonomous decisions independently from some other institutional authority. If a region is independent, it can pass its own legislation without the need to be granted a permission from some other authority. This in turn should enable regions to be more active and pass more green policies in the aftermath to nuclear disasters.

As a control for the *Current Political Coalition*, we use the variable *Party orientation* from the same database. It indicates the political orientation for the formed coalition. It assigns value (1) for right-wing, (2) for center, (3) for left-wing.

The variable *Resource Constraints* is proxied by several variables to control for the economic context and the scope for initiating renewable policies in countries.

Control variables:

Energy price: shrinking fossil fuel sources will increase energy prices. This, in turn, should also increase the incentive to search for alternatives and therefore foster policies supporting renewable energy production. Data on end-user electricity prices in both residential and industrial sectors were collected from the IEA database. The calculated price index was constructed by averaging the price indices for both sectors, similar to Johnstone et al. (2010b) or Nesta et al. (2014).

Whether countries have the scope to invest in new technologies, also depends on available funds in countries. The *GDP per capita* will, therefore, serve as a further control for a country's resource constraints.

To control for the structure of the energy production system, we will also use the total installed capacity in energy production, the amount of energy produced by renewables as well as the share of renewables in total primary energy supply. All the variables, except for the shocks and the ACF parameters are logged.[13] For robustness checks, however we will be using both forms of the dependent variables (absolute and logged values).

Table (4.1) collects the summary statistics of variables and additional correlation table can be found in appendix (table A.6).

Name	Unit	Obs	Mean	Std_dev	Min.	Max.
REPs	number	1224	1.475	1.281	0	4.625
GDP p. c.	Billion US$ (2005)	1152	10.22	0.443	8.535	11.42
Total Capacity	Installed MW	1220	9.856	2.504	0	14.87
Renewables gen.	KTOE	1204	8.004	1.755	1.269	11.94
Share of Renewables	% of total supply	1204	13.05	15.59	0.0100	89.75
Energy price	US$ per unit (2005)	1130	4.630	0.529	0	5.763
Established Democratic	number	1175	43.57	26.41	1	85
Autonomous Region	Dummy	1175	0.254	0.435	0	1
Party orientation	Indicator	1063	1.898	0.920	1	3

Table 4.1 Descriptive statistics (time span: 1980-2015)

[13]This transformation smooths the skewness of the data and brings it closer to a normal distribution. It also reduces the influence of exterme values, i. e. possible outliers. Moreover, the estimated coefficients of the so-called log-log-model offer a convenient way for interpretation, as they represent changes measured in elasticities.

4.3.2 Econometric Specification

To test whether nuclear shocks positively correlate with political activity, according to the stylized ACF in Figure (4.2), we state the following basic econometric specification:

$$\mathrm{REP}_{it} = \beta_0 + \boldsymbol{\nu}'\mathbf{N}_{it} + \boldsymbol{\rho}'\mathbf{R}_{it} + \boldsymbol{\phi}'\mathbf{S}_{it} + \boldsymbol{\psi}'\mathbf{P}_{it} + y_t + \mu_i + \epsilon_{it} \tag{4.1}$$

with $i = 1, 2, .., n$ as number of countries, $t = 1, 2, .., \mathrm{T}$ as time span, and REP_{it} as dependent variable. A constant term is assumed with β_0. The nuclear disaster dummies are summarized in vector $\mathbf{N}_{it}$ with the associated coefficient vector $\boldsymbol{\nu}$. The controls referring to the ACF are contained in the following vectors: $\mathbf{R}_{it}$ for *Resource Constraints* with $\mathbf{R}_{it}$ = {GPD p.c., Total Capacity, Renewables gen., Energy price}, $\mathbf{S}_{it}$ for *Relatively Stable Parameters* with $\mathbf{S}_{it}$ = {Established Democracies, Autonomous Region}, and $\mathbf{P}_{it}$ for *Current Political Balance of Powers* with $\mathbf{P}_{it}$ = {Party orientation}; the associated coefficients are $\boldsymbol{\nu}$, $\boldsymbol{\rho}$, and $\boldsymbol{\phi}$, respectively. For two-way fixed effect models, y_t and μ_i denote the time and country fixed effects, respectively.

4.3.3 Procedure

In a first step, we run linear panel regression models on the pooled sample. Beforehand, we perform several unit-root and cointegration tests. Since the panel as a whole is unbalanced, we draw on the augmented Dickey-Fuller unit-root test (see appendix A.3).[14] The null hypothesis of the panel containing a unit root can be rejected with a p-value of 0.0054. For cointegration, we run the Kao test and the Pedroni residual cointegration test (see appendix tables A.4 and A.5), which we performed using STATA 15.

The analysis begins with LSDV models, table 4.2, presented in equation 5.1. These models are applied to test the first hypothesis, whether nuclear accidents exert a positive impact on the number of adopted renewable energy policies, in the aftermath of a nuclear accident. To check the robustness of the results, additional pre-sample mean and binomial regression models are added, presented in tables 4.2 and 4.3. Then, to calculate the effectiveness of the “window of opportunity”, we apply a Dynamic Heterogeneous Panel Model presented in table 4.4. In table 4.6, we split the policies into R & D and diffusion policies to test our third hypothesis, whether we can observe a change in the type of policy measures. We expect that at the beginning of the period under consideration R & D supporting policy

[14] In addition, as the dependent variable has no missing values, we add table A.2 in the appendix with additional unit-root tests for robustness.

measures should prevail, whereas in later time, diffusion-oriented policy should gain importance.

4.4 Results

Table (4.2) shows the first five models. Using logged values in regression allows us to interpret estimated coefficients as elasticities.[15] So we take logs of the dependent variable REP (renewable energy policies). In later models, we use unlogged values when we turn to count data models, since the dependent variable REP is countable.

Model (1) in table (4.2) regresses REP on the three dummy variables: Chernobyl, Ibaraki, and Fukushima, which represent the starting point of the periods after the respective nuclear disaster. Simultaneously, we included panel fixed effects (FE) to account for unobserved heterogeneity.[16] After the accident in Chernobyl in 1986, the average number of effective renewable energy policies increases significantly, which is also the case for the accidents of Ibaraki and Fukushima. Adding resource constraints, i. e. GDP p.c, Total Capacity, Renewables gen., and Energy price as controls in model (2) leaves the significance of the coefficients of the nuclear disaster dummies unchanged, except for the Chernobyl dummy. Concerning the controls, the coefficient of GDP p.c. is significant and positive as to be expected. Countries with a higher per capita income should also have the financial capacity to induce a costly green policy change and pass more renewable energy policies. They might be less financially constraint.[17] Total Capacity takes a significantly negative coefficient. If the share in renewable energy production increases, so does the number of renewable energy policies. The control *Energy price* refers to the standard textbook argument that increasing prices simultaneously increase the attractiveness to invest in new technologies – a relationship that governments try to exploit through passing supportive policy measures. Alternatively, model (3) includes the stable system parameters *Established Democracies* and *Autonomous Region* as well as the *Balance of Powers* indicator variable Party orientation. The coefficient for Established Democracies is positive and significant, indicating that the longer a country has experienced democracy, the more active it is in renewable policy making. The autonomy of a country also plays a positive role in renewable

[15] See also footnote 12 for further advantages of logging variables.

[16] The Hausmann tests suggests to use a fixed-effect model.

[17] GDP p. c. is a blurred proxy for financial constraints of and within a country. In regard to the adoption of green energy technologies, however, access to financial funds is crucial. Because of the risks involved in renewable energy projects and the uncertainty of their returns, as argued by Taghizadeh-Hesary and Yoshino (2019), Yoshino et al. (2019), or Taghizadeh-Hesary et al. (2017), the actual adoption of those technologies hinges on these institutional settings, which, unfortunately, we could not capture in our regressions, because of the lack of a control variable available for all countries.

energy policies. If countries reflect an Autonomous Region in their policy making, they pass more policy initiatives in renewable energy.

Combining the two groups of constraints, resource (model 2) and political (model 3), introduces high multicollinearity, rendering the estimation inefficient, though consistent. Model (4) reports the respective results;[18] additionally, year fixed effects are included. Aside from Chernobyl also Fukushima loses its significance. Only Ibrahaki remains significant. Model (5) replicates the previous model. Instead of the fixed-effects estimator, we use a pre-sample mean (PSM) approach.[19] With all controls included, Ibaraki and Fukushima remain significant and positive.

In the next step, we concentrate on the fact that the dependent variable REP is count data. Table (4.3) reports three count data models. Because of overdispersion, we use negative binomial regression instead of Poisson regression.[20] In all models, the resource constraint variables take the same sign as in the previous models and they are significant. In model (7), we alternatively use the share of renewable energy production instead of the absolute amount of production as in the remaining models.[21] All coefficients of the system parameters which remain significant also keep their sign. The Balance of Powers coefficients for left-wing coalitions are throughout positive (Party orientation=L).[22] This suggests a positive effect of a left-wing coalition in governments passing significantly more renewable energy policies than other constellations.

Models (6) to (8) uses the standard fixed-effects estimator of Hausman et al. (1984), model (8) applies the pre-sample mean (PSM) estimator by Blundell et al. (2002) and uses information before the actual years of investigation; in our case, the pre-sample mean is calculated from the years 1975 to 1979.[23] As the PSM coefficient in model (8) shows, there is significant unobserved heterogeneity across countries. Moreover, models (7) and (8) include year fixed effects.[24] The coefficient of Autonomous Regions becomes significant in all three models. Concerning Party orientation, left-wing parties seem to pass more green energy policies than the remaining ones. The coefficients of main interest, i.e. the coefficients of the nuclear shocks remain always positive and significant except for Fukushima.

[18] The variance inflation factors of Chernobly and Ibaraki are far beyond 10.

[19] The advantage of the PSM estimator is that the loss of information is less compared to the Hausman et al. (1984) fixed-effect estimator, which simply demeans all variables wiping out a major part of level effects. In addition, the PSM estimator has better finite sample properties (Nesta et al., 2014).

[20] An LR-test rejects the null of a unique parameter λ for the first two moments.

[21] Due to multicollinearity, we did not include both variables simultaneously into regressions.

[22] For ease of reading, we recoded the variable Party orientation as in the following: left wing (=L), right wing (=R) and center (=C).

[23] In contrast to the remaining variables, the policy measure variable (Rep) contains a longer time span, starting in 1975. This allows calculating a pre-sample mean without loss of information.

[24] The inclusion of years dummies takes away the significance of some of the control variables.

VARIABLES	(1) FE	(2) FE	(3) FE	(4) LSDV	(5) PSM
Chernobyl	0.399***	0.116	0.109	0.110	0.094
	(0.075)	(0.109)	(0.165)	(0.189)	(0.093)
Ibaraki	1.609***	1.070***	1.091***	1.225***	1.035***
	(0.108)	(0.151)	(0.236)	(0.159)	(0.137)
Fukushima	0.728***	0.356***	0.356**	-0.135	0.269***
	(0.068)	(0.083)	(0.155)	(0.126)	(0.084)
GDP p.c. (in logs)		1.346***		0.291	0.574**
		(0.430)		(0.183)	(0.274)
Total Capacity Mw		-0.112***		-0.043**	-0.058**
		(0.032)		(0.019)	(0.027)
Renewables gen. (in KTOE)		0.205*		0.051	0.165**
		(0.115)		(0.038)	(0.069)
Energy price (in logs)		0.525***		0.223***	0.542***
		(0.159)		(0.072)	(0.152)
Established Democratic			0.045**	0.038***	0.020***
			(0.018)	(0.008)	(0.005)
Autonomous Region			0.221	0.131	0.150
			(0.281)	(0.104)	(0.172)
Party orientation = C			-0.069	-0.031	-0.024
			(0.079)	(0.065)	(0.055)
Party orientation = L			-0.034	0.031	0.017
			(0.063)	(0.037)	(0.069)
Pre-sample Mean					0.468
					(0.335)
Constant	0.282***	-15.834***	-1.169**	-4.591***	-9.145***
	(0.077)	(3.517)	(0.547)	(1.692)	(2.509)
Observations	1,224	1,057	1,063	955	955
R-squared	0.773	0.821	0.800	0.857	
R2 adj.	0.772	0.820	0.799	0.845	
Number of ctry	34	33	33	32	32
Year dummies	no	no	no	yes	no
Fixed effects	yes	yes	yes	yes	no

Standard errors in parentheses — *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: All regressions include robust standard errors.

Table 4.2 Linear regression models. Dep. variable: ln(REP)

One of the caveats in the regressions above is the treatment of the nuclear disaster dummies. Before the disaster, the respective dummy is 0, after the accident it remains 1 till the end of the observed time span. One may argue that the effect of a nuclear disaster opening up a window of opportunity for a policy change is not lasting eternally, but fades out after some time. The length of effectiveness of a shock, we identify via Dynamic Heterogeneous Panel Models (DHPM). The technical description can be consulted in appendix A.1. This technique is based on an autoregressive distributed lag model, it includes an error correction, and allows addressing endogeneity issues. In a nutshell, it estimates a long-run dynamic to which the system returns after an exogenous shock, and additionally, it estimates short-run effects.

Dep. variable: REP

	(6) NBREG	(7) NBREG	(8) NBREG
Chernobyl	0.540***	0.565***	0.453***
	(0.141)	(0.141)	(0.119)
Ibaraki	1.140***	1.131***	0.958***
	(0.080)	(0.083)	(0.074)
Fukushima	0.035	0.023	-0.015
	(0.050)	(0.051)	(0.048)
GDP p.c. (in logs)	1.075***	1.117***	1.243***
	(0.261)	(0.264)	(0.269)
Total Capacity (in Mw)	-0.110***	-0.088***	-0.098***
	(0.033)	(0.034)	(0.030)
Renewables gen. (in KTOE)	0.144***		0.064
	(0.049)		(0.044)
Gen. share of Renewables (in %)		0.014*	
		(0.007)	
Energy price (in logs)	1.055***	1.074***	1.163***
	(0.093)	(0.092)	(0.098)
Established Democracy	0.016***	0.018***	0.019***
	(0.006)	(0.007)	(0.006)
Autonomous Region	0.341**	0.446***	0.263*
	(0.167)	(0.160)	(0.150)
Party orientation = C	0.062	0.058	0.017
	(0.078)	(0.077)	(0.078)
Party orientation = L	0.075**	0.077**	0.088***
	(0.034)	(0.033)	(0.031)
REP psm			2.707**
			(1.143)
Constant	-15.985***	-15.666***	-18.099***
	(2.415)	(2.431)	(2.451)
Observations	955	955	955
Number of ctry	32	32	32
Fixed effects	yes	yes	yes
LL	-1953	-1955	-1944

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.3 Count data regressions

In models (9) to (11) in table (4.4), we report three dynamic heterogeneous panel models. As the Hausmann test suggests, we apply dynamic fixed-effects estimation. The long-run variables contain the same variables as in previous models except for Established Democracies, because all three models calculate a long-run trend with which the variable Established Democracies is in conflict due to multicollinearity. For the short-run, we include nuclear shock dummies, although in an aggregated manner by adding up all three dummy variables. Because the short-term variables are differenced in this error-correction model, dummy variables were infeasible, therefore we aggregated the three accidents and built a single variable

Dep. variable: ln(Rep)

	VARIABLES	(9)	(10)	(11)
Long run	Chernobyl	-0.166	-0.367	-0.331
		(0.253)	(0.281)	(0.250)
	Ibaraki	0.702***	0.462*	0.553*
		(0.222)	(0.261)	(0.303)
	Fukushima	2.283***	1.858***	1.502***
		(0.323)	(0.303)	(0.244)
	GDP p.c. (in logs)		1.456**	1.381
			(0.729)	(0.961)
	Total Capacity Mw		-0.084	-0.070
			(0.082)	(0.070)
	Renewables gen. (in KTOE)		0.176	0.195
			(0.182)	(0.139)
	Energy price (in logs)			0.470
				(0.342)
	Autonomous Region			-0.172
				(0.274)
	Party orientation			-0.093
				(0.084)
Short run	EC	0.097***	0.117***	0.141***
		(0.014)	(0.016)	(0.021)
	Nuc accidents	0.127***	0.132***	0.144***
		(0.028)	(0.031)	(0.042)
	Gen. share of Renewables (in %),		-0.000	0.000
			(0.006)	(0.006)
	Constant	-0.029	1.717**	2.257*
		(0.020)	(0.797)	(1.207)
	Observations	1224	1104	955
	Number of countries	34	34	32
	R2 adj.	0.262	0.275	0.282

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.4 Dynamic Heterogeneous Panel regressions

collecting the three accidents.[25] The long-run coefficients indicate a persistently positive and significant effect on the number of renewable policies only for Ibaraki and Fukushima. The short-run analysis, illustrated in the lower part of this table, also suggests significantly positive effects of nuclear disasters on renewable energy policies. Equivalently, nuclear disasters correlate in the short run positively with the number of renewable energy policies.

The statistic of this table, in which we are particularly interested, is the so-called error correction term (EC). The EC coefficient is significant and ranges from 0.097 to 0.14. This indicates that serial correlation is present in our data. Unless we correct for serial correlation, this leads to inconsistent estimates. Since the EC coefficient reports the required error correction, its interpretation is straight

[25]Including further variables in the short-run part of the models prevents models to converge.

forward. It denotes the persistence of shocks. After a shock, the system returns to the long-run equilibrium after about $1/0.141 = 7$ years. In other words, a shock such as a nuclear disaster, which increases political activity, fades out after about 7 years. This result can be interpreted as the length of the window of opportunity.

These results we use for a further robustness check. Again, we rerun the preferred models form above while changing the nuclear accident dummy variables to windows. That is, before the accident the dummy remains 0, after the accident it takes the value 1 for 7 years to finally return to 0. The results are presented in Table 4.5. The treatment of the nuclear accident dummies also allows us to include year dummies, because multicollinearity becomes less prevalent. Hence, model (12) reports the results of a two-way fixed-effects model with a 7-year window for each nuclear accident dummies. All three dummies are positive and significant, which supports the hypothesis that more renewable energy policies are passed after a nuclear accident.

In model (13), we include all control variables, which makes the Chernobyl dummy lose significance. Taking the count data quality of the dependent variable into account, as done in model (14), Chernobyl remains insignificant, whereas the Ibaraki and Fukushima dummies are positive and significant. The control variables keep their signs, if significant. Hence, also with a window of 7 years, which we inferred from the dynamic heterogeneous panel regressions in table (4.4), we still observe that nuclear accidents have a significant effect on political activity in countries. To check for robustness, we additionally tried a 5-year (model 15) and a 9-year (model 16) window for the nuclear shock dummies. Model 15 provides less explanatory power comparing the R^2-values between this model and model (13). Model (16) generates the same goodness of fit as model (13), in other words, it does not add more information. Hence, we pick model (13) as the preferred model being in line with the PMG estimations in table (4.4).

Except for Chernobyl, the results of our regression models suggest a robust correlation between nuclear accidents and renewable energy policies. The fact that no significant effect, despite the severity of the nuclear accident in Chernobyl, could be detected may have several reasons: first, the large geographical distance and the different type of reactor used in Ukraine compared to those used in Western Europe or in the USA (Nohrstedt, 2008). Second, it could be the restricted technological opportunities in 1986. Renewable energies could not be introduced as a solution, after the accident, owing to their immaturity level at the time and the fact that they could not maintain a stable and sufficient energy supply (Trainer, 1995).

Taking the historicity of technical change into account, we now test, whether the type of policy changes over time. As argued above, while technological opportunities, in terms of green technologies, were limited in the 1980's, it seems straight

Dep. variable: ln(REP) for LSDV and REP for NBREG					
	(12)	(13)	(14)	(15)	(16)
VARIABLES	LSDV	LSDV	NBREG	LSDV	LSDV
Chernobyl	0.333***	-0.152	0.375	-0.165	-0.049
	(0.116)	(0.162)	(0.363)	(0.173)	(0.199)
Ibaraki	2.044***	1.009***	2.051***	0.877***	1.074***
	(0.116)	(0.240)	(0.352)	(0.276)	(0.320)
Fukushima	2.710***	1.200***	2.405***	1.200***	1.200***
	(0.116)	(0.309)	(0.392)	(0.334)	(0.334)
GDP p.c. (in logs)		0.291	0.848***	0.291	0.291
		(0.183)	(0.266)	(0.419)	(0.419)
Total Capacity Mw		-0.043**	-0.111***	-0.043	0.043
		(0.019)	(0.032)	(0.027)	(0.027)
Renewables gen. (in KTOE)		0.051	0.093*	0.051	0.051
		(0.038)	(0.051)	(0.113)	(0.113)
Energy price (in logs)		0.223***	0.591***	0.223	0.223
		(0.072)	(0.120)	(0.143)	(0.143)
Established Democratic		0.038***	-0.002	0.038***	0.038***
		(0.008)	(0.007)	(0.010)	(0.010)
Autonomous Region		0.131	0.227	0.131	0.131
		(0.104)	(0.150)	(0.267)	(0.267)
Party orientation = C		-0.031	0.071	-0.031	-0.031
		(0.065)	(0.072)	(0.059)	(0.059)
Party orientation = L		0.031	0.066*	0.031	0.031
		(0.037)	(0.034)	(0.065)	(0.065)
Constant	0.313***	-4.591***	-10.105***	-4.591	-4.591
	(0.082)	(1.692)	(2.497)	(3.759)	(3.759)
Observations	1,224	955	955	955	955
R-squared	0.837	0.857		0.837	0.857
Number of ctry	34	32	32	32	32
Year dummies	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes
Window (years)	7	7	7	5	9
LL			-1895		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5 Windows size for 7 years. Additional 5 and 9 years windows are added for robustness checks.

forward to pass R & D-oriented policies. With increasing technological progress, diffusion-oriented policies should gain in importance. Having the opportunity to decompose our dependent variable from being an aggregated index to single policy types, we may shed light on the kind of policies introduced after the respective nuclear accidents. We decompose the dependent variable (REP) into two categories: policies with an explicit focus on R & D and those designed to boost the diffusion of renewable energy production technologies. We hypothesize that after an early accident like Chernobyl an increase in policies supporting research and development should occur. Conversely, we would expect that after Ibaraki and Fukushima diffusion policies should have prevailed.

4.4.1 R & D versus Diffusion-oriented Policies

Table (4.6) documents the results for the two types of renewable policy measures. Model (17) and (18) regress the number of R & D-oriented policies on the nuclear dummies and the controls, respectively. The dummy for the Chernobyl accident is insignificant, the dummies for Ibaraki and Fukushima significantly positive in model (17). With the controls, as used in the previous models, this does not change. And an increase in R & D policies, to foster the development of renewable energy technologies, can only be detected after Ibaraki and Fukushima. Note that both models, (17) and (18) contain a full set of year and country dummies. Moreover, the calculations were exerted with a 7-year window for the nuclear accident dummies. The preferred model, according to a likelihood-ratio and a Wald test, respectively, is model (18). The full model renders a statistically significant improvement in model fit compared to the nested model (17).

Model (19) and (20) perform the same exercise using the number of diffusion-oriented renewable energy policies. Including year and country dummies in addition to 7-year windows as nuclear accident dummies, the cross-correlation between the nuclear accident dummies and the number of active, diffusion-oriented policies renders all three nuclear dummies positive and significant. Hence, an increase in diffusion-oriented policies emerged after Chernobyl. However, when including the controls, which all have the expected signs in case they are significant, the coefficient of the Chernobyl dummy loses its significance. We also performed post estimation tests such as a likelihood-ratio and a Wald test: model (20) appears to be a better fit than model (19) and the coefficients of the added control variables are significantly different from zero, indicating that model (20) is more informative. In sum, we could not identify that R & D-oriented policies lose in importance, while diffusion-oriented policies gain in importance.

4.5 Discussion

Overall, we observe an elevated political activity in renewable energy support across countries after nuclear accidents. The results, however, have to be put into perspective. In table (4.2), only model (1) and (5) pass the specification test of an omitted variable bias, model (2), (3), and (4) do not. In addition, model (4) suffers from high multicollinearity. Hence, model (5) is the preferred model supporting the hypothesis that after external shocks policy activity increases – as far as Ibaraki and Fukushima are concerned.

Using count data models (table 4.3), the Chernobyl dummy becomes significant and the Fukushima dummy insignificant. Distinguishing between a short-run and

VARIABLES	(17) NBREG (R & D)	(18) NBREG (R & D)	(19) NBREG (DI)	(20) NBREG (DI)
Chernobyl	0.511	0.409	0.861***	0.204
	(0.422)	(0.498)	(0.261)	(0.276)
Ibaraki	2.209***	2.076***	2.900***	1.616***
	(0.351)	(0.511)	(0.227)	(0.274)
Fukushima	2.693***	2.440***	3.584***	1.852***
	(0.344)	(0.559)	(0.225)	(0.294)
GDP p.c. (in logs)		0.045		1.166***
		(0.541)		(0.262)
Total Capacity Mw		0.024		-0.129***
		(0.074)		(0.030)
Renewables gen. (in KTOE)		0.057		0.046
		(0.107)		(0.049)
Energy price (in logs)		0.346		0.814***
		(0.248)		(0.115)
Autonomous Region		0.234		0.434***
		(0.237)		(0.140)
Party orientation = C		0.325**		0.034
		(0.130)		(0.070)
Party orientation = L		0.109*		0.072**
		(0.059)		(0.031)
Constant	-0.176	-2.843	0.081	-13.561***
	(0.341)	(5.278)	(0.227)	(2.552)
Observations	1,296	955	1,224	955
Year dummies	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes
Window = 7 years	yes	yes	yes	yes
LL	-1141	-936.9	-2423	-1961

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6 R & D and Diffusion Policies

a long-run perspective (table 4.4), the DHP-models maintain the significance of the dummies for Ibaraki and Fukushima. As these regression models contain and error correction, we can calculate the average time span of a "window of opportunity", which amounts to about 7 years. Taking this information into account in previous regressions, as reported in table 4.5, the correct version in model (14) is the preferred model. It advocates again that there is a significantly positive effect on policy activities after the nuclear accidents in Ibaraki and Fukushima.

The only exception is the effect for Chernobyl, which is mixed. Only in a few models, we could identify a significant correlation between the shock and policy measures. Hence, there is no robust evidence in the case of Chernobyl. There could be various explanations for this result. In 1979, before the starting year of our data set, there had already been a nuclear accident on Three Mile Island, which was rated 5 on the INES-scale (Broughton et al., 1989). Hence, the time span between Three Mile Island and Chernobyl are only seven years, the length of the window of opportunity we calculated and consequently, the differential impacts of both accidents have become unidentifiable. This is in line with Nohrstedt (2005) arguing that some countries such as Sweden responded immediately after Three Mile Iland by initiating renewable energy programs so that later on, policy makers were already alert and unlikely to take additional measures as a response to the accident in Chernobyl.

Another angle for explaining the aforementioned effect of Chernobyl disaster, is the public "perception of need" for nuclear energy, as argued by Bisconti (2018). In 1980s, renewable energy technologies were considered complementary energy sources alongside nuclear energy, rather than a reliable substitution (Trainer, 1995). Therefore, the public saw a need for nuclear energy and thus the impact of relevant accidents on their attitudes was low. For instance, the decline in public acceptance for nuclear energy in the US faded out only three months after the Chernobyl accident (Bisconti, 2018). While in the UK the level of support in 1987 was back to its initial values as before the accident (Renn, 1990; Rosa and Dunlap, 1994). This, in turn, was translated in a lower activity on political level (Flavin, 1987).

A further explanation could be that the index is blurred by aggregation. Renewable energy policies are quite diverse. Some focus on the development of new technologies, others focus on the diffusion of renewable energy technologies. The state of the art of renewable energy technologies was certainly different at the time of each accident. One might expect that more R & D policies should be identifiable after Chernobyl. Likewise, diffusion-oriented policies should be more frequent after Fukushima, because of the advancements in renewable energy technologies. While there is evidence for an increase in both policy types after Fukushima and Ibaraki, no strong empirical support was found for either of the policies after Chernobyl. The two preferred models in table 4.6, model (18) for R & D-oriented policies and model (20) for diffusion-oriented policies, do not provide empirical evidence to support this hypothesis. With respect to the theoretical foundation, the conceptual model, chosen from communication science, describes the underlying mechanism of policy change. The architecture of this concept consists of several dimensions. It contains a micro, a meso, and a macro perspective to trace individual behavior via the formation of subgroups to coalitions which finally take influence on the political decision-making process. With the data at hand, the empirical exercise cannot give any insights neither on the micro nor on the meso level. We assume the aggregated elements of the system as given and thus construct the context in which external shocks unfold, either leading to policy change or not. As claimed beforehand, this paper is just a first attempt to quantify the most general propositions of the ACF. Certainly, it needs a more in-depth analysis both of the theoretical as well as of the empirical perspective.

With respect to the empirical layout, a further weakness of the analysis roots in the discrepancy between the frequency of events in the political decision-making process and the frequency in the data. Political change is discontinuous and occurs often within a shorter time than associated with annual data. Hence, we cannot claim to provide evidence on the complete causal chain from nuclear accidents to actual policy change. For this, we would require data of higher frequency (e.g., monthly). Thay is why most studies concentrate on case studies, because for a country-level comparison, such kind of meticulous investigation remains tedious (Hogan and Feeney, 2012; Nohrstedt, 2005, 2008), but should be pursued in future research.

4.6 Conclusion

The empirical study presented here is a first step toward quantifying the effect of external shocks, i. e. nuclear disasters, on political activity in renewable energy policy making. As for the theoretical foundation, we use the Advocacy Coalition Framework (ACF) which describes the process of how policy change comes along.

The ACF in nature focuses on the formation of advocacy coalitions, beliefs and coordination within and among coalitions (Sabatier and Weible, 2014, 2007; Sabatier and Jenkins-Smith, 1999). With the introduction of the policy network approach and social network analysis (Pappi and Henning, 1998; Schneider, 1992; Leifeld, 2013), the interest has gradually shifted from solely investigating the role of beliefs (Jenkins-Smith and Sabatier, 1994) to the analysis of coordination mechanisms (Ingold, 2011; Lubell et al., 2012; Leifeld, 2013). Partially, this is due to methodological advancements such as the introduction of network analysis into the ACF. In this work, we suggest a frequentist perspective to the ACF.

From a methodological point of view, it is not surprising that the majority of the research work applies qualitative techniques, mostly case studies (Schlager, 1995; Sotirov and Memmler, 2012; Sabatier, 1998, 1987; Henry et al., 2014; Kübler, 2001; John, 2003), because of the inherent complexity of the political process. This challenge becomes even more complex, when it comes to trans-regional comparisons. On these grounds, we tried to add a first, modest, cross-country quantitative view on the ACF. Hence, the contribution of this paper is less in elaborating on micro or meso aspects, which still do require a lot more of research to better understand the process of policy change, but rather provide a first step in applying a quantitative approach to compare political systems across countries based on the main concepts of the ACF. For these reasons, we had to simplify the ACF to a major extent, neglecting many important determinants usually considered within this framework.[26]

In doing this, we give a complementary perspective on the ACF when applying a quantitative approach as we belief that a quantitative replenishment may facilitate detecting commonalities and dissimilarities in policy change across policy systems and regions – i. e. countries. As the results suggest, the aftermath of external shocks (nuclear disasters) point toward an increase in green policy initiatives across countries – evidence which is in line with our main hypothesis that such external shocks function as "focusing events" giving a little push toward green policy change.

A further observation in terms of commonalities, although this concerns the controls of our regression models we did not focus on; yet, it further advocates a quantitative inductive approach: we identified a positive correlation between left-wing parties (beliefs) and an increase in green policy activities. Observing such kind of, to our minds, unexpected commonality is a further advantage of applying a quantitative approach to the ACF. It were an intriguing research question to investigate whether there is an explanation to this correlation or whether it simply is a methodological artefact. This approach nonetheless helps disclose new research avenues.

With respect to the regressions we performed in this study, i. e. OLS, LSDV, negative binomial, pre-sample mean, and dynamic panel regressions, and given the fact that they point toward a positive correlation between nuclear accidents and a subsequent increase in renewable energy policies, we emphasize that we do not claim that these correlations describe a causal chain of political reactions induced by external shocks. We simply tried to find the consequential correlation which should be observable after external shocks to support the hypothesis that external shocks, i.e. nuclear accidents, serve as a focusing event, after which the number of green policies adopted by countries has increased. Solely for Chernobyl, we could not detect robust evidence, although one would expect that energy policies should have surged dramatically thereafter.

In future research, we should consider additional determinants as substantiated e. g. in the policy change literature (Hogan and Feeney, 2012), such as the role of political entrepreneurs being the crucial agents of change (Dahl Robert, 1961). Or in a similar vein, the impetus of political institutions to the extent to which they either are conducive or inhibiting policy change (Hogan and Feeney, 2012). From a modelling perspective, the role of mass media in setting policy agendas must be included (Walgrave and Van Aelst, 2006), since mass media not only influence public opinion but also attract the attention of policy makers to relevant

[26] See e. g. Sabatier and Weible (2014, 2007) or Sabatier and Jenkins-Smith (1999) for all the specificities in the ACF and its research fields.

topics. The holistic picture, as insinuated with the ACF, should help understand the mechanisms that bring along policy change.

To derive explicit policy implications from this empirical exercise seems futile, because external shocks, especially nuclear accidents, are no favorable events people would be longing for in order to induce policy change. It rather is a further evidence to a very sad revelation that policy makers as much as mankind as a whole apparently need disasters to make a change.

Appendix A

A.1 Dynamic Heterogeneous Panel Models

The general model of the dynamic heterogeneous panel estimation, which will be presented here, is discussed by (Blackburne and Frank, 2007; Freeman, 2000; Pesaran et al., 1999).

A.2 General Model

The general model assumes that the input data on time period $t = 1,2,...,T$ and across section groups $i = 1,2,...,N$ can be estimated by an autoregressive distributive lag model ARDL$(p,q,..,q_k)$:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} X_{i,t-j} + \mu_i + \epsilon_{it} \tag{A.1}$$

where X_{it} is the $(k \times 1)$-vector of explanatory variables, λ_{ij} a scalar of constants, δ_{it} the $k \times 1$ coefficient vectors, μ_i the group specific effect and, ϵ_{it} the group specific effect. As T is large enough, each group can be estimated separately. The variables in Eq. 5.2 are cointegrated $I(1)$ and the error term is an $I(0)$ process for all i, therefore, the error correction equation can be reparameterized:

$$\triangle y_{it} = \phi_i (y_{i,t-1} - \beta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \triangle y_{i,t-1} + \sum_{j=0}^{q-1} \delta'^*_{ij} \triangle X_{i,t-1} + \mu_i + \epsilon_{it} \tag{A.2}$$

for $i = 1,2,...,N$ and $t = 1,2,...,T$. The error correction speed of adjustment parameter is expressed as in the following:

$$\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}), \tag{A.3}$$

$$\beta_i' = \sum_{j=0}^{q} \delta_{ij}, \tag{A.4}$$

$$\lambda_{ij}^* = -\sum_{m=j+1}^{p} \lambda_{im} \quad j = 1, 2, ..., p-1 \tag{A.5}$$

and

$$\delta_{ij}^* = -\sum_{m=j+1}^{q} \delta_{im} \quad j = 1, 2, ..., q-1 \tag{A.6}$$

assuming that the ARDL model in Eq. 5.2 is stable in that the roots of $\sum_{j=1}^{p} \lambda_{ij} z^j = 1$ for $i = 1, 2, ..., N$ lie outside the unit circle, ensuring that the error correcting speed of adjustment term $\phi_i < 0$. This implies that there is a long run relationship between the dependent variable y_{it} and the regressors x_{it} . It is calculated as:

$$y_{it} = -(\beta_i'/\phi_i) x_{it} + \eta_{it} \tag{A.7}$$

Estimators for Heterogeneous slopes

Micro panels with small time series (T) and a large number of cross section observations (N) usually rely on either fixed effects, random effects, static fixed effect (SFE), or a combination of those (Arellano and Bond, 1991). As Pesaran and Smith (1995) point out, with large T, such traditional estimators may generate inconsistent results, because they assume homogeneous slopes among panel units.[1]

In general, the assumption of homogeneous slope parameters does not hold in dynamic panel data with large T and large N (Phillips and Moon, 2000; Im et al., 2003). With T increasing, more attention has to be paid to issues like serial correlation caused by shocks, whether temporary or persistent, as this may lead to biased estimation results. Pesaran and Smith (1995), for example, show that GMM estimation in dynamic panel models has inconsistent long-term coefficients, when actual slopes are heterogeneous. For these reasons, we apply the pooled mean group model (PMG) introduced by Pesaran and Smith (1995) and Blackburne and Frank (2007).

The PMG model distinguishes short-run and long-run effects. It allows short-term coefficients, the convergence adjustments speed (the coefficient of error correction term), and the error variances to differ across countries. However, it assumes homogeneity of slope parameters across countries on the long run (Blackburne and Frank (2007)).

The PMG estimator is a combination of the mean group (MG) and the dy-

[1] Compare Pesaran et al. (1999).

namic fixed-effects (DFE) models. Whereas the MG model averages the slope coefficients of separate regressions by panel-unit, the DFE model is similar to the one-way fixed effects or least square dummy variable (LSDV) approach allowing for heterogeneous intercepts but homogeneous slope coefficients. In contrast to the fixed-effects model, the DFE approach also distinguishes between short-run and long-run effects. There are various reasons to assume common long-run coefficients across OECD countries. OECD countries have access to common technologies and similar policy trends. Popp et al. (2011), for example, put forward that the Kyoto protocol played a fundamental role in shaping the investment in renewable energy capacity at the country level during 1979 to 2008; all member countries were exposed to the same international pressure to introduce further environmental regulations. The positive effect induced by the Kyoto protocol with respect to renewable energy policies was also identified by Nesta et al. (2014).

Conversely, assuming the speed of convergence across countries to be similar is rather implausible, as countries' institutional frames differ. Together with the fact that our data set is a large $\mathbf{T}$, large $\mathbf{N}$ data set, the PMG appears feasible. The mathematical background of the PMG model is described in the following:

A.3 Adapted Model

When adapting the general model to our case, we obtain the following long-run function:

$$\text{REP}_{it} = \theta_{0t} + \theta_{1t}\text{Chernobyl}_t + \theta_{2t}\text{Ibaraki}_t + \theta_{3t}\text{Fukushima}_t + \theta_{4t}\mathbf{B}\,\mathbf{X}_{it} + \mu_i + \epsilon_{it} \quad (A.8)$$

where $i = 1,2,..,\text{N}$ is the number of countries, $t = 1,2,..,\text{T}$ the time span, and y_{it} the respective dependent variable. $\mathbf{X}_{it}$ stands for the control and explanatory variables and $\mathbf{B}$ is the vector of corresponding coefficients. According to a cointegration test, the data appears to be cointegrated $\text{I}(1)$ and the error term is an $\text{I}(0)$ process for all i. This transforms the ARDL(1,1,1) dynamic panel specification of eq. 5.9 into our basic regression equation:

$$\begin{aligned}\triangle ln(\text{REP})_{it} = {} & \phi_i(\theta_{0i} + \theta_{1i}\text{Chernobyl}_{it} + \theta_{2i}\text{Ibaraki}_t + \theta_{3i}\text{Fukushima}_t + \theta_{4i}\mathbf{B}\,\mathbf{X}_{it}) \\ & + \delta_{11i}\triangle\text{Nuclear accidents}_{it} + \delta_{41i}\triangle ln(\mathbf{B}\,\mathbf{X})_{it} + \epsilon_{it}\end{aligned} \quad (A.9)$$

where $\phi_i = -(1-\lambda_i)$, $\theta_{0i} = \frac{\mu_i}{1-\lambda_i}$, $\theta_{it} = \frac{\delta_{i0i}+\delta_{i1i}}{1-\lambda_i}$, and $\phi_i = -(1-\lambda_i)$. The error correction speed of adjustment parameter is ϕ_i. The long-run coefficients are

$\theta_{1i}, \theta_{2i}, \ldots, \theta_{Ni}$.

A.4 Data

no.	iso3	Freq.	Percent	Cum.
1	AUS	36	2.94	2.94
2	AUT	36	2.94	5.88
3	BEL	36	2.94	8.82
4	CAN	36	2.94	11.76
5	CHE	36	2.94	14.7
6	CHL	36	2.94	17.64
7	CZE	36	2.94	20.58
8	DEU	36	2.94	23.52
9	DNK	36	2.94	26.46
10	ESP	36	2.94	29.4
11	EST	36	2.94	32.34
12	FIN	36	2.94	35.28
13	FRA	36	2.94	38.22
14	GBR	36	2.94	41.16
15	GRC	36	2.94	44.1
16	HUN	36	2.94	47.04
17	IRL	36	2.94	49.98
18	ISL	36	2.94	52.92
19	ISR	36	2.94	55.86
20	ITA	36	2.94	58.8
21	JPN	36	2.94	61.74
22	KOR	36	2.94	64.68
23	LUX	36	2.94	67.62
24	MEX	36	2.94	70.56
25	NLD	36	2.94	73.5
26	NOR	36	2.94	76.44
27	NZL	36	2.94	79.38
28	POL	36	2.94	82.32
29	PRT	36	2.94	85.26
30	SVK	36	2.94	88.2
31	SVN	36	2.94	91.14
32	SWE	36	2.94	94.08
33	TUR	36	2.94	97.02
34	USA	36	2.94	100
	Total	1,224	100	

Table A.1 List of OECD countries

A.5 Unit root test

Unit root tests			
	Levin-lin-Chu	Harris-Tzavalis	Breitung
REP (log)	(0.0054)	(0.000)	(0.0786)

Table A.2 Unit root tests for the dependent variable

Dickey-Fuller test		Statistics	P-value
REP (logs)			
Inverse chi-squared(68)	P	233.3003	(0.000)
Inverse normal	Z	-10.1908	(0.000)
Inverse logit t(174)	L*	-10.7846	(0.000)
Modified inv. chi-squared	Pm	14.1744	(0.000)
Total capacity (logs)			
Inverse chi-squared(72)	P	140.1075	(0.000)
Inverse normal	Z	-5.8337	(0.000)
Inverse logit t(184)	L*	-5.6435	(0.000)
Modified inv. chi-squared	Pm	5.6756	(0.000)
Renewable energy generation (Logs)			
Inverse chi-squared(68)	P	170.4037	(0.000)
Inverse normal	Z	-7.1095	(0.000)
Inverse logit t(174)	L*	-7.2888	(0.000)
Modified inv. chi-squared	Pm	8.781	(0.000)
Energy price (logs)			
Inverse chi-squared(66)	P	412.5097	(0.000)
Inverse normal	Z	-12.8986	(0.000)
Inverse logit t(169)	L*	-19.5533	(0.000)
Modified inv. chi-squared	Pm	30.1598	(0.000)
GDP p.c (logs)			
Inverse chi-squared(68)	P	169.3637	(0.000)
Inverse normal	Z	-6.5891	(0.000)
Inverse logit t(174)	L*	-6.9195	(0.000)
Modified inv. chi-squared	Pm	8.6919	(0.000)
H_0: All panels contain unit roots			
H_a: At least one panel is stationary			

Table A.3 Unit root tests for the independent variables

A.6 Cointegration tests

A.6.1 KOA test

	Statistic	p-value
Modified Dickey-Fuller t	-3.9136	0
Dickey-Fuller t	-3.3478	0.0004
Augmented Dickey-Fuller t	-2.3319	0.0099
Unadjusted modified Dickey-Fuller t	-4.8799	0
Unadjusted Dickey-Fuller t	-3.759	0.0001

Table A.4 Kao test for cointegration

A.6.2 Pedroni test

	Statistic	p-value
Modified Phillips-Perron t	1.6324	0.0513
Phillips-Perron t	-4.9322	0.0000
Augmented Dickey-Fuller t	-4.3479	0.0000

Table A.5 Pedroni cointegration test

A.7 Additional lists

Nomenclature

ACF	Advocacy Coalition Framework
ARDL	Autoregressive Distributive Lag Model
DFE	Dynamic Fixed-Effects
DHPM	Dynamic Heterogeneous Panel Model
EC	Error Correction Term
IAEA	International Atomic Energy Agency
IEA	International Energy Agency
INES	International Nuclear Event Scale
LSDV	Least Square Dummy Variable
MG	Mean Group
OIM	Observed Information Matrix
PMG	Pooled Mean Group Model
PSM	Pre-Sample Mean
REP	Renewable Energy Policies
SFE	Static Fixed Effect

	REP	Chernobyl	Ibrakai	Fukushima	GDP.p.c	Total Capacity	Renewables gen.	Energy price
REP	1							
Chernobyl	0.4165	1						
Ibrakai	0.7596	0.423	1					
Fukushima	0.4836	0.1796	0.4246	1				
GDP.p.c	0.5127	0.2239	0.3676	0.2186	1			
Total Capacity	0.3786	0.1263	0.1826	0.094	0.3214	1		
Renewables gen.	0.3709	0.1829	0.2222	0.1647	0.1241	0.6509	1	
Energy price	0.3886	0.2669	0.4691	0.4015	-0.0398	0.109	0.0027	1
Established Democratic	0.4179	0.1601	0.2504	0.1978	0.7879	0.2103	0.1141	-0.2202
Autonomous Region	0.19	0.0253	0.0642	0.0383	0.148	0.2851	0.2687	0.0775
Party orientation	-0.024	0.0338	0.024	-0.069	0.0247	0.0337	0.0842	-0.0691
REP pre-sample	0.272	0	0	0	0.1477	0.2026	0.3336	-0.284

	Established Democratic	Autonomous Region	Party orientation	REP pre-sample
REP				
Chernobyl				
Ibrakai				
Fukushima				
GDP.p.c				
Total Capacity				
Renewables gen.				
Energy price				
Established Democratic	1			
Autonomous Region	0.0909	1		
Party orientation	-0.0704	0.0909	1	
REP pre-sample	0.185	0.2089	-0.0223	1

Table A.6 Correlation matrix

Chapter 5

The impact of mass media on environmental policy making

Author: Sherief Emam

In this paper we want to understand and highlight the effect of media to draw public attention to climate change. Such an attention can drive politicians to increase renewable energy policies introduced. Using a macro panel of 34 OECD countries between 1985-2013 collected from the IEA, Lexis Nexis and CSTPR, we run several regression models such as OLS, negative Binomial regression and pooled mean group estimation. The results show that media does support introducing more renewable energy policies through drawing public attention and increasing the pressure on politicians supporting them.

5.1 Introduction

Governments have set ambitious targets to increase the share of renewable energies. The EU sets a binding target in 2020 to reach 20% final energy consumption from renewable sources (Menegaki, 2013; EIA, 2014). While considerable progress has been achieved to increase the share of some renewable energy sources, some are still too immature to compete directly with fossil energies (Menanteau et al., 2003). This can be partially related, first, to the difficulties to diffuse RE technologies (Foxon and Pearson,2007; Friebeetal.,2014, 2013; Veugelers, 2011; Polzin et al. (2015)). Secondly, to the market failures in the energy sector (Dinica, 2006; Helm, 2002; Jefferson, 2008; Wüstenhagen and Menichetti,2012). Overcoming and mitigating market failure justifies government interference (Abdmouleh et al., 2015; Menanteau et al., 2003; Polzin et al., 2015; Ayoub and Yuji, 2012). Without such an involvement, market forces would result in a limited diffusion of renewable energy sources only in niches markets (Menanteau et al., 2003). Governments can pass adequate policies to support RES. They have a variety of instruments to regulate the energy market (Feed-in tariff, subsidies and tax systems, Investment, R & D support). Most of the research done is concentrated on evaluating the efficiency of renewable energy policies and their outcomes (Nesta et al., 2014;

Johnstone et al., 2010a; Polzin et al., 2015). The majority have indicated the positive outcome of different policies. In other words, the more policies adapted, the better the overall results for renewable energy. To our knowledge, few empirical studies have been done to investigate if mass media can support adopting new environmental policies. The objective of our paper is to shed light on this research gap.

The research question is not typical in the economic field. Traditionally the study of political agendas has been accomplished through the lens of political science and other non-economic disciplines. Yet as more and more economists have turned their attention to mass media, new interdisciplinary perspectives and frameworks have emerged (McCluskey and Swinnen, 2010).

A significant part of literature attempts to explain the role that mass media play in political markets and thus the effects on public policy-making processes. The bulk of the literature addressing the relationship between public policies and the mass media are theoretical. However, there are a few studies that have assessed the effects of mass media on policy outcomes empirically. Some key findings suggest that increased media coverage on political activities of representatives leads to greater activity in passing policies (Strömberg and Snyder, 2008). These effects have been found in numerous countries and across various government initiatives, for instance, unemployment relief programs in the United States (Strömberg, 2004), increased spending on education in Uganda and Madagascar (Reinikka and Svensson, 2005; Francken et al., 2009), and state food provision in India (Besley and Burgess, 2002).

These studies provide valuable insights into media effects on political agenda setting within a single country context, but on the downside, they do not consider the variance in government and media systems.

To address the shortcomings of prior research, this study is set out to contribute to the growing empirical evidence by analyzing the impact of mass media on policy-making over an extensive period of time and across a wide range of countries. We utilize panel data obtained from Lexis Nexis and IEA which includes measures for renewable energy policies for four countries and the time period of 28 years. The contribution of this paper is twofold. First, this paper contributes to the literature on the political economy of environmental policies. There is an ample body of theoretical and empirical literature on what regulates and influences environmental policy-making, yet there is a scarcity of empirical evidence for mass media role in this process. The findings of this longitudinal cross-country analysis indicate that mass media have a substantive impact on environmental policies and serve as an external pressure for political accountability.

The rest of the paper is organized as follows: section (5.2) discusses the theories describing the relationship between media and political agenda setting. Additionally, we illustrate the state-of-the-art and and derive our research hypothesis. In section (5.3) we lay out the empirical protocol, an overview about our data set, aggregation of variables and descriptive statistics, followed by the methodological approach used in section (5.3.2). In section (5.4) we present our base results, robustness checks, controlling for endogeneity and differentiation of long and short run effect. Section (5.5) discusses the results, summarizes the main findings and gives suggestions for future work.

5.2 Theoretical background

Studies concerned with renewable energy policies (REP) have delivered mixed results about their effectiveness. Yet the majority of the research done still showed positive results of REP implementation. Fiscal and financial incentive policies, for example, loan guarantees, government loans and tax-based incentives were all linked to spur RE deployment (Bergek et al., 2013; De Jager et al., 2011; Barradale, 2010; Bird et al., 2005; Quirion, 2010; Polzin et al., 2015). Menz and Vachon (2006) evaluated the positive role of five policy instruments[1] from 1998 to 2003 across a 39 US states on Wind energy. In similar but broader research done by Kilinc-Ata (2016) analyzing renewable energy policies in a cross-country study covering 27 EU countries and 50 US states for 18 years. They state the benefits of feed-in tariffs, tender and tax on the capacity of RE deployment. In addition, Neuhoff et al. (2008); Smith and Urpelainen (2014); Kilinc-Ata (2016) linked the introduction of supportive policies to an increase in the capacity of RE deployment, however Kilinc-Ata (2016) could not provide a significant effect. Regarding policies supporting the technological change in the field of renewable energies, the work of Johnstone et al. (2010b) showed a positive impact of targeted policies in OECD countries on the number of registered patents for different renewable energy technologies. Nesta et al. (2014) extended the later work and showed a further positive impact on the quality of innovation.

Our contribution in this work, however, is not to evaluate the effectiveness specific renewable energy policies. Because governments and policymakers tend to pass mixed policies supporting RE, and based on the above mentioned research we will not be concentrating either on a specific technology or policy but on a global view over renewable energy policy making process. We are trying to understand the policy making process and the role mass media can play in fostering the renewable energy policies. To understand the process, we need to have a closer

[1] renewable portfolio standard, fuel generation disclosure requirement, mandatory green power option, public benefit fund, and retail choice

look at the political science theories. Two main theories are related to our work are: the "political" and "media" agenda setting theories.

Political agenda defines topics, which political actors and policy makers pay attention to. Determining the issues on the agenda is a requirement to meet any political decision (Walgrave et al., 2008); therefore setting or codetermining the topics to be considered in the agenda is a sensitive issue. Some studies ascertain the role mass media can play on setting the political agenda and boosting political attention; however, the evidence is mixed and precise empirical studies on this effect have been given little attention (Walgrave et al., 2008; Walgrave and Van Aelst, 2006). These varying findings are "related to the fact" that media effects vary across political agendas and topics. In this contribution, we want to fill the void concerning the explicitly environmental agenda. The main question we are trying to answer in our study is: Can media boost the political attention to the environment and set topics in the agenda to pass more policies?

Answering this question by just ascertaining the contingency of media power will not be enough to build a theory on the political agenda setting by the media. Therefore, looking deeper into the reasons behind political responsiveness to media and the tools media has to interfere in the policy making cycle is valuable.

Comprehensive studies on why political actors react to media coverage might be still missing, but researchers suggest multiple reasons for media responsiveness (Mathias Kepplinger, 2007; Walgrave and Van Aelst, 2006). The first straightforward reason for policymakers to adopt media issues is the association of media coverage with public opinion (Walgrave and Van Aelst, 2006). Since the public opinion is difficult to measure (Protess (1992)), politicians see media coverage as a proxy for the public agenda or as mentioned by Pritchard (1992, p.105) media as surrogate for public opinion. When mass media emphasize a topic, the public audience will consider this topic to be important (Cohen, 1963; McCombs and Shaw, 1972), or, as explained by Mccombs et al., that public opinion is a reflection of the extent and prominence of media coverage (McCombs, 2014; Dumitrescu and Mughan, 2010; Brulle et al., 2012). Strömberg and Snyder (2008) give an example that if media devotes a large amount of articles to unemployment, then the public may in return give more attention to unemployment issues. Also, Brulle et al. (2012) came to a similar conclusion that media coverage has a significant impact and directly affects the level of public concern over climate change. Taking into account that the ultimate goal for politicians is to be reelected by the public, reacting and being responsive to the public opinion is critical (Pritchard, 1992; Cook, 1989).

Despite the fact that politicians might have accurate information about public opinion and whether the media agenda really aligns with the public one or not, this might be irrelevant (Walgrave and Van Aelst, 2006), and politicians will still tend to listen to the media. The reason for this is the perception among political actors that the media has a profound impact on the general public (Protess, 1992), explained by Gunther and Storey (2003) as "*the influence of presumed influence*" effect. Politicians know the effect media might have on public, if they start reporting about a specific topic. Political actors, in this case, do not react directly to the media coverage but rather on the predicted impact on the public and thus build their political strategies on that premise (Eichhorn, 1996; Eilders, 1997). Schudson (1995) points out that the potential of mass media lies not only in the direct influence of mass media on the general public, but also in the perception of politicians that the media has a profound impact on the general public (Protess, 1992).

A second reason to make us believe that media can influence the policy making process is the ability of media to interfere in the *speed* of policy making. Because the media is often the only way for politicians to reach out to the public (Pritchard, 1992) and since the media´s issue attention cycle is relatively short (Downs, 1972), political actors are pushed to react as fast as possible (Walgrave and Van Aelst, 2006). Most clearly the media can direct politicians to react, take positions to different topics and alter the policy making timetable by accelerating or even decelerating it (Linsky et al., 1986, p: 107-112). The more coverage media advocate to a specific topic, the higher the level of government engagement. Livingston (1997) imposed the importance of media as an accelerator in policy making. However, the effect of mass media can be exactly the the opposite. Increased attention by the media can create political frictions and debates as much as it can lead to slowing down the policy making process rather than accelerate it (Koch-Baumgarten and Voltmer (2010, p:216);Wolfe (2012)).

A third way media can shape the political agenda is related to the "*gate-keeping*" concept by Shoemaker (1991) or as Walgrave et al. (2010) called it the "*Agenda-constraining*". The straightforward relationship is: the more media coverage given to a topic, the more prominent position it gets on the political agenda (Van Aelst et al., 2013). This relationship is described mostly positively; however, the power of media as concluded by Brants et al. (1999, p: 199) lies more in denying access, filtering and selecting specific topics to cover.

The last reason on how media and policymakers interact is that politicians react to media cues to communicate with each other. In this case politicians do not react to public demands, but "go public" through media. They pass information about their policies in order to garner support for particular policies (Wuestenhagen et al., 2007; Sigal, 1973; Kernell, 1997). In this scenario media as stated by Bennett (1990) tends to collect their information from elite politicians and government representatives to provide legitimacy to reports (Sigal, 1973). In this way, politicians can alter the content of what is reported by the media. This is what the “Indexing” theory explains, where policymakers set the media agenda and feed it with relevant information to pass it to the general public (Bennett, 1990).

The relationship between media and policy making still can not be simply described by who sets the others’ agenda, but rather as a relationship, where both intersect with each other. Elder and Cobb (1983, p: 394) defined five stages for any policy making process: problem definition, policy formulation, -adoption, -implementation and finally policy evaluation. The importance of media appears in the first and last phases of the policy process because of its ability to focus attention (Esser and Pfetsch (2013, p: 388); Baumgartner and Jones (1993)). This feedback effect as mentioned by Sellers (2009) shows an alternating effect of mass media. At the beginning it quietly report about policies and later actively evaluate them.

There are plenty of examples to support our outcome that media interfere and can set the political agenda. In the case of the Exxon Valdez oil spill, media reported intensively and regulatory policy changes followed (Birkland, 1997). A similar case is the development of an oil slick off the California coast in 1969. Reconsideration of offshore drilling regulations (Elder and Cobb, 1983) were passed afterwards. In Germany, after Fukushima, reports from the print and television media were in-depth and dominated headlines for weeks. As a result of this coverage, Germany decided to reverse decisions to extend the life-time of its nuclear reactors, accelerated a nuclear energy phase out and closed immediately eight out of its 17 reactors (Skea et al., 2013). Similar policy changes took place in Indonesia (Fauzan and Schiller, 2011).

From the above mentioned theories we drive two hypothesis. The first one is to test if there is a relationship between media coverage about renewable energies and the adoption of new environmental policies.

Hypothesis 1: *Media coverage do positively influence the policy agenda and lead to the introduction of more environmental policies.*

Secondly, Although the focus of this work is not on determining the first-movers with respect to climate change; whether mass media take the lead (set agendas) or lag (index) as described in both the “policy agenda-Setting” theory or government officials lead the media as explained in the “indexing” theory by Bennett (1990). However, based upon the outcome, it can either be concluded that policymakers concerned with environmental issues are more likely to work based on their own predefined agenda, which they actively apply or it rather is an external catalyst (media coverage) that increases the pressure on them to pass supportive policies.

Hypothesis 2: *Governments representatives are more likely to act first when media reports start.*

5.3 Data and Econometric Protocol

We apply panel data econometrics to estimate the relationship between media coverage in four countries (The United States, United Kingdom, Germany and Austria), relying on a data set covering a time span from 1985 till 2012. We apply various econometric models like OLS, negative binomial regressions and pooled mean group estimators.

5.3.1 Data

A. Dependent variables

Similar to Johnstone et al. (2010b); Nesta et al. (2014); Dasgupta et al. (2001), we build an index for renewable energy policies by aggregating the number of policies for each of the four countries. The index is based on a detailed dataset available from the international energy agency (IEA). It contains the information about the year of adoption and expiration of a renewable energy policy.

Although policy measures do certainly not compare on a cardinal basis and the aggregation of different types of policies in a single index might imply a loss of information in terms of policy-specific individual effects (Johnstone et al., 2010b), policy measures still allow us to trace the activity level of policymakers.

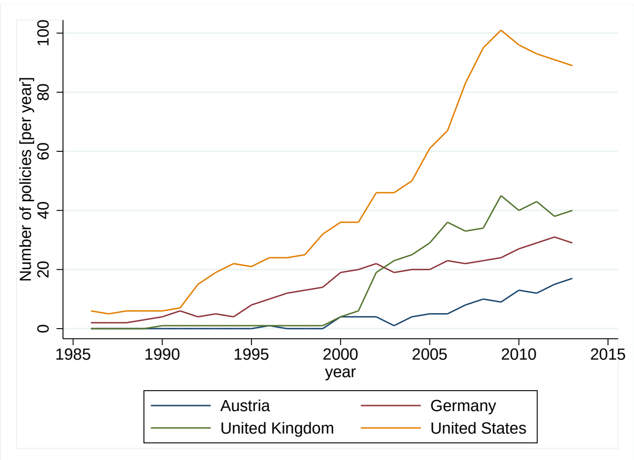
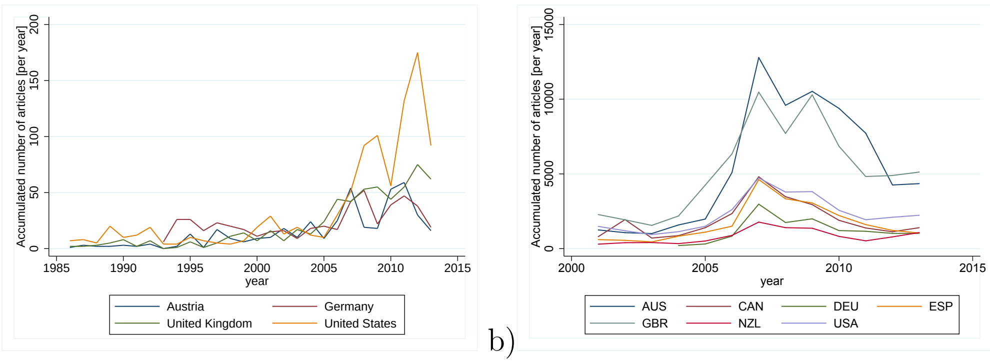


Figure 5.1 Renewable energy policy index the four chosen countries.

B. Explanatory variables

Our main explanatory variable about media coverage is collected from Lexis Nexis. We search for renewable energy policy articles in newspapers. The search includes keywords like wind power, geothermal and solar energy, excluding words like wars. Figure (5.2a). shows the accumulated number of articles for the time span from 1985 until 2013. The full command can be found in the Appendix (5.6).

For a robustness check we also include a dataset collected by the center for science and technology policy research from Colorado university. The dataset covers four more countries (Australia, Canada, New Zealand and Spain) and covers the period between year 2000 and 2013. Despite the short time span, adding more countries will increase the heterogeneity of our dataset.



a) b)

Figure 5.2 Numbers of articles per country per year.

C. Control variables

Energy prices: The interaction between shrinkage of fossil fuel sources and increasing energy prices can lead policymakers to support renewable energy sources, see figure (5.3). Both effects should increase the incentive to search for alternatives and therefore foster policies supporting renewable energy production. Data on end-user electricity prices in both residential and industry sectors was collected from the IEA database. The calculated price index was constructed by weighting price indices for both sectors with their corresponding consumption levels, similar to (Johnstone et al., 2010b; Nesta et al., 2014). A positive significant is expected.

Stock of Knowledge: is a particularly relevant variable from the policy theory perspective. Accumulated learning, scientific results and evidence lead to a policy change as discussed by Sabatier and Jenkins-Smith (1999). The more scientific knowledge a country owns, the more policy alternatives they can apply (Weible et al., 2011). We include the number of patents per country for each year. They can be seen as proxy for the scientific and technical information available.

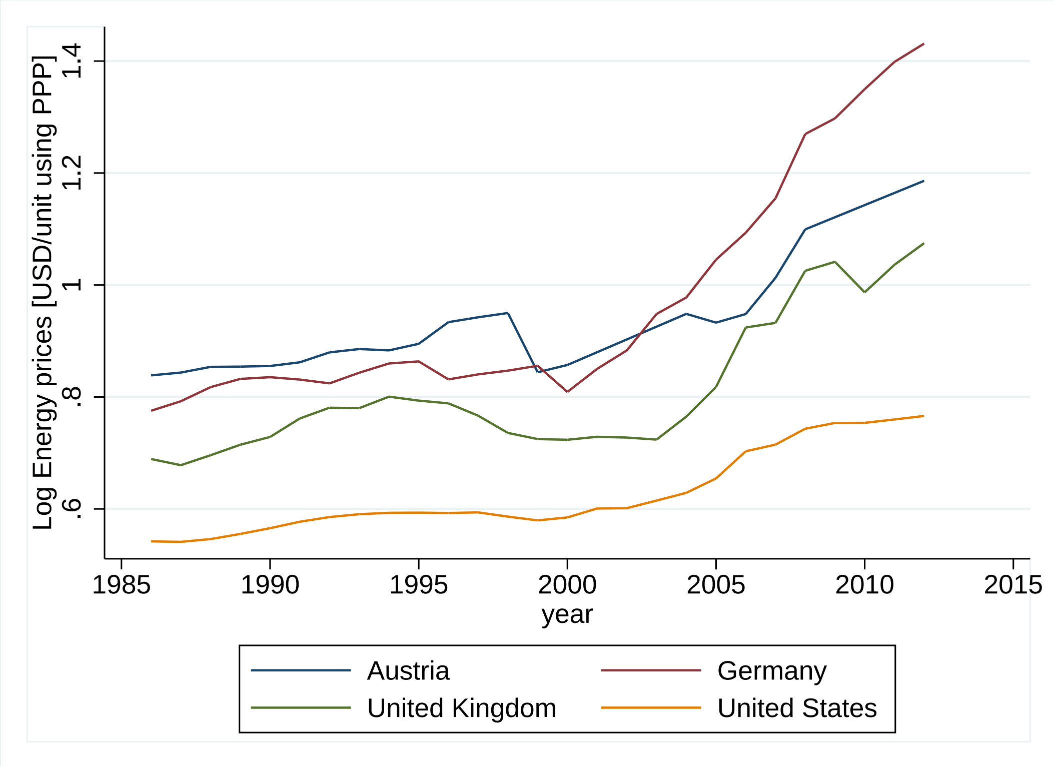


Figure 5.3 Energy Price Index. Source: own calculations.

Despite several empirical and conceptual caveats (Griliches, 1990), patents have been widely used in quantitative empirical studies in the environment domain as an indicator for innovation (Lanjouw and Mody, 1996; Brunnermeier and Cohen, 2003; Costantini and Crespi, 2013). Just counting the annual number of patents in green technologies does not reflect the actual stock of knowledge of a country. The Stock of Knowledge, by nature, is difficult to measure. Accumulating patent counts instead would ignore the fact that knowledge wears off over time (Popp, 2002). Therefore, we use the perpetual inventory method (PIM) as suggested and applied by (Meinen et al., 1998; Hall, 1993; Hall et al., 2000; Nesta and Saviotti, 2006). The number of patents (Pat_t at time t) is counted while depreciating past patent counts. Correspondingly, the stock of green knowledge (GK) is calculated as $\mathrm{GK}_{it} = (1-\delta)\mathrm{GK}_{t-1} + Pat_t$.[2] The patent data originates from PATSTAT.[3] Due to a change in classification, we had to merge green patents from the IPC classification with the new CPC, the Cooperative Patent Classification. The latter is the outcome of harmonizing the EPO classification system (IPC) with the USPTO classification system (CPC). For patents identification purposes, we used the OECD Indicator of Environmental Technologies (OECD, 2012). We expect that the higher the stock of knowledge in a country, the more they introduce new

[2]The annual depreciation rate δ is assumed to be 15%

[3]We used the 2015 version of the EPO database PATSTAT EPO (2015).

REPs.

GDP and *population*: are the simplest measures used to account for the economic growth and the size of the country. To decrease the correlation between variables, we calculate *GDP per capita* as a combined variable. By including this variable we expect that the bigger and richer a country, the higher the level of renewable energy policies.

Renewable energy production : To control for the energy mix and as an indicator for the deployment of renewable energy sources, we include the production capacity of renewable energy in our dataset. We expect that the more a country produces energy from green sources, the more policies are introduced.

Table (5.8) provides an overview of the variables, references to the data sources and expected signs in the econometric analysis. Table (5.1) displays the descriptive statistics.

Name	Obs	Mean	Std_dev	Minimum	Maximum
REP	116	2.161	1.420	0	4.625
Media Attention	108	2.614	1.112	0	5.170
Energy price	106	0.822	0.188	0.541	1.431
GK	116	6.228	1.595	2.732	8.965
Ren. production	115	3.989	1.316	1.626	6.270
GDP per Capita	116	3.460	0.203	3.002	3.845
Kyoto	116	0.414	0.495	0	1

Table 5.1 Dataset descriptive Statistics.

5.3.2 General Empirical Approach

In this section we apply panel-data regression. When researching using long time series, it is important to understand and distinguish the requirements of each econometric model and the restrictions. We start our analyzes with a typical OLS regression, expressed in equation (5.1).

$$ln(\mathrm{REP})_{it} = \beta_0 + \theta_{1t} ln(\mathrm{M}edia\mathrm{A}ttention)_t + \theta_{4t}\mathbf{B}\mathbf{X}_{it} + \epsilon_{it} \qquad (5.1)$$

where $i = 1,2,..,\mathrm{N}$ is the number of countries, $t = 1,2,..,\mathrm{T}$ the time span, and REP_{it} the respective dependent variable. $\mathbf{B}_i\mathbf{X}_{it}$ stands for the explanatory variables. We extend our models and run a clustered standard errors fixed effect.

For additional robustness, we use the original format of the dependent variable as a count data and run negative binomial regressions. Poisson regression is suitable for count data, but it assumes that the mean and variance of the errors are equal. Therefore and because of over dispersion we preferred a negative binomial regression to a Poisson model. Finally, we introduce variables sequentially to see whether there are changes in th estimation significance, while further covariates are considered.

It is important to take into consideration that our panel data is a macro dynamic panel data (Long (T) period and few number of cross section observations (N)) and therefore, we shall expect inconsistent results from the above mentioned models because of the endogeneity and the false assumption of homogeneous slopes among panel units.[4] In addition to the models mentioned above, we will use the Dynamic Heterogeneous Panel Model (DHPM) explained following.

Estimators for Heterogeneous slopes

Micro panels with small time series (T) and a large number of cross section observations (N) usually rely on either fixed effects, random effects, static fixed effect (SFE), or a combination of those (Arellano and Bond, 1991). As Pesaran and Smith (1995) point out, with large T, such traditional estimators may generate inconsistent results, because they assume homogeneous slopes among panel units.[5]

In general, the assumption of homogeneous slope parameters does not hold in dynamic panel data with large T and large N (Phillips and Moon, 2000; Im et al., 2003). With T increasing, more attention has to be paid to issues like serial correlation, and endogeneity may lead to biased estimation results. Pesaran and Smith (1995), for example, show that GMM estimation in a dynamic panel model has inconsistent long-term coefficients when actual slopes are heterogeneous. For these reasons, we apply the pooled mean group model (PMG) introduced by Pesaran and Smith (1995) and Blackburne and Frank (2007).

The PMG model distinguishes short-run and long-run effects. It allows short-term coefficients, the convergence adjustments speed (the coefficient of error correction term), and the error variances to differ across countries. However, it assumes homogeneity of slope parameters across countries on the long run (Blackburne and Frank, 2007).

The PMG estimator is a combination of the mean group (MG) and the dynamic fixed-effects (DFE) models. Whereas the MG model averages the slope coefficients of separate regressions by panel-unit, the DFE model is similar to the one-way fixed effects or least square dummy variable (LSDV) approach allowing for heterogeneous intercepts but homogeneous slope coefficients. In contrast to the fixed-effects model, the DFE approach also distinguishes between short-run and long-run effects. There are various reasons to assume common long-run coefficients across our dataset countries. Conversely, assuming the speed of convergence across

[4]Compare Pesaran et al. (1999).
[5]Compare Pesaran et al. (1999).

countries to be similar is rather implausible, as countries' political frames differ. Together with the fact that our data set is a large T, large N data set, the PMG appears feasible. The mathematical background of the PMG model is described in the following:

Dynamic Heterogeneous Panel Models

The general model of the dynamic heterogeneous panel estimation, which will be presented here, is discussed by (Blackburne and Frank, 2007; Freeman, 2000; Pesaran et al., 1999).

General Model

The general model assumes that the input data on time period $t = 1,2,...,T$ and across section groups $i = 1,2,...,N$ can be estimated by an autoregressive distributive lag model ARDL$(p,q,..,q_k)$:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} X_{i,t-j} + \mu_i + \epsilon_{it} \tag{5.2}$$

where X_{it} is the $(k \times 1)$-vector of explanatory variables, λ_{ij} a scalar of constants, δ_{it} the $k \times 1$ coefficient vectors, μ_i the group specific effect and, ϵ_{it} the group specific effect. As T is large enough, each group can be estimated separately. The variables in equation(5.2) are cointegrated at level 1 ($I(1)$) and the error term is an $I(0)$ process for all i, therefore, the error correction equation can be reparameterized:

$$\triangle y_{it} = \phi_i (y_{i,t-1} - \beta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \triangle y_{i,t-1} + \sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{i,t-1} + \mu_i + \epsilon_{it} \tag{5.3}$$

for $i = 1,2,...,N$ and $t = 1,2,...,T$. The error correction speed of adjustment parameter is expressed as in the following:

$$\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}), \tag{5.4}$$

$$\beta'_i = \sum_{j=0}^{q} \delta_{ij}, \tag{5.5}$$

$$\lambda^*_{ij} = -\textstyle\sum_{m=j+1}^{p} \lambda_{im} \quad j = 1,2,...,p-1 \tag{5.6}$$

and

$$\delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im} \quad j = 1,2,...,q-1 \tag{5.7}$$

assuming that the ARDL model in equation (5.2) is stable in that the roots of $\sum_{j=1}^{p} \lambda_{ij} z^j = 1$ for $i = 1,2,...,N$ lie outside the unit circle, ensuring that the error correcting speed of adjustment term $\phi_i < 0$. This implies that there is a long-run relationship between the dependent variable y_{it} and the regressors x_{it} . It is calculated as:

$$y_{it} = -(\beta_i^{'}/\phi_i)x_{it} + \eta_{it} \tag{5.8}$$

Adapted Model

When adapting the general model to our case, we obtain the following long run function:

$$\text{REP}_{it} = \theta_{0t} + \theta_{1t}\text{Media}_t + \theta_{2t}\text{Energy prices}_t + \theta_{3t}\text{Stock of knowledge}_t + \theta_{4t}\mathbf{B}\mathbf{X}_{it} + \mu_i + \epsilon_{it} \tag{5.9}$$

where $i = 1,2,..,N$ is the number of countries, $t = 1,2,..,T$ the time span, and y_{it} the respective dependent variable. $\mathbf{X}_{it}$ stands for the control and explanatory variables and $\mathbf{B}$ is their corresponding coefficient. According to a cointegration test, the data appears to be cointegrated $I(1)$ and the error term is an $I(0)$ process for all i. This transforms the ARDL(1,1,1) dynamic panel specification of equation (5.9) into our basic regression equation:

$$\begin{aligned}\triangle ln(\text{REP})_{it} = \phi_i(\theta_{0i} + \theta_{1i}\text{Media}_{it} + \theta_{2i}\text{Energy prices}_t + \theta_{3i}\text{Stock of knowledge}_t \\ + \theta_{4i}\mathbf{B}\mathbf{X}_{it}) + \delta_{11i}\triangle\text{Media}_{it} + \delta_{21i}\triangle\text{Energy prices}_{it} + \delta_{31i}\triangle\text{Stock of knowledge}_{it}\end{aligned} \tag{5.10}$$

$$+ \delta_{41i}\triangle ln(\mathbf{B}\mathbf{X})_{it} + \epsilon_{it} \tag{5.11}$$

where $\phi_i = -(1-\lambda_i)$, $\theta_{0i} = \frac{\mu_i}{1-\lambda_i}$, $\theta_{it} = \frac{\delta_{i0i}+\delta_{i1i}}{1-\lambda_i}$, and $\phi_i = -(1-\lambda_i)$. The error correction speed of adjustment parameter is ϕ_i. $\theta_{1i}, \theta_{2i}, ..., \theta_{Ni}$ are the long run coefficients.

5.3.2.1 The direction of information

To test our second hypothesis and determine the direction of information between mass media and policymakers, we apply a Granger causality test (Granger, 1969), expressed in following equation (5.12).

$$y_t = \alpha + \sum_{k=1}^{k} \beta_k y_{t-k} + \sum_{k=1}^{k} \gamma_k x_{t-k} + \epsilon_t \quad (5.12)$$

$$y_{i,t} = \alpha_i + \sum_{k=1}^{k} \beta_{ik} y_{i,t-k} + \sum_{k=1}^{k} \gamma_{ik} x_{i,t-k} + \epsilon_{i,t} \quad (5.13)$$

If past values of x are significant predictors of y, while including the past values of y, we can conclude that x Granger causes y (Lopez et al., 2017). While equation (5.12) is for time series, we follow the work by Dumitrescu and Mughan (2010). He proposed a Granger causality test for panel data. He states under the null hypothesis equation (5.14) the absence of a homogeneous Granger causality. The alternative hypothesis states that a relationship exists at least in one unite, equation (5.15).

$$H_0: \ \gamma_{i1} = \ ... = \gamma_{ik} = 0 \qquad \forall i = 1, ..., N \quad (5.14)$$

$$H_1: \ \gamma_{i1} \neq \ 0\,or....or\,\gamma_{ik} \neq 0 \qquad \forall i = N_1 + 1, ..., N \quad (5.15)$$

5.4 Empirical results

The aim of our research is to uncover the influence of mass media on the environmental policy making process. We are trying to answer two questions. First, whether mass media reporting can encourage policy and decision makers to pass more renewable energy policies or not. The second question is the direction of influence between mass media and policy making; can it be described as a unidirectional relationship or a bidirectional one. Stata 15 is used to estimate all our 28 models.

In table (5.2) we present the findings for the fixed effects OLS regression (Models 1-3) and standard error fixed model (Models 4-6). We applied fixed effects models after performing the Hausman test, which was in favor of a fixed effect model rather than random effect one. Model 1 is a univariate regression of forwarded value of REP on media coverage log variable. The correlation suggests a positive relationship between media coverage and renewable energy policies. We start adding the control and explanatory variables sequentially to capture any changes in the estimates when further covatriates are considered. Through Model 1-3 the value of media coverage indicator decreased but stayed positively significant. Stock of green knowledge remains positive and significant through all models, indicating that countries with higher technological background and innovation tend to pass more renewable energy policies.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Media Attention	0.823***	0.298***	0.165***	0.823***	0.298	0.165*
	(0.065)	(0.068)	(0.061)	(0.118)	(0.138)	(0.052)
Energy price		-0.694	-2.237***		-0.694	-2.237**
		(0.495)	(0.542)		(0.533)	(0.452)
GK		0.848***	0.399***		0.848***	0.399**
		(0.079)	(0.131)		(0.052)	(0.093)
Ren. production			0.913***			0.913**
			(0.175)			(0.253)
GDP per Capita			2.668***			2.668**
			(0.854)			(0.464)
Constant	0.154	-3.231***	-11.722***	0.154	-3.231***	-11.722***
	(0.181)	(0.389)	(2.166)	(0.303)	(0.496)	(1.692)
Observations	104	98	98	104	98	98
R-squared	0.615	0.833	0.893	0.615	0.833	0.893
Number of ctry	4	4	4	4	4	4
R2 adj. within	0.615	0.833	0.893	0.615	0.833	0.893
R2 adj. between	0.817	0.982	0.719	0.817	0.982	0.719
R2 adj. overall	0.577	0.885	0.677	0.577	0.885	0.677

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Dep. variable is forwarded by one lag.

Table 5.2 Model (1-3) Fixed effects. Model (4-6) standard errors fixed effect.

For models (4-6) we run a robustness check. We re-estimate the regression with standard error fixed models. As was the case for the OLS regression, we added the variables in the same order as in models 1-3. The positive significance still stands except in model 5. In model 3 and 6 the stock of knowledge in green technologies correlates positively with the number of policies initiated in a country. This finding is similar to the results reached by Johnstone et al. (2010a) and Nesta et al. (2014). However, the results of energy prices seem to be mixed. Models 3 and 6 show that countries with a higher share of renewable energy in their energy mix tend to pass more supportive policies. The GDP per Capita variable is positively significant, indicating that the richer the country, the higher the likelihood of passing more renewable energy policies. Finally, by having a short look at the determination coefficients, we notice that the R^2 value increases, while adding more variables into our model, we reach almost 90% in model 6. The results, so far, deliver evidence to support our alternative hypothesis, that media can alternate the political agenda and lead to the introduction of more environmental supportive policies.

To verify further robustness of the results presented in table (5.2), we tested a series of alternative specifications. In table (5.3), we run the same regression models but changed the dependent variable and the media attention one. In other words, models (7-12) regress the renewable energy policies on the growth rates of

VARIABLES	(7)	(8)	(9)	(10)	(11)
Media Attention	0.045**	0.081*	0.076*	0.075*	0.079*
	(0.011)	(0.031)	(0.031)	(0.028)	(0.031)
Energy price		-2.901	-2.726	-2.723	-2.927
		(2.123)	(2.115)	(2.115)	(2.136)
GK			0.516***	0.522***	0.573***
			(0.019)	(0.026)	(0.020)
Ren. production				0.040	0.047
				(0.263)	(0.272)
GDP per Capita					-1.490
					(0.869)
Constant	0.104***	0.144**	0.077*	0.074**	0.097*
	(0.001)	(0.028)	(0.030)	(0.019)	(0.032)
Observations	100	92	92	92	92
R-squared	0.013	0.138	0.182	0.182	0.192
Number of ctry	4	4	4	4	4
R2 adj. within	0.0126	0.138	0.182	0.182	0.192
R2 adj. between	0.973	0.108	0.0716	0.0815	0.0501
R2 adj. overall	0.0131	0.133	0.172	0.173	0.182

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Dep. variable is forwarded by one lag.

Table 5.3 Differenced variables REP and Media. Model (7-9) Fixed effects. Model (10-12) standard errors fixed effect.

media variable to test the short-run effect. In models (7-9) we run a fixed effect OLS regression and in models (10-11) a standard error fixed effect regression for robustness. The results are homogeneous, consistent and complementary to the results shown before. The media attention effect on the short-run correlates positively with the increase in renewable energy policies. Therefore, we can interpret the results that a media campaign will result in increasing the supportive policies on the short-run. Rapid increase in the technological advances will help politicians to pass more related policies. The coefficient of green stock of knowledge is strongly significant. Energy prices results are still however mixed.

Table (5.4) presents another robustness check. We use the original index for the renewable energy policies as a count data variable and solving the over dispersion negative binomial regression is preferred to the Poisson model. As done before, we introduce the variables sequentially to monitor changes in the estimates, when further covariates are added. The results in models (12-16) are consistent with the prior results. The media attention variable correlates positively with REPs. More media attention will lead to an increase in the number of green policies intro-

VARIABLES	(12)	(13)	(14)	(15)	(16)
Media Attention	0.969***	1.262***	0.541***	0.537***	0.235***
	(0.119)	(0.128)	(0.092)	(0.091)	(0.091)
Energy price		-2.377***	-1.136***	-1.230***	-0.730***
		(0.472)	(0.281)	(0.358)	(0.218)
GK			0.685***	0.710***	0.589***
			(0.049)	(0.062)	(0.044)
Ren. production				-0.039	-0.286***
				(0.073)	(0.072)
GDP per Capita					3.758***
					(0.460)
Constant	0.112	1.252***	-2.536***	-2.457***	-13.376***
	(0.393)	(0.422)	(0.382)	(0.446)	(1.423)
Observations	104	98	98	98	98
Log Likelihood	-380.7	-349.2	-297.9	-297.7	-279.4
Pseudo R^2	0.0693	0.0994	0.232	0.232	0.280

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Dep. variable is forwarded by one lag.

Table 5.4 Negative Binomial regression. Dep. Variable REP as count variable.

duced. Energy prices appear to be consistently significant and negative; however, technological advances in green energy has maintained a positive effect on REP through all the models.

Final results in this robustness regression series are presented in table (5.5). In this series of regressions, we changed the independent variable to the media coverage variable from the Center of Science and Technology Policy Research as described in section (5.3.1). This variable covers 7 countries instead of four with time span between the years 2000 and 2013. We run the same regressions as done before to test the robustness of the results. For models 17 and 18 we applied a standard error fixed effects model, followed by the growth rates models (19-20). Finally, in models 21 and 22 we use the count data of the dependent and the explanatory variables and run a negative binomial regression.

In model (17) we correlate the new explanatory variable to our renewable energy policies index. Both variables are logged and the dependent variable is forwarded by one lag, the same configuration as all past regressions. The results show a strong positive correlation at significance level 1%. When adding subsequently more variables, the significance of media seems to fade out. In models (19-20) we use the logged growth rates values, where the effect of media is positive and consistent. The different results between models (18-20) reveal an interesting finding, where the effect of media seems to fade out on the long run and just have

VARIABLES	(17)	(18)	(19)	(20)	(21)	(22)
Media Attention CSTPR	0.423***	0.039	0.169**	0.155*	0.468***	0.149***
	(0.071)	(0.094)	(0.053)	(0.079)	(0.066)	(0.039)
Energy price		0.544		-0.082		0.593**
		(1.190)		(0.647)		(0.261)
GK		0.503**		0.295**		-0.030
		(0.190)		(0.095)		(0.063)
Ren. production		0.184		-0.357		-0.047
		(0.342)		(0.370)		(0.039)
GDP per Capita		1.386		-1.102		4.287***
		(1.742)		(0.659)		(0.660)
Constant	0.125	-6.377	0.068***	3.731	-0.086	-13.059***
	(0.525)	(6.265)	(0.005)	(3.200)	(0.500)	(1.974)
Observations	87	78	80	71	87	78
Number of ctry	7	7	7	7	7	7
R-squared	0.497	0.749	0.137	0.232		
R2 adj. within	0.497	0.749	0.137	0.232		
R2 adj. between	0.340	0.692	0.00105	0.360		
R2 adj. overall	0.395	0.687	0.130	0.0696		
Log Likelihood					-360.2	-257.9
Pseudo R2					0.0491	0.233

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Dep. variable is forwarded by one lag.

Table 5.5 Model (17-18) standard errors fixed effect. Model (19-20) differenced Dep. variable. Model (21-22) level data-negative binomial regression.

a short-run effect. Running negative binomial regression in models (21-22) show a strong positive influence of media coverage over the number of passed policies.

The regressions in table (5.6) refer to the heterogeneous panel techniques introduced in equation (5.10) and discussed in section (5.3.2). We apply dynamic heterogeneous panel models, which offer an alternative estimator in addition to the traditional fixed-effects estimators, i.e. the pooled mean-group estimator by Pesaran and Smith (1995). The advantage of using this models is its ability to capture serial correlation between the variables themselves as well as with the error term (endogeneity). In all the models we applied a pooled mean group method, where the speed of adjusted convergence and the error variances are allowed to differ across countries on the short run but restrict homogeneity of slope parameters across countries on the long run.

The model introduced in equation (5.10) delivers numerous results: long-run, short-run effects, and error correction coefficients and allows us to monitor the short and long run effect of media on REP in the same regression model. The

	VARIABLES	(23)	(24)	(25)	(26)	(27)
Short run	Error correction	-0.040	0.013	0.017	0.033	0.034
		(0.098)	(0.111)	(0.041)	(0.052)	(0.044)
	Media Attention = L,	0.039***	0.045***	0.041***	0.046***	0.049***
		(0.007)	(0.011)	(0.009)	(0.012)	(0.016)
Long run	Media Attention	0.261***	0.421	1.265	1.005	0.645
		(0.094)	(0.325)	(1.896)	(1.214)	(1.020)
	Energy price		-0.299	1.507	6.484	13.251
			(0.941)	(4.630)	(10.810)	(21.074)
	GK			-2.167	-1.179	-6.230
				(4.862)	(2.806)	(11.178)
	Ren. production				-3.095	-4.848
					(4.749)	(7.452)
	GDP per Capita					24.434
						(41.397)
	Constant	0.252	0.219	0.139	-0.100	2.031
		(0.192)	(0.150)	(0.397)	(0.533)	(2.148)
	Observations	100	100	100	100	100
	Esigma	0.0634	0.0634	0.0634	0.0634	0.0634

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5.6 Pooled mean group estimator.

results in table (5.6) are homogeneous and complementary to the results presented before. The main finding of the series of regressions, in models (23-27), is the positively consistent effect of media coverage on REP on the short-run. The same effect on the long run does not hold and loses its significance while adding more covariates to the regression equation.

The results in tables (5.2 - 5.6) deliver consistent results that media has a positive effect on green energy policies on the short run but not on the long run. Policymakers start to increase their activity in passing new green policy measures after an increase in the media coverage about environmental issues. Evidence does support the hypothesis that media can encourage policymakers to introduce more renewable energy policies.

5.4.1 Direction of information

As discussed in section (5.2), different theories, such as the political agenda setting, state that mass media can interfere in the political agenda. We have empirically applied this theory to our model and dataset. Indexing theory refers to the opposite effect, where policymakers set the media agenda (Bennett, 1990). To understand the information and the influence direction between mass media and policy making, we run a Granger causality test. This test shows whether the results are uni- or bidirectional, namely if media Granger causes policies or the other way around.

Null Hypothesis	Granger-Causality Wald statistics	Probability
Media does not Granger-cause Policies	33.7641	0.0000
Policies does not Granger-cause Media	-0.2144	0.5715

Table 5.7 Granger Causality test after (Dumitrescu and Hurlin, 2012).

We follow the same methodology presented by Dumitrescu and Hurlin (2012). The results are presented in table (5.7) and they indicate a unidirectional relationship between mass media and policy making. It appears that mass media does Granger cause policymakers with a strong significance. The hypothesis that policymakers does not Granger causes media cannot be rejected because of the high $P-value$.

5.5 Discussion and conclusion

This paper is a part of ongoing research done to understand the intersection influence of mass media on policy making process. We base our research on two main theories from communication and political science, “Political agenda setting” and “Indexing” theory. The political agenda theory illustrates the tools mass media has to interfere in the political agenda. It also tries to answer the question: why policymakers react to mass media coverage. We explained in the theoretical background that politicians are influenced by mass media because of three different reasons. First because of the association of media coverage with public opinion. The more media covers an issue, the higher the likelihood that the general audience will consider this issue important. Even if this reason does not stand, politicians still know the effect mass media can have and therefore react to media topics. Secondly, mass media can interfere in the speed of policy making by intensively reporting about a specific topic, which can result in either speeding up or sometimes slowing down the policy making process. The third reason is that mass media is a gate keeper to public policies. They act as a filter which can constrain reporting specific policies to the public. The second theory we explained is the “Indexing” theory which puts mass media more in the follower position. It explains that mass media get their information from policymakers and government representatives. In this case politicians use media to communicate with the public and seek their support. Based on these two theories, we push two hypothesis. First, we study the effect of mass media on policymakers regarding environmental issues and secondly the direction of information between mass media and politicians. Are politicians pro-active regarding renewable energy plans and have their own policy agenda or are they more likely to react after an intensive media coverage?

To investigate these two hypotheses, we build a dataset from different sources covering a time span from 1985 to 2013 . The dependent variable is an aggregated index of active renewable energy policies collected from IEA. For mass media coverage we collected the number of articles in the main newspapers publishing about renewable energy for four countries (USA, UK, Germany and Austria). We added to our study the energy prices in each country as well as their own stock of knowledge about green technologies. We account as well for the size of the country and their current production of renewable energy power. For robustness checks we also added a dataset for media coverage collected by the Center for science and technology policy research from the university of Colorado. The dataset covers 7 countries and has a time frame from 2000 till 2013.

We use different regression methods during our study: OLS fixed effect model, negative binomial regression and pooled mean group for heterogeneous panel data. The later regression is relevant to solve the endogeneity and serial correlation problem between variables specially in long panel data, as in our case.

The results are presented in tables (2-6). In all 27 models the dependent variable is forwarded by one lag and logged except in the negative binomial regression, where we use the level count data. The results shade out a consistency and show a positive effect of mass media on the number of renewable policies. An increase in the number of published articles will reflect in more policies passed. In other words, the mass media can interfere in the political agenda and help pass new supportive policies. This effect is strongly correlated on the short-run more than on the long run. The advantage of using the pooled mean group is testing both effects in one equation. The results are consistent with the finding that the effect of media is more significant and consistent on the short-run rather than on the long term.

The finding is aligned to the issue of attention cycle introduced by Downs (1972). He explains that keeping the public attention sharp can only be done on the short run while exploring the problem, reporting on it and introducing solutions. After that the public attention enters a phase of inattention. This is the same cycle mass media has when covering specific topics.

The second finding of our study is the relationship between policy making and mass media. In this content we try to analyze the direction of the information flow, either media driven political activities regarding green energy policies, or politicians leading the media and telling them what to report. This analysis is important to know if policymakers are proactively increasing and supporting the share of renewable energy or if they need a catalyst to pass more policies. The findings indicate that it is more likely that policymakers tend to pass more renewable energy policies after mass media intensively reports about renewable energy and climate change. The Granger causality test also prove evidences that policymakers do not Granger cause any increase in the media reporting activities. In other words, policymakers do not interfere in the media agenda but rather the other way around.

There are shortcomings and caveats which have to be considered in further work. Including social media would give us more insight and direct information about public attention and concern; however, the short time span of social media will be difficult to be compared to policy changes, especially when policy making processes take a long legislative time. Also another improvement is to collect more data and cover more countries with different political positions.

5.6 Appendix

Lexis Nexis search command

policy W/25 offshore wind power OR geothermal energy OR solar energy OR hydro power NOT war OR Film OR book OR space AND byline (letters OR Anonymous)

Data

Name	Label	Source	Unit
REP	Renewable energy policies	IEA	Count
Media Attention	Media articles	Lexis Nexis	Count
Media Attention CSTPR	Media coverage	CSTPR[a]	Count
Energy price	Index for Energy price	IEA	$/unit using PPP
GK	Accumulated Green knowledge	Patstat	PIM / Count
Ren. production	Renewable energy production	IEA	MW
GDP per Capita	Gross Domestic Product	IEA	Billion 2005 $ using PPPs
Population	population per country	IEA	Millions

[a]International Collective on Environment, Culture & Politics. Center for Science and Technology Policy Research

Table 5.8 Data properties and sources.

6

Conclusion

Our modern life and welfare depend on the energy sector. It eases our daily life and enables us with more opportunities and enjoyable live. The economy benefits as well from the energy sector. The more energy produced is translated into products and increasing trade and hence a flourishing economic growth.

Yet an increase in the economic growth and energy consumption depend mainly on fossil fuels. In 2018, 85% of the global energy production was generated from fossil energy sources. While fossil fuel energy may supply us with a relatively cheap and stable energy supply, it come with two major challenges, namely scarcity and GHGs emissions. Fossil energy sources are scarce and will be depleted one day, and greenhouse gases such as carbon dioxide do contribute to global warming. A consistent increase in the global average temperature can lead to climate change and affect not only the environment, Eco-system but also the public health and, in consequence, labour productivity and the economy.

It is in everyone's interest to find solutions for those challenges and limit any undesirable consequences for society. The intention of this dissertation project was to analyze the energy market from an economic viewpoint and to investigate the determinants of a successful shift toward low carbon technologies, that is, renewable energy. The main research question raised in the first part of the dissertation is: Whether energy markets have the endogenous capacity to switch the market from the current fossil fuel based to more environmental friendly sources, like renewable energies. The second part of the dissertation concentrates on the determinants to increase the introduction of renewable energy policies. i.e. mass media and major accidents.

If energy markets were perfect, we expect the market to shift endogenously toward renewable energy. With dwindling fossil energy sources, energy prices will rise as demand is non-decreasing. The consequence of a price increase is twofold. As it increases competitive pressure, rising prices should force energy suppliers to increase the efficiency in production. In addition, producers will search for alternative energy sources such as renewable energy, since their relative prices go down. Technologies which used to be not competitive become gradually competitive. This, in turn, should give producers the incentive to invest in new renewable energy technologies.

If the energy market does not function as expected or the shift is slow, governments do interfere and introduce proper policies to accelerate the shift toward low carbon technologies. With adequate policies governments try to boost the implementation and diffusion process of renewable energy technologies. Policies can vary between, taxes, tradable quotes, R & D programs, subsidies such as feed-in tariffs and regulation instrument. This set of policies can induce innovation activities, increase efficiency, decrease emissions and contribute in economic growth .

Against this background, the objective of this dissertation is to shed light on the changes in energy systems. It consists of four papers which can be partitioned into two groups of papers. The first group of papers (paper 1 and 2) investigates the functioning of the market mechanisms, while the second group (paper 3 and 4) takes up the empirical findings, asking about the inhibiting determinants to introduce new policy measures to support the change toward renewable energies.

The first step to understand the energy market mechanism is to investigate the link between raising energy prices and the resulting effect on the energy efficiency and innovation activities. The first paper, titled "Can rising energy prices lead to higher efficiency levels in energy production?" tries to answer this question regarding the link between energy prices and improvement in energy efficiency. Evidence can be found that an increase in energy prices can lead to an improvement in energy efficiency on both the log-run and the short-run. In addition, public policies and competition have a positive effect in boosting the efficiency levels.

With regards to induced innovation activities, the second paper, "Rising Energy Prices and Advances in Renewable EnergyTechnologie", looks at the link between energy prices and the number of registered patents. Patent data for wind technologies are used as an index for innovation, and oil prices are proxies for energy prices. The result concludes that energy prices can induce innovation activities in OECD Countries. Prices have a positive long-run effect on the innovation process in wind technologies. Additionally, beside the main result, we find that renewable energy policies, such as R & D funding can increase innovation activities on both the short as well as the long-run.

The outcome from the first two research papers is the observation that energy markets are shifting toward low carbon technologies. This conclusion can be drawn by monitoring the increase in the efficiency as well as innovation levels. Nonetheless, this shift does not meet either the public demands nor policy maker plans. Although, achievements have been made, the rate of diffusion of renewable energies is still relatively slow. To accelerate the shift, more stringent policies shall be adopted. This outcome emphasizes the importance of governmental interference and the introduction of supportive policies in achieving the climate change mitigation plans.

For policy and lawmakers to pass more policies in favour of renewable energies, they need to be focused on the environment. This can be achieved, for instance, through major accidents or mass media coverage. The third paper is meant to provide empirical evidence for identifying whether major accidents (i.e. nuclear accidents) focus decision makers attention and create incentives to pass new supportive renewable energy policies. The conclusion is that such accidents can function as a catalyst; that is, as a focusing event for policy making and drive for major non-incremental policy changes. Evidences were found that nuclear disasters can exert a positive impact on the enactment of renewable energy policies. This effect, according to the calculations, fades out after about seven years. Within these seven years, a window of opportunities is opened for supportive political collations to introduce new policies.

Another main player that can push policymakers to pass more legislation is mass media. When mass media intensively reports on a topic, it signals its importance to the policymakers to adopt the topic. Mass media can influence the political agenda directly through three main mechanisms. Primarily due to policymakers' perception that media represents the public and policymakers tend to listen to the public demands. Secondly, by forcing policymakers to take positions and show their fast responses. Finally, mass media can act as a gate keeper which allows politicians to communicate to the public or perhaps not. For these reasons, policymakers tend to react to the mass media and respond accordingly.

The results reveal a consistent positive effect of mass media on the number of active policies. An increase in the number of published articles about environmental issues will be translated into passing more policies. In other words, mass media can interfere in the political agenda by raising the importance of environmental topics. Policymakers respond accordingly and pass more supportive legislation. The effect of mass media is measurable only on the short run, which corresponds well with the theory of attention cycle. The theory suggests that keeping the public attention share can be only done on the short run while exploring the problem and introducing solutions.

From the last two research papers, a pattern can be concluded. External catalysts can help policymakers, pushed by public demands, to increase their activity levels to fight climate change. Through Crisis and intensive reporting, policymakers can sense the seriousness of the topic and understand its consequences and yet pass supportive policies.

Outlook

Despite the efforts accomplished so far, the challenge still exists on how we can sustain global economic performance while reducing and hopefully eliminate climate change impacts. If reducing the overall energy consumption is not applicable, then achieving both targets simultaneously requires innovation of low or zero emitting energy technologies. Trying to induce and strengthen the energy price signal can lead to this kind of innovation and a technological shift, but it might be not in the pace needed to mitigate climate change consequences. Unfortunately, we are working under a tight time schedule. Figure 6.1 indicates the development of CO_2 and the future scenarios. If we continue further with the same technologies and attitude then climate change is inevitable. Additional and further steps have to be taken to cut emissions and reach the required path. This is a challenging task and it entails economists to focus their efforts. Correcting the price alone will not solve the climate change challenge. They shall induce the market to shift towards renewable energies and reduce related CO_2 emissions before it is too late (see Fig 6.1). As Sachs (2008) wrote "Economists like to set corrective prices and then be done with it, leaving the rest decisions to the magic of the market ... This hands-off approach will not work in the case of a major overhaul of energy technology.". While the energy market shows signs to function correctly, yet supportive policies are well needed to ensure the swift shift toward carbon free technologies.

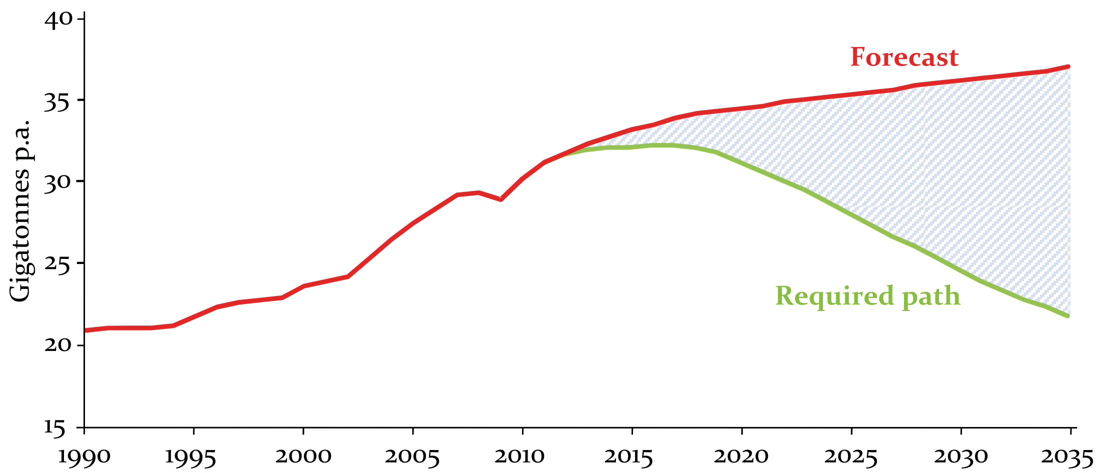


Figure 6.1 Energy related CO_2emissions. Source: King et al. (2015)

At the moment, the economic system is "locked-in" to an unsustainable large scaled fossil fuel energy system. Solving this problem obligates the development of alternatives to this system as a whole (Smith et al., 2009; King et al., 2015). Nevertheless, innovating such technologies require dedicated government support (Storm, 2017; Smith et al., 2009).

Truly, the technological challenge of generating and most notably storing energy on a large scale appears at the moment to be intractable, but similar challenges have been solved, such as rapidly searching and retrieving vast volumes of information. These technologies were unforeseeable only a short time ago, however advocated policy programs allow them to happen. In a similar vein, fighting climate change needs targeted policies to motivate incremental, disruptive as well as radical innovations, by which new methods and technologies can be introduced to assure a regime shifting from fossil fuel energy system to a more sustainable and renewable one.

Bibliography

Agnolucci, P., 2008. Factors influencing the likelihood of regulatory changes in renewable electricity policies. Renewable and Sustainable Energy Reviews 12 (1), 141–161.

Alcamo, J., Puig, D., Metz, B., Demkine, V., Farrell, T. C., 2013. The emissions gap report 2013: a UNEP synthesis report. United Nations Environment Programme.

Atkinson, S. E., Halvorsen, R., 1984. A new hedonic technique for estimating attribute demand: an application to the demand for automobile fuel efficiency. The Review of Economics and Statistics, 417–426.

Boyd, G. A., Karlson, S. H., 1993. The impact of energy prices on technology choice in the united states steel industry. The Energy Journal, 47–56.

Del Río, P., Unruh, G., 2007. Overcoming the lock-out of renewable energy technologies in spain: the cases of wind and solar electricity. Renewable and Sustainable Energy Reviews 11 (7), 1498–1513.

Dinica, V., 2009. Biomass power: Exploring the diffusion challenges in spain. Renewable and Sustainable Energy Reviews 13 (6-7), 1551–1559.

Fischer, C., Newell, R. G., 2008. Environmental and technology policies for climate mitigation. Journal of environmental economics and management 55 (2), 142–162.

Foxon, T. J., Gross, R., Chase, A., Howes, J., Arnall, A., Anderson, D., 2005. Uk innovation systems for new and renewable energy technologies: drivers, barriers and systems failures. Energy policy 33 (16), 2123–2137.

Gamtessa, S., Olani, A., 2016. How does energy-cost lead to energy efficiency? panel evidence from canada.

Goodman, A. C., 1983. Willingness to pay for car efficiency. Journal of Transport Economics and Policy 18, 247–266.

Johnson, A., Jacobsson, S., 2001. Inducement and blocking mechanisms in the development of a new industry: the case of renewable energy technology in sweden. Technology and the market: demand, users and innovation, 89–111.

Johnstone, N., Haščič, I., Kalamova, M., et al., 2010. Environmental policy design characteristics and technological innovation: Evidence from patent data. Tech. rep., OECD Publishing.

King, D., Browne, J., Layard, R., O Donnell, G., Rees, M., Stern, N., Turner, A., 2015. A global apollo programme to combat climate change. London School of Economics and Political Science.

Lewis, J. I., Wiser, R. H., 2007. Fostering a renewable energy technology industry: An international comparison of wind industry policy support mechanisms. Energy policy 35 (3), 1844–1857.

Lund, P. D., 2009. Effects of energy policies on industry expansion in renewable energy. Renewable energy 34 (1), 53–64.

Negro, S. O., Alkemade, F., Hekkert, M. P., 2012. Why does renewable energy diffuse so slowly? a review of innovation system problems. Renewable and Sustainable Energy Reviews 16 (6), 3836–3846.

Negro, S. O., Hekkert, M. P., Smits, R. E., 2007. Explaining the failure of the dutch innovation system for biomass digestion a functional analysis. Energy policy 35 (2), 925–938.

Newell, R., Jaffe, A., Stavins, R., 1999. The induced innovation hypothesis and energy-saving technological change. The Quarterly Journal of Economics 114 (3), 941–975.

Nesta, L., Vona, F., Nicolli, F., 2014. Environmental policies, competition and innovation in renewable energy. Journal of Environmental Economics and Management 67 (3), 396 – 411.

Nicolli, F., Vona, F., 2016. Heterogeneous policies, heterogeneous technologies: The case of renewable energy. Energy Economics 56, 190–204.

Nohrstedt, D., 2005. External shocks and policy change: Three mile island and swedish nuclear energy policy. Journal of European Public Policy 12 (6), 1041–1059.

Nohrstedt, D., 2008. The politics of crisis policymaking: Chernobyl and swedish nuclear energy policy. Policy Studies Journal 36 (2), 257–278.

Ohta, M., Griliches, Z., 1976. Automobile prices revisited: Extensions of the hedonic hypothesis. In: Household production and consumption. NBER, pp. 325–398.

Ohta, M., Griliches, Z., 1986. Automobile prices and quality: Did the gasoline price increases change consumer tastes in the us? Journal of Business and Economic Statistics 4 (2), 187–198.

Popp, D., 2002. Induced innovation and energy prices. American economic review 92 (1), 160–180.

Rao, K. U., Kishore, V., 2010. A review of technology diffusion models with special reference to renewable energy technologies. Renewable and sustainable energy reviews 14 (3), 1070–1078.

Raven, R., Verbong, G., 2004. Ruling out innovations–technological regimes, rules and failures: the cases of heat pump power generation and bio-gas production in the netherlands. Innovation 6 (2), 178–198.

Sachs, J. D., 2008. Keys to climate protection. Scientific American 298 (4), 40–40.

Smith, K., et al., 2009. Climate change and radical energy innovation: the policy issues. University of Oslo, Oslo.

Söderholm, P., Ek, K., Pettersson, M., 2007. Wind power development in sweden: Global policies and local obstacles. Renewable and sustainable energy reviews 11 (3), 365–400.

Storm, S., 2017. How the invisible hand is supposed to adjust the natural thermostat: A guide for the perplexed. Science and engineering ethics 23 (5), 1307–1331.

Wilcox, J. A., 1984. Automobile fuel efficiency: measurement and explanation. Economic Inquiry 22 (3), 375–385.

Bibliography

Abas, N., Kalair, A., Khan, N., 2015. Review of fossil fuels and future energy technologies. Futures 69, 31–49.

Abdmouleh, Z., Alammari, R. A., Gastli, A., 2015. Review of policies encouraging renewable energy integration and best practices. Renewable and Sustainable Energy Reviews 45, 249–262.

Abernathy, W. J., Utterback, J. M., 1978. Patterns of industrial innovation. Technology Review (80), 41–47.

Abolhosseini, S., Heshmati, A., 2014. The main support mechanisms to finance renewable energy development. Renewable and Sustainable Energy Reviews 40, 876–885.

Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D., 2012. The environment and directed technical change. American economic review 102 (1), 131–66.

Alcamo, J., Puig, D., Metz, B., Demkine, V., Farrell, T. C., 2013. The emissions gap report 2013: a UNEP synthesis report. United Nations Environment Programme.

Alexakhin, R., Anspaugh, L., Balonov, M., Batandjieva, B., Besnus, F., Biesold, H., Bogdevich, I., Byron, D., Carr, Z., Deville-Cavelin, G., et al., 2006. Environmental consequences of the Chernobyl accident and their remediation: twenty years of experience. Report of the Chernobyl Forum Expert group Environment. International Atomic Energy Agency.

Allen, M., Antwi-Agyei, P., Aragon-Durand, F., Babiker, M., Bertoldi, P., Bind, M., Brown, S., Buckeridge, M., Camilloni, I., Cartwright, A., et al., 2019. Technical summary: Global warming of 1.5 c. an ipcc special report on the impacts of global warming of 1.5 c above pre-industrial levels and related global greenhouse gas emission pathways.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. The review of economic studies 58 (2), 277–297.

Atkinson, A. B., Stiglitz, J. E., 1969. A new view of technological change. The Economic Journal 79 (315), 573–578.

Atkinson, S. E., Halvorsen, R., 1984. A new hedonic technique for estimating attribute demand: an application to the demand for automobile fuel efficiency. The Review of Economics and Statistics, 417–426.

Ayoub, N., Yuji, N., 2012. Governmental intervention approaches to promote renewable energies – special emphasis on japanese feed-in tariff. Energy Policy 43, 191–201.

Barnett, J., Adger, W. N., 2003a. Climate dangers and atoll countries. Climatic change 61 (3), 321–337.

Barnett, J., Adger, W. N., Dec 2003b. Climate dangers and atoll countries. Climatic Change 61 (3), 321–337.
URL `https://doi.org/10.1023/B:CLIM.0000004559.08755.88`

Barradale, M. J., 2010. Impact of public policy uncertainty on renewable energy investment: Wind power and the production tax credit. Energy Policy 38 (12), 7698–7709.

Bauer, N., Bosetti, V., Hamdi-Cherif, M., Kitous, A., McCollum, D., Méjean, A., Rao, S., Turton, H., Paroussos, L., Ashina, S., et al., 2015. Co2 emission mitigation and fossil fuel markets: dynamic and international aspects of climate policies. Technological Forecasting and Social Change 90, 243–256.

Baumgartner, F. R., Jones, B., 1993. Agendas and instability in american politics. Chicago: Univer-sity of Chicago Press. BaumgartnerAgendas and Instability in American Politics1993.

Baumgartner, F. R., Jones, B. D., 1991. Agenda dynamics and policy subsystems. The journal of Politics 53 (04), 1044–1074.

Bennett, W. L., 1990. Toward a theory of press-state relations in the united states. Journal of communication 40 (2), 103–127.

Bergek, A., Mignon, I., Sundberg, G., 2013. Who invests in renewable electricity production? empirical evidence and suggestions for further research. Energy Policy 56, 568–581.

Besley, T., Burgess, R., 2002. The political economy of government responsiveness: Theory and evidence from india. The Quarterly Journal of Economics 117 (4), 1415–1451.

Beveridge, R., Kern, K., 2013. The energiewende in germany: background, developments and future challenges. Renewable Energy L. and Pol'y Rev. 4, 3.

Bird, L., Bolinger, M., Gagliano, T., Wiser, R., Brown, M., Parsons, B., 2005. Policies and market factors driving wind power development in the united states. Energy Policy 33 (11), 1397–1407.

Birkland, T., Warnement, M., 2013. Defining, explaining, and testing the role of focusing events in agenda change: 30 years of focusing event theory. In: APSA 2013 Annual Meeting Paper.

Birkland, T. A., 1997. After disaster: Agenda setting, public policy, and focusing events. Georgetown University Press.

Birkland, T. A., 1998. Focusing events, mobilization, and agenda setting. Journal of public policy 18 (01), 53–74.

Bisconti, A. S., 2018. Changing public attitudes toward nuclear energy. Progress in Nuclear Energy 102, 103–113.

Blackburne, E. F., Frank, M. W., 2007. Estimation of nonstationary heterogeneous panels. Stata Journal 7 (2), 197.

Blundell, R., Griffith, R., Windmeijer, F., 2002. Individual effects and dynamics in count data models. Journal of econometrics 108 (1), 113–131.

Boin, A., 'T Hart, P., Jan. 2007. The crisis approach. In: Handbook of Disaster Research. Springer.

Bosworth, B., Collins, S. M., 2008. Accounting for growth: comparing china and india. Journal of Economic Perspectives 22 (1), 45–66.

Boyd, G. A., Karlson, S. H., 1993. The impact of energy prices on technology choice in the united states steel industry. The Energy Journal, 47–56.

Brants, K., van Praag, P., et al., 1999. The 1998 campaign: An interaction approach. Acta Politica 34.

Bretschger, L., Valente, S., 2011. Climate change and uneven development. The Scandinavian Journal of Economics 113 (4), 825–845.

Broughton, J. M., Kuan, P., Petti, D. A., Tolman, E. L., 1989. A scenario of the three mile island unit 2 accident. Nuclear Technology 87 (1), 34–53.
URL `https://doi.org/10.13182/NT89-A27637`

Brugger, F., Gehrke, C., 2017. The neoclassical approach to induced technical change: From hicks to acemoglu. Metroeconomica 68 (4), 730–776.

Brulle, R. J., Carmichael, J., Jenkins, J. C., 2012. Shifting public opinion on climate change: an empirical assessment of factors influencing concern over climate change in the us, 2002–2010. Climatic change 114 (2), 169–188.

Brunnermeier, S. B., Cohen, M. A., 2003. Determinants of environmental innovation in us manufacturing industries. Journal of environmental economics and management 45 (2), 278–293.

Calderón, C., Liu, L., 2003. The direction of causality between financial development and economic growth. Journal of Development Economics 72 (1), 321–334.

Caves, D. W., Christensen, L. R., Diewert, W. E., 1982. The economic theory of index numbers and the measurement of input, output, and productivity. Econometrica: Journal of the Econometric Society, 1393–1414.

Cheney, E., Hawkes, M., 2007. The future of hydrocarbons: Hubberts peak or a plateau. GSA Today 17 (6), 69–70.

Chung, Y., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: A directional distance function approach. Journal of Environmental Management 51 (3), 229 – 240.
URL http://www.sciencedirect.com/science/article/pii/S0301479797901468

Cohen, B. C., 1963. T he press and foreign policy. Princeton, NJ: Princeton UniversityPress. Cohen, J.(1988) Statistical Power Analysisfor the Behavioral Sciences.

Conway, P., Janod, V., Nicoletti, G., 2005. Product market regulation in oecd countries.

Cook, T. E., 1989. Making laws and making news. Washington, DC: Brookings Institution.

Costantini, V., Crespi, F., 2013. Public policies for a sustainable energy sector: regulation, diversity and fostering of innovation. Journal of Evolutionary Economics 23 (2), 401–429.

Costello, A., Abbas, M., Allen, A., Ball, S., Bell, S., Bellamy, R., Friel, S., Groce, N., Johnson, A., Kett, M., et al., 2009. Managing the health effects of climate change: lancet and university college london institute for global health commission. The Lancet 373 (9676), 1693–1733.

Dahl Robert, A., 1961. Who governs? democracy and power in an american city.

Dasgupta, S., Mody, A., Roy, S., Wheeler, D., 2001. Environmental regulation and development: A cross-country empirical analysis. Oxford development studies 29 (2), 173–187.

Day, E., Fankhauser, S., Kingsmill, N., Costa, H., Mavrogianni, A., 2019. Upholding labour productivity under climate change: an assessment of adaptation options. Climate policy 19 (3), 367–385.

De Jager, D., Klessmann, C., Stricker, E., Winkel, T., de Visser, E., Koper, M., Ragwitz, M., Held, A., Resch, G., Busch, S., et al., 2011. Financing renewable energy in the european energy market. Final report by Ecofys, Fraunhofer ISI, TU Vienna EEG and Ernst andYoung, Ecofys, Utrecht.

Deffeyes, K. S., 2008. Hubbert's peak: the impending world oil shortage (New Edition). Princeton University Press.

Di Stefano, G., Gambardella, A., Verona, G., 2012. Technology push and demand pull perspectives in innovation studies: Current findings and future research directions. Research Policy 41 (8), 1283–1295.

Dopfer, K., 2004. The economic agent as rule maker and rule user: Homo sapiens oeconomicus. Journal of Evolutionary Economics 14 (2), 177–195.

Dopfer, K., Foster, J., Potts, J., Jul. 2004. Micro-meso-macro. Journal of Evolutionary Economics V14 (3), 263–279.
URL http://dx.doi.org/10.1007/s00191-004-0193-0

Dopfer, K., Potts, J., 2008. The General Theory of Economic Evolution. Routledge, London and New York.

Dosi, G., Jun. 1982. Technological paradigms and technological trajectories : A suggested interpretation of the determinants and directions of technical change. Research Policy 11 (3), 147–162.
URL http://www.sciencedirect.com/science/article/B6V77-45BCNM0-21/2/e3657d09b1e4d35bd792120e5f8fdebf

Downs, A., 1972. Up and down with ecology: The issue-attention cycle. The public.

Dudley, B., et al., 2015. Bp statistical review of world energy 2016. London, UK.

Dudley, B., et al., 2019. Bp statistical review of world energy. BP Statistical Review, London, UK, accessed Aug 6.

Dumitrescu, D., Mughan, A., 2010. Mass media and democratic politics. In: Handbook of politics. Springer, pp. 477–491.

Dumitrescu, E.-I., Hurlin, C., 2012. Testing for granger non-causality in heterogeneous panels. Economic Modelling 29 (4), 1450–1460.

Eboli, F., Parrado, R., Roson, R., 2010. Climate-change feedback on economic growth: explorations with a dynamic general equilibrium model. Environment and Development Economics 15 (5), 515–533.

Eichhorn, W., 1996. Agenda-setting-prozesse: Eine theoretische analyse individueller und gesellschaftlicher themenstrukturierung (kommunikationswissenschaftliche studien band 16).

Eilders, C., 1997. The impact of editorial content on the political agenda in germany: Theoretical assumptions and open questions regarding a neglected subject in mass communication research. Tech. rep., WZB Discussion Paper.

Elder, C. D., Cobb, R. W., 1983. The political uses of symbols. Longman Publishing Group.

EPO, 2015. European patent office worldwide patent statistical database patstat.

Esser, F., Pfetsch, B., 2013. Comparing political communication. In: The Handbook of Comparative Communication Research. Routledge, pp. 47–69.

Fankhauser, S., Tol, R. S., 2005. On climate change and economic growth. Resource and Energy Economics 27 (1), 1–17.

Färe, R., Grosskopf, S., Lindgren, B., Roos, P., 1992. Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. In: International Applications of Productivity and Efficiency Analysis. Springer, pp. 81–97.
URL http://www.jstor.org/stable/41770574?seq=1#page_scan_tab_contents

Fauzan, A. U., Schiller, J., 2011. After Fukushima: The Rise of Resistance to Nuclear Energy in Indonesia. German Asia Foundation/Asia House Essen, Germany.

Fernandez, D., Galetovic, A., 1994. Schumpeter might be right–but why? explaining the relation between finance, development and growth. Johns Hopkins University SAIS Working Paper in International Economics (96-01).

Fesenko, S. V., Alexakhin, R. M., Balonov, M. I., Bogdevitch, I. M., Howard, B. J., Kashparov, V. A., Sanzharova, N. I., Panov, A. V., Voigt, G., Zhuchenka, Y. M., 2007. An extended critical review of twenty years of countermeasures used in agriculture after the chernobyl accident. Science of the total environment 383 (1-3), 1–24.

Fischer, C., Newell, R. G., 2008. Environmental and technology policies for climate mitigation. Journal of environmental economics and management 55 (2), 142–162.

Fisher, B., Nakicenovic, N., Alfsen, K., Corfee-Morlot, J., Riahi, K., 2007. Issues related to mitigation in the long-term context (chapter 3).

Flanagan, S. C., 1973. Models and methods of analysis. Crisis, choice, and change: Historical studies of political development. Boston: Little, Brown.

Flavin, C., 1987. Chernobyl: The political fallout in western europe. In: Forum for Applied Research and Public Policy (Summer). pp. 16–28.

Førsund, F. R., 2009. Good modelling of bad outputs: Pollution and multiple-output production. International Review of Environmental and Resource Economics 3 (1), 1–38.

Francken, N., Minten, B., Swinnen, J. F., 2009. Media, monitoring, and capture of public funds: evidence from madagascar. World Development 37 (1), 242–255.

Freeman, C., 1982. The Economics of Industrial Innovation, 2nd Edition. Francis Pinter, London.

Freeman, D. G., 2000. Alternative panel estimates of alcohol demand, taxation, and the business cycle. Southern Economic Journal, 325–344.

Gamtessa, S., Olani, A., 2016. How does energy-cost lead to energy efficiency? panel evidence from canada.

Gerhartz-Muro, J. L., Kritzer, J. P., Gerhartz-Abraham, A., Miller, V., Pina-Amargós, F., Whittle, D., 2018. An evaluation of the framework for national marine environmental policies in cuba. Bulletin of Marine Science 94 (2), 443–459.

Glaser, A., 2011. After fukushima: preparing for a more uncertain future of nuclear power. The Electricity Journal 24 (6), 27–35.

Goodman, A. C., 1983. Willingness to pay for car efficiency. Journal of Transport Economics and Policy 18, 247–266.

Gough, I., 2013. The challenge of climate change for social policy.

Granger, C. W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: Journal of the Econometric Society, 424–438.

Grebel, T., 2018. Measuring technical change in energy production with dea.

Griliches, Z., 1990. Patent statistics as economic indicators: a survey. Tech. rep., National Bureau of Economic Research.

Gunther, A. C., Storey, J. D., 2003. The influence of presumed influence. Journal of Communication 53 (2), 199–215.

Hadjilambrinos, C., 2000. Understanding technology choice in electricity industries: a comparative study of France and Denmark. Energy Policy 28 (15), 1111 – 1126.

Hall, B. H., 1993. The stock market's valuation of randd investment during the 1980's. The American Economic Review 83 (2), 259–264.

Hall, B. H., Jaffe, A. B., Trajtenberg, M., 2000. Market value and patent citations: A first look. Tech. rep., national bureau of economic research.

Hallegatte, S., 2005. The long time scales of the climate–economy feedback and the climatic cost of growth. Environmental Modeling and Assessment 10 (4), 277–289.

Hamdi, H., Hakimi, A., Sbia, R., 2013. Multivariate granger causality between financial development, investment and economic growth: Evidence from tunisia. Journal of Quantitative Economics 11 (1and2), 111–129.

Hamilton, L. C., Bell, E., Hartter, J., Salerno, J. D., 2018. A change in the wind? us public views on renewable energy and climate compared. Energy, Sustainability and Society 8 (1), 11.

Hausman, J., Hall, B. H., Griliches, Z., 1984. Econometric models for count data with an application to the patents-randd relationship. Econometrica 52 (4), 909–938.
URL http://www.jstor.org/stable/1911191

Havenaar, J. M., 1996. After chernobyl. psychological factors affecting health after a nuclear disaster.

Heaton Jr, G. R., Banks, R. D., 1997. Toward a new generation of environmental technology: The need for legislative reform. Journal of Industrial Ecology 1 (2), 23–32.

Helm, D., 2015. The Carbon Crunch: Revised and Updated. Yale University Press.

Helm, D., 2016. The future of fossil fuelsis it the end? Oxford Review of Economic Policy 32 (2), 191–205.

Henry, A. D., Ingold, K., Nohrstedt, D., Weible, C. M., 2014. Policy change in comparative contexts: Applying the advocacy coalition framework outside of western europe and north america. Journal of Comparative Policy Analysis: Research and Practice 16 (4), 299–312.

Hepburn, C., 2010. Environmental policy, government, and the market. Oxford Review of Economic Policy 26 (2), 117–136.

Herrnstadt, E., Muehlegger, E., 2014. Weather, salience of climate change and congressional voting. Journal of Environmental Economics and Management 68 (3), 435–448.

Hewitt, K., 1983. ªthe idea of calamity in a technocratic age «. Interpretations of Calamity: From the Viewpoint of Human Ecology, London: Allen and Unwin.

Hicks, J., 1932. The theory of wages. London: Macmillan.

Hogan, J., Feeney, S., 2012. Crisis and policy change: The role of the political entrepreneur. Risk, Hazards and Crisis in Public Policy 3 (2), 1–24.

Hoppe, T., van den Berg, M. M., Coenen, F. H., 2014. Reflections on the uptake of climate change policies by local governments: facing the challenges of mitigation and adaptation. Energy, sustainability and society 4 (1), 8.

IAEA, 2016. The international nuclear and radiological event scale (ines).

IEA, 2013. Co2 emissions from fuel combustion.

IEA, 2018. CO2 Emissions from Fuel Combustion 2018. International Energy Agency.

IEA, 2018a. World energy investment 2018. International Energy Agency Paris.

IEA, 2018b. World Energy Outlook 2018.

ILO, 2019. Working on a warmer planet: the impact of heat stress on labour productivity and decent work. International Labour Office.

Im, K. S., Pesaran, M. H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. Journal of econometrics 115 (1), 53–74.

Ingold, K., 2011. Network structures within policy processes: Coalitions, power, and brokerage in swiss climate policy. Policy studies journal 39 (3), 435–459.

International Atomic Energy Agency, 2008. Ines: The international nuclear and radiological event scale user's manual.

International Energy Agency, 2004. Renewable energy – market and policy trends in IEA countries. Tech. rep., IEA, Paris.

IPCC, 2013. Climate Change 2013-The Physical Science Basis: Summary for Policymakers. Intergovernmental Panel on Climate Change.

Jaffe, A. B., Newell, R. G., Stavins, R. N., 2003. Technological change and the environment. Handbook of environmental economics 1, 461–516.

Jaffe, A. B., Stavins, R. N., 1995. Dynamic incentives of environmental regulations: The effects of alternative policy instruments on technology diffusion. Journal of environmental economics and management 29 (3), S43–S63.

Jenkins-Smith, H. C., Sabatier, P. A., 1994. Evaluating the advocacy coalition framework. Journal of public policy 14 (02), 175–203.

John, P., 2003. Is there life after policy streams, advocacy coalitions, and punctuations: Using evolutionary theory to explain policy change? Policy Studies Journal 31 (4), 481–498.

Johnstone, N., Haščič, I., Kalamova, M., et al., 2010a. Environmental policy design characteristics and technological innovation: Evidence from patent data. Tech. rep., OECD Publishing.

Johnstone, N., Hascic, I., Popp, D., 2010b. Renewable energy policies and technological innovation: Evidence based on patent counts. Environmental and Resource Economics 45, 133–155.

Jorgenson, D. W., Ho, M. S., Stiroh, K. J., 2008. A retrospective look at the us productivity growth resurgence. Journal of Economic perspectives 22 (1), 3–24.

Kammen, D. M., 2006. The rise of renewable energy. Scientific American 295 (3), 84–93.

Keeler, J. T., 1993. Opening the window for reform mandates, crises, and extraordinary policy-making. Comparative Political Studies 25 (4), 433–486.

Kemp, R., 2000. Technology and environmental policy innovation effects of past policies and suggestions for improvement. Innovation and the Environment 1, 35–61.

Kernell, S., 1997. Going public: new strategies of presidential leadership.

Khan, M. S., Semlali, A. S., 2000. Financial development and economic growth: an overview. International Monetary Fund.

Kilinc-Ata, N., 2016. The evaluation of renewable energy policies across eu countries and us states: An econometric approach. Energy for Sustainable Development 31, 83–90.

King, D., Browne, J., Layard, R., O Donnell, G., Rees, M., Stern, N., Turner, A., 2015. A global apollo programme to combat climate change. London School of Economics and Political Science.

Kingdon, J. W., 2003. Agendas, alternatives, and public policies. Longman Pub Group.

Klepper, S., June 1996. Entry, exit, growth, and innovation over the product life cycle. American Economic Review 86 (3), 562–583.

Klepper, S., 1997. Industry life cycles. Industrial and Corporate Change 6 (1), 145–81.

Koch-Baumgarten, S., Voltmer, K., 2010. Public policy and the mass media: The interplay of mass communication and political decision making. Routledge.

Kozluk, T., Zipperer, V., 2015. Environmental policies and productivity growth. OECD Journal: Economic Studies 2014 (1), 155–185.

Kübler, D., 2001. Understanding policy change with the advocacy coalition framework: an application to swiss drug policy. Journal of European public policy 8 (4), 623–641.

Lanjouw, J. O., Mody, A., 1996. Innovation and the international diffusion of environmentally responsive technology. Research Policy 25 (4), 549–571.

Le Quéré, C., Raupach, M. R., Canadell, J. G., Marland, G., Bopp, L., Ciais, P., Conway, T. J., Doney, S. C., Feely, R. A., Foster, P., et al., 2009. Trends in the sources and sinks of carbon dioxide. Nature geoscience 2 (12), 831.

Leifeld, P., 2013. Reconceptualizing major policy change in the advocacy coalition framework: A discourse network analysis of german pension politics. Policy Studies Journal 41 (1), 169–198.

Lemoine, D., Kapnick, S., 2016. A top-down approach to projecting market impacts of climate change. Nature Climate Change 6 (1), 51.

Linn, J., 2008. Energy prices and the adoption of energy-saving technology. The Economic Journal 118 (533), 1986–2012.

Linsky, M., O'Donnell, W., Moore, J., 1986. Impact: How the press affects federal policymaking. WW Norton New York.

Livingston, S., 1997. Clarifying the cnn effect: An examination of media effects according to type of military intervention.

Loiter, J., Norberg-Bohm, V., 1999. Technology policy and renewable energy: public roles in the development of new energy technologies. Energy Policy 27, 85 – 97.

Lopez, L., Weber, S., et al., 2017. Testing for granger causality in panel data. Stata Journal 17 (4), 972–984.

Lubell, M., Scholz, J., Berardo, R., Robins, G., 2012. Testing policy theory with statistical models of networks. Policy Studies Journal 40 (3), 351–374.

Lund, P. D., 2009. Effects of energy policies on industry expansion in renewable energy. Renewable energy 34 (1), 53–64.

Ma, Q., 1998. Greenhouse gases: Refining the role of carbon dioxide. NASA Goddard Institute for Space Studies. http://www. giss. nasa. gov/research/intro/ma 1.

Malmquist, S., 1953. Index numbers and indifference surfaces. Trabajos de Estadistica y de Investigacion Operativa 4 (2), 209–242.

March, J. G., Olsen, J. P., 1996. Institutional perspectives on political institutions. Governance 9 (3), 247–264.

Mardani, A., Zavadskas, E. K., Streimikiene, D., Jusoh, A., Khoshnoudi, M., 2017. A comprehensive review of data envelopment analysis (dea) approach in energy efficiency. Renewable and Sustainable Energy Reviews 70, 1298–1322.

Markandya, A., 2009. Can climate change be reversed under capitalism? Development and Change 40 (6), 1139–1152.

Marquart-Pyatt, S. T., 2007. Concern for the environment among general publics: A cross-national study. Society and Natural Resources 20 (10), 883–898.

Marquart-Pyatt, S. T., 2008. Are there similar sources of environmental concern? comparing industrialized countries. Social Science Quarterly 89 (5), 1312–1335.

Marquart-Pyatt, S. T., 2012. Contextual influences on environmental concerns cross-nationally: A multilevel investigation. Social science research 41 (5), 1085–1099.

Mathias Kepplinger, H., 2007. Reciprocal effects: Toward a theory of mass media effects on decision makers. Harvard International Journal of Press/Politics 12 (2), 3–23.

McCluskey, J. J., Swinnen, J. F., 2010. Media economics and the political economy of information. In: The Oxford handbook of business and government.

McCombs, M., 2014. Setting the agenda: Mass media and public opinion. John Wiley and Sons.

McCombs, M. E., Shaw, D. L., 1972. The agenda-setting function of mass media. Public opinion quarterly 36 (2), 176–187.

McConnell, A., 2008. Ripples not waves: A policy configuration approach to reform in the wake of the 1998 sydney water crisis. Governance 21 (4), 551–580.

Meinen, G., Verbiest, P., Wolf, P. d., 1998. Perpetual inventory method. Service lives, discard patterns, and depreciation methods. Heerlen-Voorburg: Statistics Netherlands.

Menanteau, P., Finon, D., Lamy, M.-L., 2003. Prices versus quantities: choosing policies for promoting the development of renewable energy. Energy policy 31 (8), 799–812.

Menz, F. C., Vachon, S., 2006. The effectiveness of different policy regimes for promoting wind power: Experiences from the states. Energy policy 34 (14), 1786–1796.

Milliman, S. R., Prince, R., 1989. Firm incentives to promote technological change in pollution control. Journal of Environmental economics and Management 17 (3), 247–265.

Millner, A., Ollivier, H., 2016. Beliefs, politics, and environmental policy. Review of Environmental Economics and Policy 10 (2), 226–244.

Mokyr, J., 1990. The Lever of Riches. Oxford University Press, Oxford.

Mowery, D., Rosenberg, N., 1979. The influence of market demand upon innovation: a critical review of some recent empirical studies. Research policy 8 (2), 102–153.

Nelson, R. R., Winter, S. G., 1982. An Evolutionary Theory of Economic Change. Cambridge University Press, Cambridge, MA.

Nemet, G. F., 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Research Policy 38 (5), 700 – 709.

Nesta, L., 2008. Knowledge and productivity in the world's largest manufacturing corporations. Journal of Economic Behavior and Organization 67 (3-4), 886–902.

Nesta, L., Saviotti, P.-P., 2006. Firm knowledge and market value in biotechnology. Ind Corp Change 15 (4), 625–652.

Nesta, L., Vona, F., Nicolli, F., 2014. Environmental policies, competition and innovation in renewable energy. Journal of Environmental Economics and Management 67 (3), 396 – 411.

Neuhoff, K., Johnston, A., Fouquet, D., Ragwitz, M., Resch, G., 2008. The proposed new eu renewables directive: an interpretation. Cambridge 11, 2008.

Newell, R., Jaffe, A., Stavins, R., 1999. The induced innovation hypothesis and energy-saving technological change. The Quarterly Journal of Economics 114 (3), 941–975.

Nicolli, F., Vona, F., 2016. Heterogeneous policies, heterogeneous technologies: The case of renewable energy. Energy Economics 56, 190–204.

Nohrstedt, D., 2005. External shocks and policy change: Three mile island and swedish nuclear energy policy. Journal of European Public Policy 12 (6), 1041–1059.

Nohrstedt, D., 2008. The politics of crisis policymaking: Chernobyl and swedish nuclear energy policy. Policy Studies Journal 36 (2), 257–278.

Nohrstedt, D., Weible, C. M., 2010. The logic of policy change after crisis: Proximity and subsystem interaction. Risk, Hazards and Crisis in Public Policy 1 (2), 1–32.

Nordhaus, W. D., 2007. A review of the stern review on the economics of climate change. Journal of economic literature 45 (3), 686–702.

OECD, 2012. Indicators of environmental technologies (env-tech indicators). OECD, Paris.

Oh, D.-h., Lööf, H., Heshmati, A., et al., 2009. The icelandic economy: A victim of the financial crisis or simply inefficient? Tech. rep., Royal Institute of Technology, CESIS-Centre of Excellence for Science and .

Ohta, M., Griliches, Z., 1976. Automobile prices revisited: Extensions of the hedonic hypothesis. In: Household production and consumption. NBER, pp. 325–398.

Ohta, M., Griliches, Z., 1986. Automobile prices and quality: Did the gasoline price increases change consumer tastes in the us? Journal of Business and Economic Statistics 4 (2), 187–198.

Orr, L., 1976. Incentive for innovation as the basis for effluent charge strategy. The American Economic Review 66 (2), 441–447.

Pajo, J., 2015. Danger explodes, space implodes: the evolution of the environmental discourse on nuclear waste, 1945–1969. Energy, Sustainability and Society 5 (1), 36.

Pappi, F. U., Henning, C. H. C. A., October 1998. Policy Networks: More Than a Metaphor? Journal of Theoretical Politics 10 (4), 553–575.
URL `https://ideas.repec.org/a/sae/jothpo/v10y1998i4p553-575.html`

Pesaran, M. H., Shin, Y., Smith, R. P., 1999. Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association 94 (446), 621–634.

Pesaran, M. H., Smith, R., 1995. Estimating long-run relationships from dynamic heterogeneous panels. Journal of econometrics 68 (1), 79–113.

Phillips, P. C., Moon, H. R., 2000. Nonstationary panel data analysis: an overview of some recent developments. Econometric Reviews 19 (3), 263–286.

Pierson, P., 2000. Increasing returns, path dependence, and the study of politics. American political science review 94 (02), 251–267.

Pol, E., 2013. Reconciling the invisible hand and innovation. Economics of Innovation and New Technology 22 (5), 431–446.

Polzin, F., Migendt, M., Täube, F. A., von Flotow, P., 2015. Public policy influence on renewable energy investments: A panel data study across oecd countries. Energy Policy 80, 98–111.

Popp, D., 2002. Induced innovation and energy prices. American economic review 92 (1), 160–180.

Popp, D., Hascic, I., Medhi, N., 2011. Technology and the diffusion of renewable energy. Energy Economics 33 (4), 648–662.

Popp, D., Newell, R. G., Jaffe, A. B., 2010. Energy, the environment, and technological change. In: Handbook of the Economics of Innovation. Vol. 2. Elsevier, pp. 873–937.

Pritchard, D., 1992. The news media and public policy agendas. Public opinion, the press, and public policy 58, 153–154.

Protess, D. L., 1992. The journalism of outrage: Investigative reporting and agenda building in America. Guilford Press.

Quirion, P., 2010. Complying with the kyoto protocol under uncertainty: Taxes or tradable permits? Energy Policy 38 (9), 5166–5173.

Reinikka, R., Svensson, J., 2005. Fighting corruption to improve schooling: Evidence from a newspaper campaign in uganda. Journal of the European economic association 3 (2-3), 259–267.

Renn, O., 1990. Public responses to the chernobyl accident. Journal of Environmental Psychology 10 (2), 151–167.

Ritchie, H., Roser, M., 2019a. Co2 and greenhouse gas emissions. Our World in DataHttps://ourworldindata.org/co2-and-other-greenhouse-gas-emissions.

Ritchie, H., Roser, M., 2019b. Fossil fuels. Our World in DataHttps://ourworldindata.org/fossil-fuels.

Ritchie, H., Roser, M., 2019c. Renewable energy. Our World in DataHttps://ourworldindata.org/renewable-energy.

Rosa, E. A., Dunlap, R. E., 1994. The pollspoll trends: Nuclear power: Three decades of public opinion. Public Opinion Quarterly 58 (2), 295–324.

Rose, N. L., Joskow, P. L., 1988. The diffusion of new technologies: evidence from the electric utility industry.

Rosenberg, N., 1976. Perspectives on Technology. Cambridge University Press, Cambridge.

Rosenberg, N., 1982. Inside the black box: Technology and economics. Cambridge University Press, Cambridge.

Rosenberg, N., Nathan, R., 1982. Inside the black box: technology and economics. cambridge university press.

Rosenthal, U., Boin, A., Comfort, L. K., 2001. Managing crises: Threats, dilemmas, opportunities. Charles C Thomas Publisher.

Sabatier, P., Weible, C., 2007. The advocacy coalition: Innovations and clarifications. Theories of the policy process 2, 189–220.

Sabatier, P. A., 1987. Knowledge, policy-oriented learning, and policy change: An advocacy coalition framework. Knowledge 8 (4), 649–692.

Sabatier, P. A., 1998. The advocacy coalition framework: revisions and relevance for europe. Journal of European public policy 5 (1), 98–130.

Sabatier, P. A., Jenkins-Smith, H. C., 1999. The advocacy coalition framework: An assessment. Theories of the policy process 118, 188.

Sabatier, P. A., Weible, C., 2014. Theories of the policy process. Westview Press.

Sachs, J. D., 2008. Keys to climate protection. Scientific American 298 (4), 40–40.

Sanyal, P., Ghosh, S., 2012. Product market competition and upstream innovation: Theory and evidence from the US electricity market deregulation. Review of Economics and Statistics forthcoming.

Scartascini, C., Cruz, C., Keefer, P., 2018. The database of political institutions 2017 (dpi2017).

Schimel, D. S., 1995. Terrestrial ecosystems and the carbon cycle. Global change biology 1 (1), 77–91.

Schlager, E., 1995. Policy making and collective action: Defining coalitions within the advocacy coalition framework. Policy sciences 28 (3), 243–270.

Schmookler, J., 1966. Invention and economic growth.

Schneider, V., 1992. The structure of policy networks. European Journal of Political Research 21 (1-2), 109–129.

Schudson, M., 1995. The power of news. Harvard University Press.

Seiford, L. M., Zhu, J., 2002. Modeling undesirable factors in efficiency evaluation. European Journal of Operational Research 142 (1), 16 – 20.
URL http://www.sciencedirect.com/science/article/pii/S0377221701002934

Sellers, P., 2009. Cycles of spin: Strategic communication in the US Congress. Cambridge University Press.

Shafiee, S., Topal, E., 2009. When will fossil fuel reserves be diminished? Energy policy 37 (1), 181–189.

Shoemaker, P. J., 1991. Gatekeeping. communication concepts 3. Newbury Park. Sage. Internetnachweise: oV: LEO. Link everything online. http://dict. leo. org 28, 2003.

Sigal, L. V., 1973. Reporters and officials: The organization and politics of newsmaking. DC Heath.

Simmons, M. R., 2007. Is the world supply of oil and gas peaking. International Petroleum Week.

Skea, J., Lechtenböhmer, S., Asuka, J., 2013. Climate policies after fukushima: three views. Climate Policy 13 (sup01), 36–54.

Smith, J. B., Schellnhuber, H.-J., Mirza, M. M. Q., Fankhauser, S., Leemans, R., Erda, L., Ogallo, L., Pittock, B., Richels, R., Rosenzweig, C., et al., 2001. Vulnerability to climate change and reasons for concern: a synthesis. Climate change, 913–967.

Smith, K., et al., 2009. Climate change and radical energy innovation: the policy issues. University of Oslo, Oslo.

Smith, M. G., Urpelainen, J., 2014. The effect of feed-in tariffs on renewable electricity generation: An instrumental variables approach. Environmental and resource economics 57 (3), 367–392.

Smith, V. K., 1972. The implications of common property resources for technical change. European Economic Review 3 (4), 469–479.

Sotirov, M., Memmler, M., 2012. The advocacy coalition framework in natural resource policy studiesrecent experiences and further prospects. Forest policy and economics 16, 51–64.

Stern, D. I., 2011a. The role of energy in economic growth. Annals of the New York Academy of Sciences 1219 (1), 26–51.

Stern, D. I., 2011b. The role of energy in economic growth. Annals of the New York Academy of Sciences 1219 (1), 26–51.

Stern, N., 2007. The economics of climate change: the Stern review. cambridge University press.

Storm, S., 2017. How the invisible hand is supposed to adjust the natural thermostat: A guide for the perplexed. Science and engineering ethics 23 (5), 1307–1331.

Strömberg, D., 2004. Radio's impact on public spending. The Quarterly Journal of Economics 119 (1), 189–221.

Strömberg, D., Snyder, J., 2008. The mediaś influence on public policy decisions. Information and Public Choice. From Media Markets to Policy Making, The World Bank, Washington, DC, 17–31.

Sueyoshi, T., Goto, M., May 2011. Measurement of returns to scale and damages to scale for DEA-based operational and environmental assessment: How to manage desirable (good) and undesirable (bad) outputs? European Journal of Operational Research 211 (1), 76–89.
URL http://ideas.repec.org/a/eee/ejores/v211y2011i1p76-89.html

Sueyoshi, T., Goto, M., 2012. Data envelopment analysis for environmental assessment: Comparison between public and private ownership in petroleum industry. European Journal of Operational Research 216 (3), 668–678.

Taghizadeh-Hesary, F., Yoshino, N., 2019. The way to induce private participation in green finance and investment. Finance Research Letters 31, 98–103.

Taghizadeh-Hesary, F., Yoshino, N., Rasoulinezhad, E., 2017. Impact of the fukushima nuclear disaster on the oil-consuming sectors of japan. Journal of Comparative Asian Development 16 (2), 113–134.

Tan, L., Zuo, L., Wang, B., 2018. Methods of decline curve analysis for shale gas reservoirs. Energies 11 (3), 552.

Tol, R. S., 2014. The economic effects of climate change. JOURNAL OF ECONOMIC PERSPECTIVES 28 (2), 221–225.

Trainer, F., 1995. Can renewable energy sources sustain affluent society? Energy Policy 23 (12), 1009–1026.

Van Aelst, P., Thesen, G., Walgrave, S., Vliegenthart, R., 2013. Mediatization and the media's political agenda-setting influence. In: Comparative Agendas Project conference, Antwerp, June. pp. 27–29.

Van Ark, B., O'Mahoney, M., Timmer, M. P., 2008. The productivity gap between europe and the united states: trends and causes. Journal of economic perspectives 22 (1), 25–44.

Walgrave, S., Soroka, S., Nuytemans, M., 2008. The mass media's political agenda-setting power: A longitudinal analysis of media, parliament, and government in belgium (1993 to 2000). Comparative Political Studies 41 (6), 814–836.

Walgrave, S., Van Aelst, P., 2006. The contingency of the mass media's political agenda setting power: Toward a preliminary theory. Journal of communication 56 (1), 88–109.

Walgrave, S., Van Aelst, P., Bennett, L., 2010. Beyond agenda-setting. towards a broader theory of agenda interactions between political actors and the mass media. In: APSA Annual Meeting, Washington. Vol. 2.

Weible, C. M., Sabatier, P. A., Jenkins-Smith, H. C., Nohrstedt, D., Henry, A. D., DeLeon, P., 2011. A quarter century of the advocacy coalition framework: An introduction to the special issue. Policy Studies Journal 39 (3), 349–360.

Weitzman, M. L., 2015. A review of william nordhaus' the climate casino: Risk, uncertainty, and economics for a warming world. Review of Environmental Economics and Policy 9 (1), 145–146.

Wenders, J. T., 1975. Methods of pollution control and the rate of change in pollution abatement technology. Water Resources Research 11 (3), 393–396.

Wilcox, J. A., 1984. Automobile fuel efficiency: measurement and explanation. Economic Inquiry 22 (3), 375–385.

Wolfe, M., 2012. Putting on the brakes or pressing on the gas? media attention and the speed of policymaking. Policy Studies Journal 40 (1), 109–126.

Wuestenhagen, R., Wolsink, M., Buerer, M. J., 2007. Social acceptance of renewable energy innovation: An introduction to the concept. Energy policy 35 (5), 2683–2691.

Yang, L., Ouyang, H., Fang, K., Ye, L., Zhang, J., 2015. Evaluation of regional environmental efficiencies in china based on super-efficiency-dea. Ecological Indicators 51, 13–19.

Yasumura, S., Goto, A., Yamazaki, S., Reich, M., 2013. Excess mortality among relocated institutionalized elderly after the fukushima nuclear disaster. public health 127 (2), 186–188.

Yoshino, N., Taghizadeh-Hesary, F., Nakahigashi, M., 2019. Modelling the social funding and spill-over tax for addressing the green energy financing gap. Economic Modelling 77, 34–41.

Zahariadis, N., 2014. Ambiguity and multiple streams. Theories of the policy process, 25–58.

Zerbe, R. O., 1970. Theoretical efficiency in pollution control. Economic Inquiry 8 (4), 364.

Zhu, J., 2014. Quantitative models for performance evaluation and benchmarking: data envelopment analysis with spreadsheets. Vol. 213. Springer.