Three Essays in Applied Economics – Empirical Analyses of Renewable Energies & the Relationship between Competitive Sports and Job Success

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

This dissertation consists of three essays in empirical economics focusing on two different fields, i.e. energy economics and sports economics. The aim is to analyse current issues in the sectors of renewable energy economics as well as sports economics at the interface of labour economics. Both fields are of a broader interest as they possess a societal component and, hence, are subject to political influence.

The expansion of renewable energies for electricity generation is socially as well as politically desired and, therefore, often promoted by governmental financial support schemes and prioritized feed-in. This results in distortions to the market process of conventional power plants. Electricity generation by the so-called intermittent renewable energies, i.e. wind and solar PV, is weather-dependent and not demand-driven. It can be interpreted as an exogenous supply shock to the conventional generation. Conventional power plants, therefore, have to cover only the residual demand, which is subject to ever greater fluctuations. Power is usually provided by several conventional power plant types, i.e. base-, mid-merit and peak-load plants, that vary according to their fixed and variable costs. Thereby, they determine their generation pattern in accordance with demand. The increased feed-in by renewable energies places considerable demands on the conventional plant fleet. For example, a flexible back-up capacity has to be maintained, that is able to step in – even at short notice – when the intermittent technologies are unable to produce, yet is not in operation most of the year. These developments will have an impact on the future market design and security of supply.

Regarding high-level competitive sports, a society usually longs for sporting heroes and it is argued that elite athletes and competitive sports play an important role in society. Many Germans enjoy a sense of pride if athletes of their country celebrate successes in international sporting events and winning medals in major sporting events motivates about a quarter of the German population to get active with sports themselves (Breuer and Hallmann, 2011). In addition, elite athletes are said to exert a positive influence on the citizens by establishing role models and communicating values such as fair play and team spirit. On the individual level, elite athletes are supposed to dispose of certain skills and personal characteristics such as commitment, discipline, self-confidence and a high stress tolerance, that are beneficial to a professional business career. However, participation in high-level competitive sports usually requires additional – financial – funding to the athletes, that is often provided by some governmental institution or foundation. Particularly since the Summer Olympic Games 2012 in London, there is an ongoing debate about the funding of elite sports. A large number of affected athletes are voicing their criticism about the current support scheme. They believe it to be inadequate in offering a continuously reliable financial support, which makes a simultaneous combination of vocational training and/or employment and top sports essential. At the same time, critics consider the funding as wasteful and question its general success (Drepper, 2012). When debating the scheme and level of elite sports funding not only the sporting performance should be taken into account, but also its long-term economic effects.

From a methodological point of view, different empirical techniques are employed in each chapter of this dissertation. Different research questions impose different requirements on the data to be used in the respective analysis. In the following chapters, several empirical techniques have been applied to time series, panel as well as survey data.

In Chapter 2, **The Green Game Changer: An Empirical Assessment of the Effects of Intermittent Generation on the Merit Order** (co-authored by Veit Böckers and Jürgen Rösch), the short-run impact of renewable energy sources on the merit order and the wholesale price in the Spanish wholesale market for electricity from 2008 to 2012 are estimated. The increased share of power generated by intermittent renewable energy sources (RES-E), i.e. wind and solar PV, leaves for the conventional generation technologies only the residual electricity demand to cover. In light of the different types of power plants as well as the altered requirements faced by the power plant fleet, this contribution empirically sheds light on the theoretical discussion which power plants are affected most by (intermittent) RES-E. Methodologically, the given structure of the merit-order is used to estimate a structural vector autoregressive (VAR) model. The coefficients of the technologies right in the merit-order of the respective technology are constrained to zero. It is argued that wind and solar production are exogenous to the system. As expected the effect is negative for the wholesale price and the produced quantities of most generation technologies. The estimated impact, however, is largest for mid-merit plants and the effect is also mainly driven by wind power.

The analysis in Chapter 3, titled **The Effect of Intermittent RES-E on the Conventional Power Plant Mix - An Empirical Analysis of 18 European Countries**, is closely related to the second chapter. It aims at evaluating if and how the generation by intermittent RES-E has affected the conventional power plant mix. In contrast to the previous chapter, it focuses on the long-run effect by investigating the change in the shares of the capacities installed of the conventional generation technologies in response to the feed-in by intermittent generation. Fixed effects as well as fixed effects instrumental variable panel data regressions are conducted using a unique data set of 18 European OECD countries for the years 2000-2010. The results suggest that an increase in the share of RES-E generation decreases the shares of coal- and oil-fired power plants, while it has a positive effect on the share of gas-fired generation capacities.

Chapter 4, titled **The Effects of High-Level Competitive Sports Participation on Later Job Success** (co-authored by Ralf Dewenter), addresses a completely different field of economics, i.e. sports economics. The income effect of participation in elite sports in the later working life of former elite athletes is estimated using an unique dataset of former German top-level athletes. As little has been said about the impact of competitive elite sports on athletes' later job success after finishing their sporting career, we contribute to this strand of research by quantifying the average treatment effect using covariate nearest-neighbour matching. The treatment group consists of formerly top-level athletes and the data is acquired by a survey conducted with the support of the German Sports Aid Foundation (Stiftung Deutsche Sporthilfe). The control group of non-athletes is drawn from the GSOEP database. On average, former athletes receive higher incomes than similar non-athletes. Moreover, team sports athletes as well as male athletes realise significantly higher incomes. Comparing the income of former female athletes with male non-athletes, participating in elite sports closes the gender-wage gap.

In the final chapter the main findings are summarized and suggestions for further research and possible extensions to the individual studies are discussed.

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Chapter 2

The Green Game Changer: An Empirical Assessment of the Effects of Intermittent Generation on the Merit Order*

*This chapter is based on a paper co-authored by Veit Böckers and Jürgen Rösch.

2.1 Introduction

European power markets are in transition towards a system based on low carbon generation. Before the increased introduction of renewable energy sources for electricity (RES-E), the generation mix of most countries consisted mainly of plants using coal, gas, oil, hydro and nuclear as the primary sources of energy. All of these plants are able to deliver power at a stable and reliable rate. The increasing public awareness on ecological issues, particularly the reduction of CO_2 emissions, forces power production to become greener and more sustainable. Different types of regulation have been introduced to influence the choice of the primary energy resource.

Two types of policies set the stage for this more eco-friendly approach in the European electricity sector. The first is the introduction of a tradable emission certificate system to internalize the cost of pollution, the EU Emissions Trading System (EU-ETS). The second is the creation of public support-schemes for power generation based on renewable resources, to incentivize the investment in more ecological power production technologies. The European Union support framework set a goal that at least 20% of the final energy consumption has to be covered by renewable energy resources by 2020. This analysis focuses on effects of renewable resources production promoted by out-of-market support schemes on market-based power generation.

Wind and sun are the most prominent renewable energy sources. Along with the regulated financial support, power production based on those renewable energy sources usually also benefits from prioritized feed-in, guaranteeing them a permanent and secure revenue stream when they produce[1]. This is, operators of wind and solar power plants produce and sell power to the market whenever the wind blows or the sun shines. Even if prioritization were abandoned, near-zero marginal costs would still leave RES-E generation the first to be fed in, as all other technologies have at least the input costs to bear.

The need to take ecological issues into account is placed exogenously on power markets. This puts the competition among conventional power producers to the test. Conventional power plants have to incorporate the production by RES-E. Their generation decisions now also depend on the expected wind and solar power production. This may have a fundamental impact on the market design and security of supply.

This leads to a one-sided competitive relationship between conventional and RES-E power plants. RES-E generation does not depend on the production decision of conventional power plants, but conventional power plants need to take RES-E generation into account. Power production from RES-E can be considered as an exogenous supply shock to the physical and commercial power system. The power market only has to cover the residual demand which is not already covered by renewable energy resources.

In general, the effect of intermittent RES-E generation on the wholesale price of electricity is

[1] Network operators can deny feed-in only for system reliability concerns.

called the *merit-order effect*. When we talk about the *merit-order effect* in this paper, we also include the effect on conventional generation in our definition. The merit order of production ranks the available power plants in ascending order according to their marginal costs. The plants with the lowest marginal costs deliver power most of the time and are dispatched first. The higher the demand rises, the more expensive plants are utilized. The power price corresponds to the marginal costs of the last power plant that is still needed to cover demand. Power from renewable energy sources with prioritized feed-in and zero marginal costs will always be fed in first to cover demand, leaving the conventional power plants competing for the remaining demand. Since RES-E production (like wind and solar) is intermittent, it cannot deliver a stable and reliable output because it is highly dependent on weather conditions; hence, it can have different effects on the merit order.

On the one hand, following the theory of the static merit-order model, the plants with the lowest bid will be dispatched first. Given the generation by renewable energies demand for power produced by conventional technologies is reduced, thereby also reducing the need to utilize power plants. The low marginal costs of RES-E production could therefore replace the most expensive peak plants. This would translate into lower power prices. On the other hand, demand for conventional plants is only reduced if the wind is blowing and the sun is shining, otherwise, the existing conventional plants will still be needed. The original merit order applies when there is little or no production by renewable energy sources and the merit order shifts to the right when they produce. Thus, the second - dynamic - effect of RES-E on the merit order is caused by its inherent unreliability. They do not reduce demand for conventional plants consistently, but depending on changing weather conditions. The residual demand, which has to be covered by the conventional power plants, is exposed to higher volatility. This reduces runtime and requires utilization of more flexible power plants. The most flexible plants, however, are also the most expensive plants in the merit order, which renders the lower marginal costs and less flexible plants to absorb the effect of RES-E. If the output of RES-E generation is not high enough, mid-merit plants would be the most affected; base-load plants would still be needed to cover the steady demand; and flexible peak-load plants would be utilized to balance the fluctuating production of wind and solar power. Consequently, prices drop when RES produces and rise when the more flexible plants are needed.

We contribute to the current debate about the effects of support schemes for renewable energy resources by using data from the Spanish power market, to estimate the effect on the conventional generation. We show the effect on the quantities sold to the wholesale market by the conventional production technologies during instances when RES-E produce. We will also show how this influences the wholesale price. We take the merit order as the given structure and incorporate it into a vector autoregressive model, i.e. we consider production of conventional power plants and price as endogenous and also take the time structure of the data into account. Wind and solar energy production are regarded as exogenous to the system, which reflects the current market situation with prioritized feed-in and support schemes.

We are able to identify and quantify the effect of wind and solar power generation on the wholesale price and on the quantities produced by each conventional power plant type, separately. This helps to understand how the current and future production mix is affected by the support schemes for renewable sources

The Spanish power market combines several characteristics which makes it very suitable for testing the merit-order effect. Renewable technologies need not compete in the power market as they are promoted through out-of-market support schemes. The energy production mix is made up by a large amount of RES-E production technologies, particularly wind and solar and the climate on the Iberian peninsula is very favorable for both wind and solar power production. Aside from this, the ample availability of data, especially on the production patterns of the different technologies, makes this analysis possible.

The rest of the paper is structured as follows: section two provides an introduction to the theory of power markets and the merit-order effect. Section three illustrates the Spanish power market. We then present the data used in section four prior to laying out the empirical strategy. The results are presented in section six. The analysis concludes in section seven.

2.2 Theoretical Background

To analyze the effects of intermittent production on the composition of the power plant fleet and the market design, we first provide a concise insight into the theoretical background of power markets to explain the merit-order effect. This is fundamental in understanding how non-market based RES-E production affects the mechanisms in the market, and in determining which conventional generation technologies will be affected most.

2.2.1 Peak-Load Pricing and the Merit Order of Production

Electricity has special characteristics which distinguishes it from other goods. It is a grid-bound good which is neither storable nor substitutable; its provision has physical limitations and its production has to equal consumption at all times. Furthermore, demand for electricity is periodic, varying substantially during the day and over the seasons of the year. Typically, demand reaches peak during the working hours of a weekday, but is relatively low during nighttime and on weekends. Depending on the geography and climate conditions, consumption patterns differ from summer to winter.

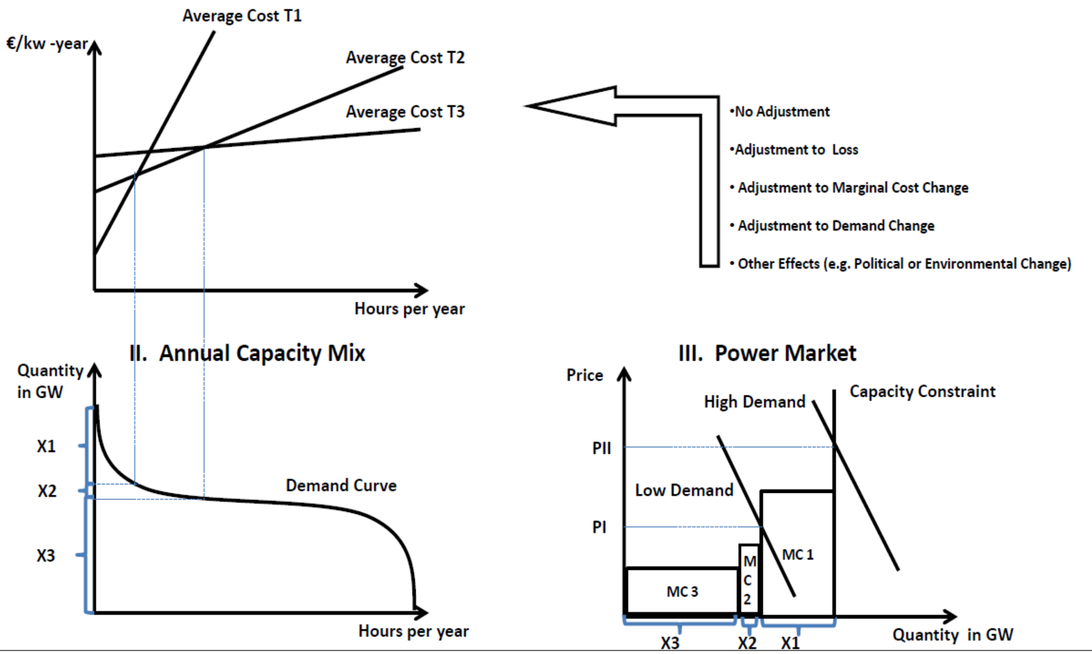
These features make power markets subject to peak-load pricing.[2] Crew et al. (1995) present a summary of the basic principle of peak-load pricing: Different production technologies are

[2]See Boiteaux, (1960) and Williamson, (1966) for some of the earliest works in this field.

needed to satisfy the fluctuating demand. These technologies differ in marginal and fixed costs. The technology with the lowest marginal cost has the highest fixed cost, while the one with the highest marginal cost has the lowest fixed cost. Hence, technologies can be put in order according to their marginal costs. The cheapest technology serves any positive demand up to its capacity. The other technologies therefore always have idle production capacities whenever demand can be at least partly covered by cheaper technologies. Hence, the price during peak-demand periods has to be such that it enables the most expensive production technologies to recover their variable and fix costs.

Ranking power plants according to their marginal costs is called merit order. In practice, the merit order consists of base-, mid-merit and peak-load plants. Base-load plants usually consist of hydro, nuclear and lignite power plants, whereas mid-merit plants consist of coal-fired and combined-cycle-combustion gas turbines (CCGT). Peak-load plants usually consist of open-cycle gas turbines or plants fired with oil or gas. A cost overview and a confirmation of the chosen classification can be found in OECD (2010). The report covers the fixed and variable costs of a large set of production technologies and countries.

The merit order is not static, and adjustments in the power plant fleet take place constantly. Aside from the effect of renewable energy resources, various factors also affect the merit order. These adjustments are explained in a stylized example in Figure 2.1.



Production Technologies T1, T2 and T3, Installed Capacities of T1 is X1, of T2 is X2 and of T3 is X3. Marginal Costs of Production for Technologies T1, T2 and T3 are MC1, MC2 and MC3. PI and PII indicate the equilibrium prices during low and high demand.

Figure 2.1: Static Optimal Capacity Choice and Peak-Load Pricing

An optimal capacity choice is made in a setting of perfect competition, merit order dispatch and a single-price auction. Three production technologies (T1, T2 and T3) are available to market participants. Based on the relationship between average costs and annual expected runtime of each production technology, an optimal plant mix for the provision of power exists. If the relative mixture of technologies is chosen optimally, its adoption to the expected yearly demand distribution yields a specific realization of the actual installed capacities (panel I and II).

Given this capacity choice, market participants bid their available capacities into the market. The optimal bid is the respective marginal cost of the plant, if the level of competition is sufficiently high. Each time overall demand exceeds the individual capacity of a dispatched technology type, profits are generated for this plant type. During these times, plants will recover their annualized investment and fix costs. This creates a specific utilization of the existing production mix and price distribution (panel III).

Depending on this mechanism and factors such as policy changes, adjustments to the current power plant portfolio may become necessary (panel IV). This could lead to temporary or permanent shifts in the technology mix or even the crowding out of plants using certain primary fuels. For instance, a planned or unplanned plant outage is temporary and usually does not lead to a permanent change in the merit order. Changes in the variable costs can lead to either persistent or temporary alterations - so-called fuel switches - depending on the size and frequency of the fluctuations. In the energy market, variable costs mainly consist of fuel costs (input price plus transportation costs), ramping costs and, depending on the technology, costs of emission certificates. Possible fuel switches mostly occur between coal-fired and gas-fired power plants (Sunderkötter and Weber (2011) for a theoretical model and simulation). Persistent changes in the merit order can be caused by advances, such as process innovation or the development of a new production technology. Other reasons can include the depletion of a resource or the general prohibition of its usage (i.e. the nuclear phase-out in Germany).

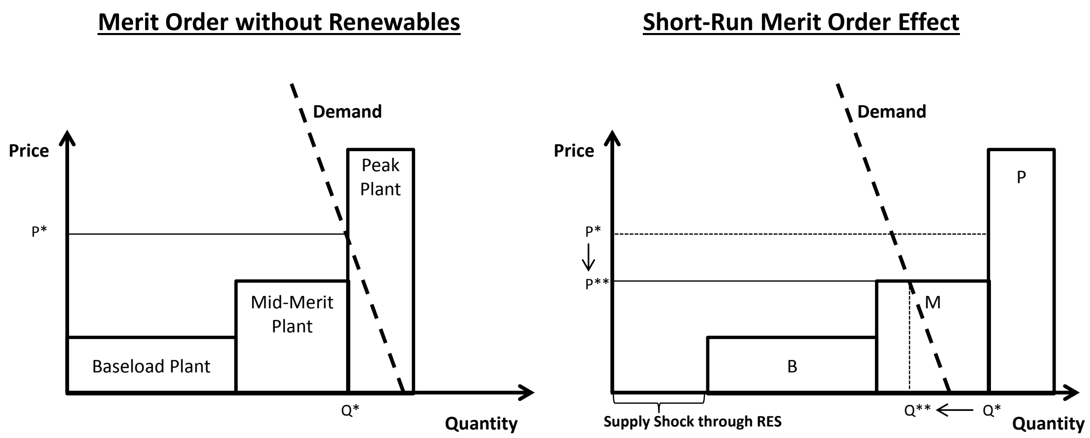
2.2.2 Merit-Order Effect

The *merit-order effect* describes the effect of weather-dependent (intermittent) RES-E on the wholesale power market, particularly on the composition of the plant fleet. The production of the most prominent renewable technologies, wind and solar, is dependent on the availability of wind and solar radiation. As no other input factor is needed for production, the marginal costs are zero or near-zero. Hence, they are located at the leftmost part of the merit order (see Figure 2.2).

The production decision of RES-E operators is not market based in the sense that it does not depend on the current wholesale price. Hence, investment and feed-in are regulated and are independent from the actual market mechanism. To incentivize investment in RES-E technologies, different support schemes for renewable energies have been developed since the 1990's, varying widely in their character (Haas et al., 2008 and Haas et al., 2004 for an overview).

These subsidies can be based on actual generation (per kWh) or on installed capacity. Sometimes also lower interest rates or tax credits are used to stimulate investment (Menanteau et al, 2003; Haas et al., 2004). Support schemes can also be divided into price or quantity driven instruments. The former pays a fixed amount independent of the actual production, while the latter seeks to reach a desired level of generation. Most of these support schemes also allow technologies a prioritized feed-in of their generation.

Consequently, the compensation for RES-E technologies is not market-based and the decision to produce or to invest does not depend on the conventional power plants' production decision. Hence, generation by RES-E is independent from competition in the power market or from any other economic factors that should be taken into consideration by the conventional power plants. For conventional power plant owners, generation by RES-E is an exogenous supply shock. Each time they produce, the demand which has to be covered by conventional plants is effectively reduced.



Base, Mid-Merit and Peak refer to the marginal costs of the respective production technology.

Figure 2.2: The Effect of RES-E on the Merit Order

The right-hand side of Figure 2.2 shows the short-run merit-order effect as described by Sáenz de Miera et al. (2008). Wind and solar power have zero marginal costs and are fed-in first; they shift the merit order to the right. Technologies with the highest marginal cost are crowded out, as they are no longer needed to satisfy demand. The price is also reduced as total demand becomes covered by cheaper technologies. Some empirical studies (such as Green and Vasilakos, 2010; APPA, 2009; Sáenz de Miera et al., 2008; Sensfuß et al., 2008; Gelabert et al., 2011) find evidence of RES-E production's price decreasing impact.

The inherent weather dependence and unreliability of wind and solar power can, however, also affect mid-merit plants. The short-run merit-order effect only occurs when the sun shines and the wind blows, but this, as well, depends on the intensity of wind and solar radiation. The intermittent technologies reduce the demand for conventional power plants whenever the conditions are favorable, but conventional power plants have to cover the full demand, whenever wind and solar energy sources cannot produce. Put differently, the residual demand for conventional power plants fluctuates, depending on weather conditions and installed RES-E capacity.

The production of fluctuating RES-E can therefore be interpreted as an increase in the uncertainty of demand for conventional power plants. Vives (1989) shows, in a general oligopoly setting, that firms tend to invest in more flexible technologies if there is an increase in basic uncertainty. This implies a shift towards more flexible and more expensive plants. The merit-order shifts to the right whenever wind and solar power produce ample supply of energy and shifts back whenever they produce less or nothing. Depending on the magnitude of the RES-E feed-in base-load, plants can just be minimally affected as they still cover the steady demand. Mid-merit plants, which are more flexible, but still need sufficient runtime, can suffer the most, as peak plants can quickly adapt to different demand situations. In the long run, mid-merit plants may exit the market and the merit order may collapse to base-load and peak plants - which would, again, lead to higher power prices in periods without RES-E production.

Furthermore, the reduced number of price peaks affects all power plants. As the last power plant accepted in the auction to satisfy demand sets the price, all the other power plants to its left in the merit-order earn money on top of their marginal costs. Base-load and mid-merit plants with relatively high fixed costs need a certain amount of high prices during the year and consecutive hours of runtime to cover the fixed costs. If peak-load plants leave the market and the price level decreases, the profitability of all power plants in the merit-order would also decrease. Also, the profitability of future investments in the power plant fleet will depend on the price level and will be influenced by this development.

Gelabert et al. (2011) conduct a study of the Spanish power market data. They analyze the effect of the Spanish *Special Regime* - which includes wind, solar, and other RES-E, as well as smaller fossil fueled plants - on the wholesale price. They take into account the production of all other power plant types and find a negative price effect of RES-E. The magnitude of the price effect, however, decreases over time. The quantity effect on the different production technologies is not considered.

Weigt (2009) could not confirm the crowding out of any specific conventional production technologies. Simulation studies by Bushnell (2011), Delarue et al. (2011) as well as Green and Vasilakos (2010), however, find the suggested switch to more flexible generation types as indicated by Vives (1989).

2.2.3 Market Design and RES-E

The merit-order effect also influences security of supply. Sufficient capacity needs to be ready to cover demand at any time. Power markets must provide investment incentives to attract the deployment of new capacities and to allow upgrade of existing plants. As the out-of-market support schemes influence the wholesale price and consequently the price signal to investors, it becomes questionable whether the energy-only market is capable of guaranteeing security of future supply.

Even without renewable energy sources it is unclear whether an energy-only market can attract sufficient investment. Cramton and Stoft (2005, 2006 and 2008) and Joskow and Tirole (2007) argue that the necessary number of high price spikes may not be realized. This so-called missing-money problem can lead to a permanent underprovision of installed capacity. To overcome this problem, it may be necessary to not only reimburse actual power production, but also the provision of capacity.

The increase of renewable power production is likely to intensify the missing-money problem. If either price peaks are cut or the runtime of power plants are reduced, the profitability of conventional power plants decreases. As conventional power plants are still needed to satisfy demand when there is little or no production by wind and solar, a market exit would jeopardize security of supply. Capacity payments can help keep essential plants in the market and attract sufficient further investment. The design of those capacity payments, however, can create other inefficiencies and disincentives (Böckers et al., 2011).

Another basic task of the market design is the production of cost-efficient energy. Out-of-market support schemes may also lead to inefficiencies in the technology mix. Firstly, not letting the market decide which RES-E technology to support can lead to an excessive expansion of a certain technology type which is desired by policy makers; this, however, is not the most efficient outcome in terms of achieving climate goals. Secondly, they lead to an adjustment in the remaining power plant fleet, but while the adjustment might be efficient under the prevailing conditions with renewable technologies, the resulting plant portfolio may nevertheless induce further costs.

RES-E plants have an impact on many aspects of the electricity wholesale market. We analyze which generation technology is affected by RES-E, and to what extent. Quantifying this effect helps evaluate the market performance, renewable support schemes and the evolution of the security of supply.

2.3 Spanish Power Market

The Spanish wholesale electricity market consists of a day-ahead market, which is organized as a pool, and a number of intra-day and balancing markets. The pool is ran as a uniform-price auction with the bid of the most expensive power plant needed to satisfy the demand setting the price.[3] Although bilateral trading is possible, the majority of the electricity is bidden into the

[3] On 1st July 2007 the Spanish and the Portuguese electricity markets were coupled to create the common Iberian electricity market, MIBEL (Mercado Iberico de Electricidad). Only the Spanish system is considered here.

pool. In the period from 2008-2012, 61%- 69% were traded in the day-ahead market (OMIE, 2013 and REE, 2013a).

To meet the renewable energy targets set by the Spanish government and the EU, a support framework was established. The Spanish targets comply with the EU's goal of having at least 20% of the final energy consumption covered by renewable energy sources by 2020 (Moreno and Garcia-Alvarez, 2012). The legal promotion of renewable energy sources in Spain was initiated in 1980. The 'Law of the Electricity Sector' implementing the requirements of the European Directive 96/92/EC on the electricity market liberalization also established the *Special Regime*.

The *Special Regime* consists of renewable energy sources, conventional plants with a generation capacity of less than 50 MW and imports. It guarantees green power producers access to the grid as well as monetary support (Law 54/97). Royal Decree 2818 (RD 2818/1998) regulates the treatment of plants in the Special Regime and lays the foundation of the two support system currently in place.

The generators in the *Special Regime* can choose from one of two payment schemes which becomes binding for the following year. They can either opt for a time-dependent feed-in tariff (FIT), where generators receive a fixed total price per MWh fed into the grid, or bidding into the pool and receiving a feed-in premium depending on the market price. If the market price is too low, this so-called cap-and-floor system guarantees producers remuneration at floor level. If the market price exceeds cap level, the producer gets the market price itself. Between the cap and floor levels, the producer receives a premium on top of the market price. Additionally, the support levels in both payment schemes vary according to peak (8 a.m. until 12 p.m.) and off-peak (12 p.m. until 8 a.m.) times.[4]

Conventional power plants including hydro power plants with generation capacities of at least 50 MW are part of the so-called *Ordinary Regime*, and they either bid their power into the pool or trade bilaterally. To stimulate the construction of new production facilities and discourage the retirement of already existing plants, a system of administrative capacity payments was introduced. The *pagos for capacidad* was introduced in 2007 and it reformed the system in place since market liberalization. The underlying idea is to support the market mechanism to achieve the desired level of supply security. Depending on the current reserve margin, power plants receive a certain amount per installed MW for the first ten years of operation. The incentive decreases with an increasing reserve margin. If the maximum reserve margin of 30% is reached, the capacity payment will gradually decline to zero (Federico and Vives, 2008).

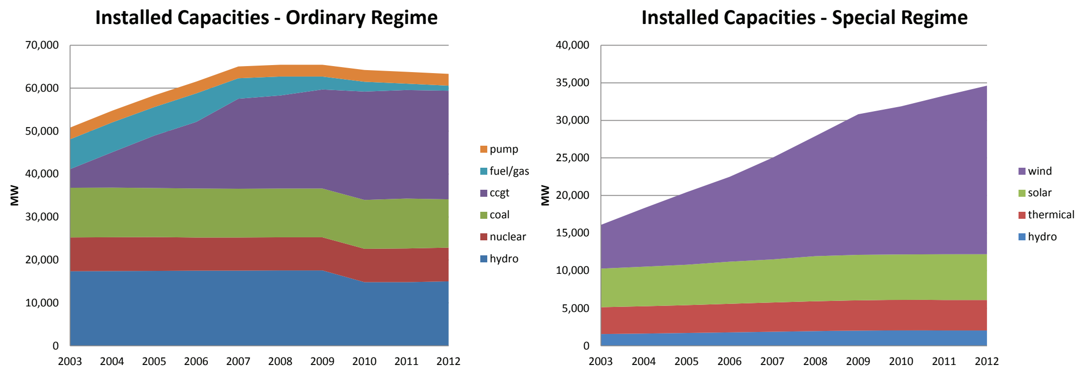
The generation mix in Spain has changed continuously since the liberalization in 1998 (see Figure 2.3). While the installed capacities of nuclear, coal and hydro power plants remained constant, those of fuel/gas plants declined over time; however, CCGTs and *Special Regime*

[4]For further information see RD 436/2004, RD661/2007, RD 1578/2008, RD 1565/2010 and RDL 14/2010. Detailed summaries and assessments of the Royal Degrees can be found in del Rio and Gual, 2007; del Rio Gonzalez, 2008 as well as del Rio and Mir-Artigues, 2012.

installed capacities increased. The latter almost increased sevenfold - from 5,713 MW in 1998 to 38,953 MW in 2011 (Platts 2011), which is about 38% of the total installed capacities (REE 2009 and 2013a).

Within the *Special Regime*, wind energy holds the largest share with 54%, but because of a reform in 2004 (RD 436/2004) solar energy production experienced significant growth from 2006 to 2009. In a span of only two years (del Rio and Mir-Artigues, 2012) its installed capacity increased from 300 MW to 3,500 MW. The subsidies for solar generators almost tripled from €2.2 Billion to €6 Billion annually. Solar power producers received 40% of the total payments in the renewable support scheme, but it only accounted for 8% of its generation (Federico, 2011).

Figure 2.3 shows the development of both the *Ordinary Regime* and the *Special Regime*, in Spain. Hydro appears in both categories because small hydro plants with an installed capacity of less than 50 MW are classified as *Special Regime*. CCGT power plants and wind power plants experienced the biggest growth. Note that the two graphs are scaled differently. *Special Regime* has now surpassed half of the installed capacity of the Ordinary Regime.



Source: Platts 2011, REE(2009 and 2013a).

Figure 2.3: Installed Capacity for the Ordinary and Special Regime

2.4 Data

We analyze the Spanish power wholesale market from the period of 2008 to 2012. Data on Spanish demand, produced quantities[5] for each conventional fuel-type, i.e. nuclear, hydro, coal and gas, and generation from the *Special Regime* is publicly available. The latter is comprised of the production of solar and wind power, as well as the generation of other renewable and non-renewable resources. We are, however, able to separate the *Special-Regime* generation in wind and solar and its other components. Furthermore, we use hourly electricity wholesale

[5] Gas is subdivided into *cc*, which is a more efficient production type called combined cycle gas turbines, and *fuel/gas*, which includes the most expensive power plants running on either coal or gas.

prices (OMIE, 2013 and REE, 2013a).

The installed capacities for each generation technology and the respective input prices are included as control variables i.e. prices for oil, gas, coal and uranium and European emission certificates (REE, 2009 and 2013a; APX, 2013; Platts, 2011; Argus/McCloskey, 2013; UX Consulting, 2013; IEA, 2013; EEX, 2013). The input prices are available either on a weekly or weekday basis. Installed capacities are available on a yearly basis stated in MW (REE, 2009 and 2013a).

Pooling all technologies in the Special Regime includes certain conventional and reliable plants (i.e. power plants with installed capacities of less than 50 MW or RES-E technology such as biomass, which can deliver reliably). From this, we divide the *Special Regime* into its components: wind generation, solar generation and others. For wind data, we use the hourly wind forecast (REE, 2013b) and for solar data, we use the mean daily (actual) solar production[6] (REE, 2013a) as there is no publicly available data on hourly solar production. To match the daily production of solar with the hourly data, we aggregate the data set to the daily average.

Spanish generation data supports the argument that wind and solar power have very low capacity credit. Their production depends on current weather conditions, so they cannot guarantee delivery at a reliable and stable rate. Very high production is followed by near zero feed-in. In 2012, the highest wind forecast in a single hour on record was 16,100 MWh while the lowest was only 174 MWh, which is less than 1% of the mean installed wind capacities, calculated on the basis of our dataset.

Windforecast					
Variable	Mean	Std. Dev.	Min	Max	Inst. Cap. (MW)
2008	3,555.07	1,890.28	551.18	8,663.24	15,977
2009	4,086.87	2,159.91	597.94	10,471.94	18,712
2010	4,861.05	2,521.63	877.29	13,088.47	19,710
2011	4,736.95	2,572.58	941.53	12,013.12	21,091
2012	5,453.75	2,775.65	1,096.54	13,693.33	22,430
2008-2012	4,538.59	2,490.38	551.18	13,693.33	19,583 (Mean)
Solar production					
Year	Mean	Std. Dev.	Min	Max	Inst. Cap. (MW)
2008	275.05	135.39	83.33	541.67	3,628
2009	677.51	219.98	166.67	1,041.67	3,481
2010	778.88	309.95	208.33	1,416.67	4,189
2011	1,021.58	375.63	250.00	1,625.00	5,069
2012	1,297.36	465.38	333.33	2,125.00	6,218
2008-2012	810.05	470.64	83.33	2,125.00	4,450 (mean)

Table 2.1: Daily Windforecast and Solar Production

Table 2.1 shows the average, minimum and maximum wind forecast and solar production over the years. Production is measured in MWh and installed capacity in MW. For both technologies, the difference between minimum and maximum production, as well as the mean production

[6] Calculated as the sum of photovoltaic and thermal solar production.

substantially fluctuates over time. This emphasizes the intermittent and unreliable character of those technologies.

Rainfall (measured in mm per m^2) and temperature are used as weather control variables (WeatherOnline, 2013). Solar and temperature are naturally higher correlated ($\rho = 0.49$) than solar and rain (*precipitation*), which are only weakly correlated ($\rho = -0.08$). The inclusion of temperature captures the effect of weather: higher temperatures are highly correlated with sunshine, but they may also affect conventional power plants. Run-of-the-River Hydro plants e.g. depend on the water level in the river; also other conventional plants use rivers for cooling. Not controlling for temperature would make the effect of solar generation biased, e.g. overestimating the effect of *solar* on *hydro*. The industry production index (OECD, 2013) serves as Spain's economic performance indicator.

Table 2.2 gives an overview on the descriptive statistics of each variable used in our analysis.

Time Series	Variable Name	Obs	Mean	Std. Dev.	Min	Max	Source
Prices							
Power	Price	1827	47.12134	12.91916	2.466667	82.13042	OMIE(2013)
Oil	brent	1827	92.19025	24.57975	33.73	143.95	IEA(2013)
Gas	ttf_price	1827	20.42837	5.802648	7.2	40.1565	APX(2013)
Uranium	uxc_price	1827	52.51631	9.651544	40	90	UXC(2013)
Emission	eua_wprice	1827	9.446716	5.623614	0.015	16.865	EEX(2013)
Coal	coal_index	1827	104.4412	32.44161	56	224.75	PLATTS(2011),Argus(2013)
Quantity Sold at Power Exchange							
Hydro	q_hydro	1827	1588.825	901.0896	270.7	6472.296	OMIE(2013)
Pump	q_pump	1827	441.9877	287.1578	0	1407.283	OMIE(2013)
Nuclear	q_nuclear	1827	1593.403	653.9276	304.0917	5820.079	OMIE(2013)
Coal	q_coal	1827	1414.727	1079.746	0	5642.158	OMIE(2013)
CCGT	q_cc	1827	4778.429	2935.616	115.125	13200.96	OMIE(2013)
Fuel/Gas	q_fuel_gas	1827	528.4486	117.6727	205.5125	759.4125	OMIE(2013)
Demand							
Demand Power Exchange	q_demand	1827	22237.38	3337.577	13326.87	33503.61	OMIE(2013)
Special Regime Quantities							
Total Special Regime	specreg_actual	1827	9909.278	2818.552	4458.333	20166.67	REE(2013a)
Power Exchange Special Regime	q_re_mercado	1827	10000.77	2656.686	4312.063	19861.38	OMIE(2013)
Wind Forecast	windforecast	1827	4538.593	2490.38	551.1765	13693.33	REE(2013a)
Solar PV Total	solarpv_actual	1827	671.5015	316.9182	83.33334	1291.667	REE(2013a)
Solar Thermal Total	solarthermal_actual	1827	138.5468	188.4821	0	833.3333	REE(2013a)
Installed Capacities							
Hydro	hidro_inst	1827	14852.63	81.25765	14808	15014.72	REE(2009, 2013a)
Pump	bombeo_inst	1827	2746.928	.1442007	2746.64	2747	REE(2009, 2013a)
Nuclear	nuclear_inst	1827	7767.809	50.63277	7716	7852.98	REE(2009, 2013a)
Coal	carbon_inst	1827	11408.85	152.5875	11247.61	11700	REE(2009, 2013a)
Fuel/Gas	fuelgas_inst	1827	2272.678	1420.547	178.16	4401	REE(2009, 2013a)
CCGT	cc_inst	1827	24106.2	1485.152	21677	25290.58	REE(2009, 2013a)
Special Regime	especial_tot_inst	1827	33938.77	3541.956	28618	38884.52	REE(2009, 2013a)
SR Wind	wind_spec_inst	1827	19582.89	2200.578	15977	22430.64	REE(2009, 2013a)
SR Solar PV	solar_pv_spec_inst	1827	3685.364	422.1233	3207	4267.526	REE(2009, 2013a)
SR Solar Thermal	solar_term_spec_inst	1827	764.902	681.7313	61	1949.97	REE(2009, 2013a)
Other							
Precipitation	precipitation	1827	0.6109329	1.216827	0	15.875	Weatheronline(2013)
Temperature	temp	1827	18.70234	5.997503	5.334043	31.45833	Weatheronline(2013)
Sunhour	sunhour	1826	7.275494	2.890185	.5882353	13.03571	Weatheronline(2013)
Industry Production	ind_prod	1827	84.97141	7.67428	75.28896	107.1877	NISS(2013)

Table 2.2: Descriptive Statistics of Data

2.5 Empirical Strategy

To estimate the effect of renewable generation on the wholesale price and the quantities produced by conventional power plants, the merit-order is used as the underlying structure. We endogenize each technology's produced quantity according to their rank in the merit order and the day-ahead price, in a VAR model. The quantity produced by each technology depends on the price and all the quantities produced by technologies to its left in the merit order. Production from renewable energies is treated as exogenous to the system. This reflects the current situation in Spain, with out-of-market support scheme for RES-E. We also include demand, installed capacities, input costs for the different technologies, temperature and rainfall to control other exogenous influences not attributable to the effect of RES-E. To capture seasonality and cyclic components, we include dummies for the days of the week (six) and years (four).

The six production technologies, in ascending order, based on their marginal costs, are: *hydro*, *nuclear*, *coal*, *CCGT*, *fuel/gas* and *pump* storage. *Hydro* and *nuclear* are base-load plants; *coal* and *CCGT* constitute the mid-merit order; and *fuel/gas* and *pump* storage are the peak plants. The ranking is based on information regarding the costs of power plants for the merit order from OECD (2010). The order is clear for most of the power plants. Fuel-switches mostly occur for coal and gas-fired plants as shown by Sunderkötter and Weber (2011), so we incorporate the change between the two technologies as a robustness check and change the order of *coal* and *CCGT* in an additional estimation.

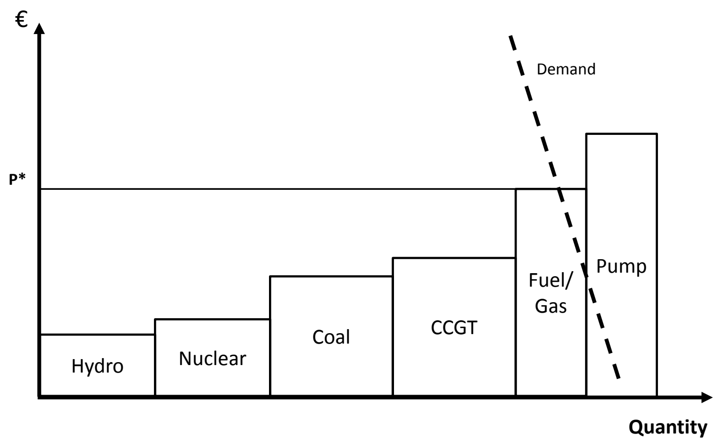


Figure 2.4: Merit Order

Vector Y comprises the endogenous variables. X is the vector of demand-specific shocks as well as fuel-type specific input factors. The vector RES describes the quantity produced under the *Special Regime*:

$Y = (price,\ q_{hydro},\ q_{nuclear},\ q_{coal},\ q_{ccgt},\ q_{fuelgas},\ q_{pump})$

$X = (Demand,\ Season,\ Installed\ Capacities,\ InputPrices)$

$RES - E = (SpecialRegime)$

The unrestricted VAR model therefore can be formalized as:

$$Y = A + BL(Y) + \Gamma RES - E + \Phi X + \epsilon \tag{2.1}$$

Figure 2.4 shows the underlying structure of the VAR model. The power plant with the highest marginal costs, which is still needed to cover demand, sets the price. All power plants to its left produce and earn money according to their marginal costs.

$$\begin{aligned} LnP_t \quad &= \quad cons_{pr} + \textstyle\sum_{i=1}^{k} \beta_{pr,1,i} LnP_{t-i} + \sum_{i=1}^{k} \beta_{pr,2,i} Hydro_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{pr,3,i} Nuclear_{t-i} + \sum_{i=1}^{k} \beta_{pr,4,i} Coal_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{pr,5,i} CCGT_{t-i} + \sum_{i=1}^{k} \beta_{pr,6,i} Fuel/Gas_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{pr,7,i} Pump_{t-i} + \Gamma_{pr} RES - E_t + \Phi_{pr} X_t + \epsilon_{pr,t} \end{aligned} \tag{2.2}$$

$$Hydro_t \quad = \quad cons_h + \textstyle\sum_{i=1}^{k} \beta_{h,1,i} LnP_{t-i} + \Gamma_h RES - E_t + \Phi_h X_t + \epsilon_{h,t} \tag{2.3}$$

$$\begin{aligned} Nuclear_t \quad &= \quad cons_n + \textstyle\sum_{i=1}^{k} \beta_{n,1,i} LnP_{t-i} + \sum_{i=1}^{k} \beta_{n,2,i} Hydro_{t-i} \\ &+ \quad \Gamma_n RES - E_t + \Phi_n X_t + \epsilon_{n,t} \end{aligned} \tag{2.4}$$

$$\begin{aligned} Coal_t \quad &= \quad cons_c + \textstyle\sum_{i=1}^{k} \beta_{c,1,i} LnP_{t-i} + \sum_{i=1}^{k} \beta_{c,2,i} Hydro_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{c,3,i} Nuclear_{t-i} + \Gamma_c RES - E_t + \Phi_c X_t + \epsilon_{c,t} \end{aligned} \tag{2.5}$$

$$\begin{aligned} CCGT_t \quad &= \quad cons_{cc} + \textstyle\sum_{i=1}^{k} \beta_{cc,1,i} LnP_{t-i} + \sum_{i=1}^{k} \beta_{cc,2,i} Hydro_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{cc,3,i} Nuclear_{t-i} + \sum_{i=1}^{k} \beta_{cc,4,i} Coal_{t-i} \\ &+ \quad \Gamma_{cc} RES - E_t + \Phi_{cc} X_t + \epsilon_{cc,t} \end{aligned} \tag{2.6}$$

$$\begin{aligned} Fuel/Gas_t \quad &= \quad cons_f + \textstyle\sum_{i=1}^{k} \beta_{cc,1,i} LnP_{t-i} + \sum_{i=1}^{k} \beta_{f,2,i} Hydro_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{f,3,i} Nuclear_{t-i} + \sum_{i=1}^{k} \beta_{f,4,i} Coal_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{f,5,i} CCGT_{t-i} + \Gamma_f RES - E_t + \Phi_f X_t + \epsilon_{f,t} \end{aligned} \tag{2.7}$$

$$\begin{aligned} Pump_t \quad &= \quad cons_p + \textstyle\sum_{i=1}^{k} \beta_{pu,1,i} LnP_{t-i} + \sum_{i=1}^{k} \beta_{pu,2,i} Hydro_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{pu,3,i} Nuclear_{t-i} + \sum_{i=1}^{k} \beta_{pu,4,i} Coal_{t-i} \\ &+ \quad \textstyle\sum_{i=1}^{k} \beta_{pu,5,i} CCGT_{t-i} + \sum_{i=1}^{k} \beta_{pu,6,i} Fuel/Gas_{t-i} \\ &+ \quad \Gamma_{pu} RES - E_t + \Phi_{pu} X_t + \epsilon_{pu,t} \end{aligned} \tag{2.8}$$

This structure (Figure 2.4) translates into equations 2.2 to 2.8. Estimating the price equation, all technologies are relevant. The equation for each technology, however, only considers technologies on its left in the merit order. The coefficients of power plants, to its right in the merit order, are constrained to zero. For instance, the production decision of a nuclear plant is not directly affected by that of a coal-fired plant as it has higher variable production costs. The opposite is true for the coal plant. If the cheaper technologies are already covering the whole demand, then the coal plant will not be dispatched. To control for temporary shifts within the merit order, we include the input prices for all power plant types and the price for emission certificates.

The inclusion of the production of the aggregated *Special Regime* does not uniquely identify the effect of intermittent technologies. It also comprises of small conventional power plants and RES-E which can produce comparatively reliable, like waste or biomass. To split the *Special Regime* into its components, we use the wind forecast instead of the actual production as for the bidding behavior of the conventional plants only the forecast, and not the actual production, is relevant (Jonsson et al., 2010). The same is true for *solar*, but since forecasts are not publicly available, we use the daily averaged actual solar production provided by the market operator.

$$q_{special\_regime} = q_{solar} + q_{wind} + q_{other_{SR}} \tag{2.9}$$

The short-run merit order effect is based on the guaranteed feed-in by RES-E and their lower marginal costs. The higher volatility of the residual demand, which has to be covered by the conventional power plant fleet, is, in contrast, due to the dependence of wind and solar power on weather. To show the effect of the intermittent RES-E, we use both the entirety of the *Special Regime* (Model I) and its components (Model II).

Power generation by conventional power plants is constrained by the installed capacity of the different technologies. Installed capacity is only available on a yearly basis and is included as exogenous variables. Since power plant construction is tedious and installed capacities do not fluctuate heavily, this might not be very restrictive.

Demand is assumed to be exogenous to the VAR system. This is common practice in power markets (e.g. Gelabert et al., 2011). Demand may not be entirely price inelastic, but not all customers are exposed to real time wholesale prices; and even those who are, can be quite inflexible. Households have habitual patterns of consumption and are not subject to real-time pricing[7] since they have fixed contracts with their energy suppliers. The tourism industry, an important sector in Spain, is also quite inflexible in terms of electricity consumption. Energy intensive producers, like a steel mill (wherein the cost of production is highly dependent on electricity price) may be able to react more flexibly to price changes. An interruption of production during peak-price times, however, may be more costly than continuous production. Stopping production will only be profitable for very high price changes. In our dataset, the average price change, compared to the preceding hour, is 3.20 €/MWh with a standard deviation of 3.93, 50% of the price changes are smaller 1.98 €/MWh and 99% of the price changes are smaller than 18.21 €/MWh. The reaction to those price changes can therefore be assumed as

[7]Weighted by industry branches, the energy industry contributes 13.04% to the Spanish industry production; intermediate and capital goods impact the index by 37.7% and 20.64%, respectively. The rest constitutes non-durable and other consumer goods, 24.21% and 4.41% (NISS, 2013).

rather small.

We also test for exogeneity of demand in the price equation using the Davidson and MacKinnon (1989) test (see Table 2.3).[8] The null hypothesis of exogeneity is not rejected. The test is based on an instrumental variable approach and is described in appendix 2.A.

Davidson&MacKinnon	Coef.	Std. Err.	t
Demand	.0000257	.0001469	0.17

Table 2.3: Exogeneity Test for Demand

Solar data is only available on a daily basis. Aggregating the production data to the daily level underestimates the effect of solar, as solar production depends on sunshine, which only occurs between sunrise and sunset. In a second estimation, we therefore only take into consideration the hours between dawn and dusk.[9]

Before estimating the model, all the included time series are tested for the existence of unit roots. We use the augmented Dickey-Fuller (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron, 1988) tests (see appendix Table 2.B.1) and find that the price time series, the input prices (except for the price for uranium) and the industry-production index are I(1) variables, thus we take the first differences of those variables, which are all found to be I(0). For the price time series we take the logarithm LnPrice which is also found to be I(0). For all other time series, the null hypothesis that the variable follows a unit-root process can be rejected. We used the results of Schwarz's Bayesian information (SBIC) and Hannan and Quinn Information Criterion (HQIC) for the lag order selection.[10]

We also used the Hannan-Quinn and the Schwarz-Bayes information criteria for the lag length selection of the whole VAR model. Eight and three lags, respectively, are found for the simultaneous lag length selection by the information criteria. From an economic point of view, a short lag length is preferable. As the dynamics over the year and during the week are captured by the seasonality dummy and we also aggregated the data to the daily level, only the previous days should have an immediate impact. Thus, for the reported results, the SBIC lag length is chosen; the result remains qualitatively unchanged for the higher lag order and is available upon request.

[8] The test is repeated for different specifications. The test results remain qualitatively unchanged in all settings.
[9] Sunrise and sunset time is for Madrid (TheWeatherChannel.com, 2013).
[10] We also tested for cointegration of the endogenous variables. As only the price series is integrated of order one and all other time series (except the input prices) are I(0) the economic interpretation of the cointegration test is misleading. The fact that there exists one or several linear combination of the variables that is I(0) does not necessarily mean that they follow a common equilibrium path, when several of the time series are already I(0). Furthermore, we also take the logarithm of price which is found to be I(0).

2.6 Empirical Findings

2.6.1 Results

We are interested in the effect the exogenous variables *Special Regime* as well as *wind*, *solar* and *other RES-E* have on the endogenous merit order, i.e. the wholesale price as well as the generation quantities of the conventional power plants. Table 2.4 reports the results for these variables in each of the seven equations. The first column shows the estimated equation and the dependent variable in this equation. The other columns show the price or quantity effect of a 1-MWh increase of either *Special Regime*, *wind*, *solar* or *other RES-E* in the respective equation. In Model I the results for the total *Special Regime* are reported. Model II shows the influence of its components, namely *wind*, *solar* and *other RES-E*.

Overall, the *Special Regime* decreases the price (Model I). A one MWh increase in *Special Regime* generation decreases the price by 0.00307% - that is a decrease of 3.07% for an increase of one GWh. This effect is induced mainly by *wind*. On the contrary, an increase in the generation of *solar* and *other RES-E* increases the price.

The effect on the merit order is negative for all technologies but insignificant for *nuclear*. Again, *wind* is the driving force behind this result. An increase in wind energy generation reduces the generated quantities of all technologies significantly - except for *nuclear* (Model II). The results for *solar* and *other RES-E* are ambiguous.

	Model I	Model II		
Eq./ Dep. Var.	Special Regime	Windforecast	Solar	Other RES-E
(2) LnPrice	-0.0000307 ***	-0.0000321***	0.0000551***	0.0000159**
(3) Hydro	-0.0236482 ***	-0.0288064***	-0.0113133	0.0911092***
(4) Nuclear	-0.0003674	0.0000481	-0.04784	-0.0011805
(5) Coal	-0.099611***	-0.1029507***	0.1198683**	-0.0648811**
(6) CCGT	-0.3546723***	-0.3579887***	-0.297166***	-0.1591054***
(7) Fuel/Gas	-0.0024668***	-0.0027309***	0.0003535	0.0046407*
(8) Pump	-0.0285223***	-0.0301962***	0.0269071	0.0300819***
N	1824	1824	1824	1824

Level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2.4: Impact of Special Regime and its Components

An increase of 1-GWh in *solar* generation increases the price by 5.51%, whereas only CCGT plants are significantly affected negatively in the merit order by *solar*: an one GWh increase in *solar* power decreases CCGT plants' production by 297.17 MWh. Coal-fired plants, on the other hand, benefit from more solar power being fed in into the system.

The same effect can be observed for *other RES-E*: the price increases with an increased generation. The production by mid-merit plants, such as *coal* and *ccgt*, decreases; but *hydro* and peak-load plants (*fuel/gas* and particularly *pump*,) benefit from more power fed in by *other*

RES-E.

Note that the model controls for the influence of temperature and rain. Aside from the effect of RES-E, weather conditions can also cause fluctuations in the generation of conventional plants. A long drought could, for example, lead to lower water levels in rivers. This forces power plants to reduce their production as cooling water becomes scarce.

The effect of *solar* is contrary to what the theory of the short-run merit-order effect suggests. Renewable generation reduces the demand which has to be covered by conventional power plants. Additionally, *solar* can only produce when the sun shines - which is mainly during peak hours, thereby cutting off price peaks. Figure 2.5 shows the price effect of an one GWh increase of the single RES-E generation technologies.

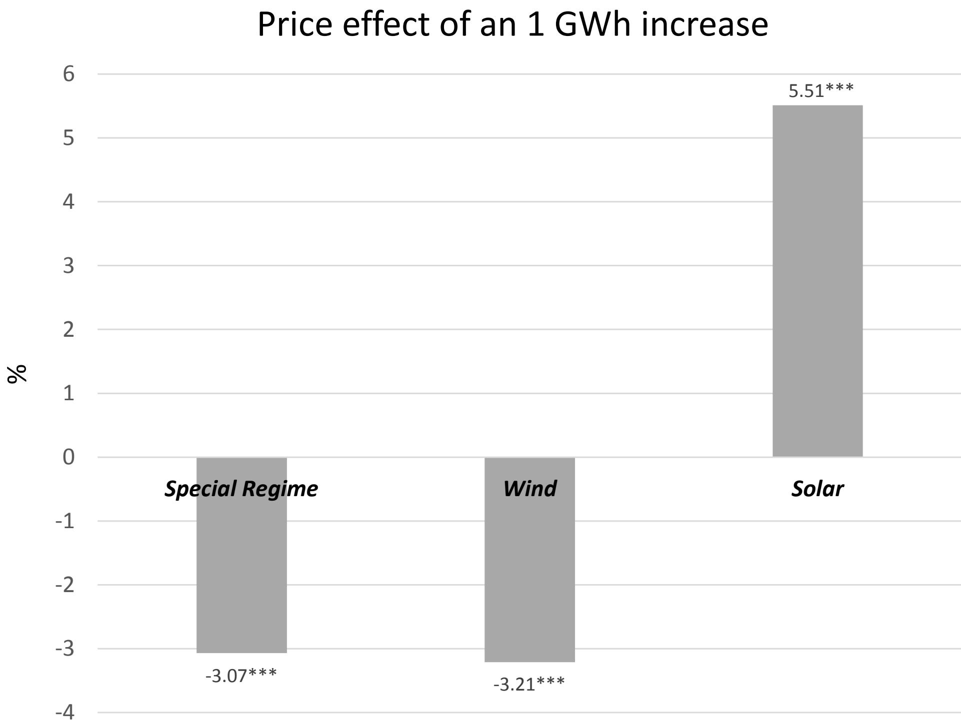


Figure 2.5: Price Effect of Renewables

The effect of *solar* is larger in magnitude than the negative price effect of *wind*. An increase of 1 GWh, however, is relatively much larger and is more unlikely to happen for *solar* than for *wind*. The average generation of*solar* for all years was 0.81 GWh, only in 2011 and 2012 did it reach an average generation of over 1 GWh for the whole year (see Table 2.1). Thus, an increase of one GWh equals twice the current production value. In the case of *wind*, an increase of 1 GWh constitutes only 22% of its average generation in the specified five years, which is still a substantial but also a more likely increase.

Not all technologies are affected to the same extent. Figure 2.6 shows that in contrast to the prediction of the short-run merit order effect (e.g. Sáenz de Miera et al., 2008), it is not the peak plants that suffer most, but the mid-merit plants. The prioritized feed-in by RES-E effectively reduces the demand to be covered by conventional power plants. But base-load plants seem to be minimally affected if not totally unaffected; moreover, the flexible peak plants seem to reduce their quantities only to a small extent, which leaves mid-merit plants the ones absorbing the influence of RES-E on the power market.

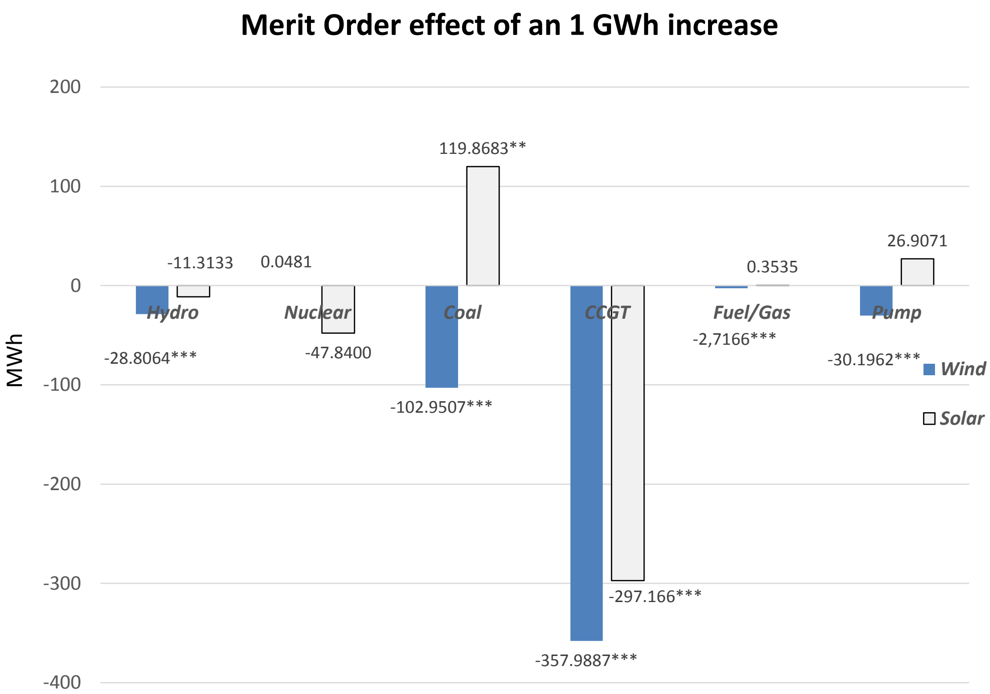


Figure 2.6: Merit Order Effect of RES-E

The generation quantities of *solar*, however, are only available on a daily basis. As we also aggregate the hourly generation data and the price to the daily average, we do not correctly estimate the effect of solar power. *Solar* can only produce during daytime but the aggregated data on quantities produced as well as the price, also contain night hours when it is impossible to generate solar energy. Table 2.5 therefore shows the effect of *solar* during daylight hours.[11]

The effects for the *Special Regime* in total become more distinct during daytime, except for nuclear. The same is true for *wind*: the effect becomes stronger for most technologies as well as for the *price*. The aggregation to daytime, however, is not very meaningful for wind power, but roughly coincides with the peak hours in Spain.

[11] We take the hours between sunrise and sunset for Madrid for each day to determine the hours of possible generation by *solar*. So far, we aggregated the data to the daily level using all 24 hours, now we only use the daylight hours to aggregate data to the daily level. Note that we have data on quantities produced within the merit order and wind forecast on an hourly base. As a result of the aggregation some days, i.e. 6, have an average price of zero. Therefore, we take the price of the hour with the lowest price during that day to calculate the logarithm of the price.

	Model I	Model II		
Eq./ Dep. Var.	Special Regime	Wind Forecast	Solar	Other RES-E
(2) LnPrice	-0.000036***	-0.0000386***	0.0000773**	0.0000328**
(3) Hydro	-0.0365342***	-0.0430045***	-0.0656136	0.1059829***
(4) Nuclear	0.0019027	0.0020494	-0.0311211	0.0039611
(5) Coal	-0.1194194***	-0.123375***	0.1279325*	-0.073997**
(6) CCGT	-0.4015186***	-0.4091456***	-0.3635755***	-0.1281672**
(7) Fuel/Gas	-0.0027362***	-0.0031349***	0.0028131	0.006231**
(8) Pump	-0.049661***	-0.0519828***	0.0172114	0.0089613
N	1824	1824	1824	1824

Level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2.5: Impact of Special Regime between Sunrise and Sunset

Interestingly, *solar* now only affects *ccgt* negatively and statistically significant. The effect for coal-fired plants is still positive but only significant at the ten percent level. All other technologies are not affected by an increased *solar* feed-in. This means that the mid-merit order reduces its generation quantities because of daytime solar power generation, making more expensive and more flexible peak plants benefit from the effect of unsteady generation.

The same is true for *other RES-E*, where only the mid merit plants reduce their generation quantities but base-load and peak plants increase production (but only *hydro* and *fuel/gas* significantly). But different from *wind* and *solar*, *other RES-E* has been quite stable and predictable in generating power.

2.6.2 Discussion

The Spanish market design already includes capacity payments for the availability of generation capacity. These could become insufficient, if CCGT and coal-fired power plants' runtimes continue to decline. If CCGTs will be crowded out in the long run, adjustments to the market design may be necessary, but this would depend on ecological goals, preferences regarding the power price and security of supply.

To guarantee security of supply, conventional power plants have to cover demand whenever unusual or unexpected weather conditions reduce wind and solar production to a minimum level. Depending on the weather conditions, certain power plants may have to operate on standby for long periods during the year or even longer. The inability to cover full demand in times when generation by RES-E unexpectedly drops can lead to blackouts in situations of scarcity. As much as power generated by renewable resources is ecologically desirable, security of supply is as essential for the industry and society.

In general, sophisticated capacity mechanisms might be necessary to complement energy-only markets to guarantee security of supply or to prevent certain technologies from leaving the market. This, however, leads to high costs of introduction and requires a European-wide change of the market design. Furthermore, this will also have a substantial influence on competition (Böckers et al., 2011). While some markets like PJM in the United States have decided to implement a full-blown capacity market, the UK has abandoned such a mechanism. This unclear development of the different market designs will increase uncertainty, but since investments in power plants are, by nature, long term, investors will need a stable environment with little changes in the market design.

The current support schemes often promote investments in certain technologies, independent of any inefficiency caused in the generation mix. The ultimate ecological goal is to reduce carbon emission and make power production more sustainable, not the promotion of certain production technologies. If conventional power plants are priced out of the market, problems inherent to the energy-only market (such as the missing-money problem) may be emphasized. Changes in the market design - aimed to stimulate investment in conventional resources or to prevent those technologies from leaving the market - may be necessary. These market designs are typically more restrictive and they induce higher costs to consumers.

We also perform a number of robustness checks to validate our findings. First, since Portugal and Spain established a common Iberian electricity market (MIBEL) in July 2007, we included the Portuguese generation of renewable power as an exogenous variable in our estimations to account for likely effects. The results remain qualitatively unchanged, which is not surprising as Portugal is a main importer of Spanish power and not vice versa. After estimating the restricted VAR models, we used the Lagrange-multiplier test (Johansen, 1995) to test for autocorrelation. We found some persistent autocorrelation in the residuals. Therefore, we use Newey and West (1987) standard errors, which are used to allow for autocorrelation up to a certain lag length.[12] Again, the results do not alter qualitatively. Lastly, the results remain qualitatively unchanged for fuel switches between coal and gas-fired power plants (Sunderkötter and Weber, 2011) and for higher order of lags.[13]

2.7 Conclusion

This paper analyzes the impact of power generation based on renewable resources on wholesale power prices and conventional power generation in Spain. The data set contains information on daily averages of actual production and quantities sold at the Spanish power exchange from 2008 to 2012.

We estimate a structural vector autoregressive model, using the merit order as the underlying structure. The empirical evidence suggests that the merit order effect is ambiguous. The main driver among the renewable resources is wind power, which exhibits the expected negative

[12] As proposed in Newey and West (1987), the lag length for the correction is chosen as the integer of $4(T/100)^{\frac{1}{4}}$ whereas T is the number of observations in the dataset.

[13] Results are available upon request.

impact on prices and on the quantities produced by conventional plants. On the contrary, solar power has a positive effect on wholesale prices.

Given the merit order of production, mid-merit plants are affected more than peak-load or base-load plants. As the share of renewable energy resources is not yet large enough, base-load plants may not be affected as of now. The residual demand is still sufficiently large for those plants to run for most of the hours during the year. Peak-load plants, on the other hand, may easily adapt to the higher volatility of the residual demand, leaving mid-merit plants to suffer the most from increasing RES-E generation. If these findings still hold for higher shares of RES-E in power generation, then mid-merit power plants could be potential candidates for a market exit.

If mid-merit power plants are increasingly shut down in the long run, a relatively cheap and reliable generation technology will leave the market. This leads to serious consequences for the security of supply. Therefore, the implementation of support mechanisms for conventional power plants may become necessary. One should be aware, however, that this constitutes yet another market intervention that will involve high costs.

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Appendix

2.A Test for Exogeneity of Demand

Using demand and supply can cause simultaneous causality problem if demand cannot be considered exogenous to the supply system. As actual demand is mostly unobservable, equilibrium prices and quantities are considered for estimation. In equilibrium supply and demand are equal and a regression of quantities on prices will not help to identify whether the supply or demand function has been estimated. To solve the identification problem demand or supply specific factors are included. Since we are interested in estimating the price supply function, we estimate the demanded quantity. Important factors for demand are the economic performance of a country, e.g. energy-intensive industry, seasonal and temperature effects (REE, 2012) as well as exogenous demand shifters like holidays. Therefore, we assume demand to be a function of the price, past demand, economic factors, etc.:

$$D = F(price,\ past\ demand,\ economic\ factors,\ weather,\ season,\ holiday). \tag{2.A.1}$$

We use industrial production as an economic performance indicator, and average daily temperature, rainfall, and dummy variables for seasons and public holidays. The simultaneity bias also depends on the elasticity of demand. If demand was entirely price inelastic, the problem would be negligible. We estimate demand using:

$$\begin{aligned} D &= cons + \sum \alpha_d D_{t-i} + \alpha_y Year_y + \alpha_m Month_m + \alpha_j Day_j + \alpha_5 Ind\_Prod \\ &+ \alpha_6 temp + \alpha_7 Precipitation + \alpha_8 Holiday + residual \end{aligned} \tag{2.A.2}$$

To test for exogeneity of demand we use the Davidson & MacKinnon (1989) test.[14] The null hypothesis of exogeneity is not rejected (see Table 2.A.1); and since exogeneity is not rejected, we include demand in our estimation.

Davidson&MacKinnon	Coef.	Std. Err.	t
Demand	.0000257	.0001469	0.17

Table 2.A.1: Exogeneity Test for Demand

[14]The test is repeated for different specifications the test results remain basically unchanged.

2.B Results of Unit Root Tests

Variable	Dickey-Fuller (SBIC) constant	trend	Dickey-Fuller (HQIC) constant	trend	Phillips-Perron (SBIC) constant	trend	Phillips-Perron (HQIC) constant	trend
price	-3.359**	-3.413**	-2.892**	-2.939	-6.923***	-7.182***	-7.240***	-7.530***
lnprice	-5.814***	-5.870***	-4.674***	-4.719***	-9.886***	-10.006***	-10.224***	-10.359***
q_demand	-4.903***	-6.604***	-4.098***	-5.429***	-12.992***	-17.496***	-14.878***	-19.832***
solar	-2.871**	-3.706**	-2.384	-2.810	-4.901***	-7.931***	-4.936***	-8.352***
windforecast	-15.721***	-16.578***	-13.861***	-14.688***	-19.373***	-20.186***	-19.039***	-19.849***
q_other_REE	-3.963***	-4.962***	-3.963***	-4.962***	-23.915***	-27.865***	-23.915***	-27.865***
sr_total	-14.076***	-14.235***	-14.076***	-14.235***	-18.478***	-18.620***	-18.478***	-18.620***
q_hydro	-4.456***	-4.746***	-3.564***	-3.876**	-6.191***	-6.543***	-6.996***	-7.411***
q_pump	-5.152***	-7.884***	-5.152***	-7.884***	-19.401***	-25.858***	-19.401***	-25.858***
q_nuclear	-5.940***	-6.420***	-4.805***	-5.233***	-12.369***	-13.484***	-13.659***	-14.955***
q_coal	-5.232***	-5.240***	-5.097***	-5.116***	-13.892***	-14.244***	-15.912***	-16.325***
q_cc	-3.209**	-6.204***	-2.816*	-5.259***	-12.829***	-21.014 ***	-14.579***	-22.798***
q_fuelgas	-7.811***	-7.811***	-7.811***	-7.811***	-9.572***	-9.570***	-9.572***	-9.570***
brent	-1.299	-1.739	-1.299	-1.739	-1.283	-1.679	-1.283	-1.679
ttf_price	-2.683*	-2.895	-2.420	-2.664	-2.716*	-2.927	-2.571*	-2.784
uxc_price	-3.950***	-3.717**	-3.950***	-3.717**	-3.937***	-3.538**	-3.937***	-3.538**
eua_wprice	-1.840	-1.428	-1.840	-1.428	-1.819	-1.393	-1.819	-1.393
coal_index	-1.629	-1.624	-1.558	-1.550	-1.380	-1.390	-1.401	-1.412
d.brent	-42.031***	-42.027***	-42.031***	-42.027***	-42.031***	-42.027***	-42.031***	-42.027***
d.uxc_price	-10.626***	-10.711***	-10.626***	-10.711***	-42.803***	-42.867***	-42.803***	-42.867***
d.ttf_price	-26.921***	-26.922***	-26.921***	-26.922***	-43.701***	-43.694***	-43.701***	-43.694***
d.eua_wprice	-40.884***	-40.918***	-40.884***	-40.918***	-40.884***	-40.918***	-40.884***	-40.918***
precipitation	-18.188***	-19.004***	-4.120***	-4.449***	-21.449***	-22.324***	-29.968***	-30.019***
temperature	-4.023***	-3.991***	-4.023***	-3.991***	-4.649***	-4.623***	-4.649***	-4.623***
ind_prod	-1.128	-1.109	-1.128	-1.109	-1.126	-1.112	-1.126	-1.112
d.ind_prod	-30.222***	-30.224***	-30.222***	-30.224***	-42.714***	-42.713***	-42.714***	-42.713***

Null hypothesis: variable contains a unit root - level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2.B.1: Results for Unit Root Tests - Daily

Variable	Dickey-Fuller (SBIC) constant	trend	Dickey-Fuller (HQIC) constant	trend	Phillips-Perron (SBIC) constant	trend	Phillips-Perron (HQIC) constant	trend
price	-14.001***	-13.998***	-11.753***	-11.749***	-45.543***	-45.538***	-45.851***	-45.859***
lnprice	-43.038***	-43.063***	-13.588***	-13.607***	-43.038***	-43.063***	-43.038***	-43.062***
q_demand	-7.995***	-9.299***	-8.098***	-9.470***	-37.050***	-37.879***	-37.073***	-37.959***
solar	-16.329***	-16.324***	-12.265***	-12.323***	-40.487***	-40.481***	-37.195***	-37.187***
windforecast	-39.444***	-39.494***	-39.444***	-39.494***	-39.444***	-39.494***	-39.444***	-39.494***
q_other_REE	-35.705***	-35.715***	-11.859***	-11.897***	-35.705***	-35.715***	-38.455***	-38.439***
sr_total	-40.358***	-40.426***	-28.646***	-28.726***	-40.358***	-40.426***	-40.354***	-40.423***
q_hydro	-13.444***	-13.729***	-10.192***	-10.798***	-33.998***	-33.986***	-35.489***	-35.643***
q_pump	-34.157***	-34.172***	-34.157***	-34.172***	-39.752***	-39.752***	-39.752***	-39.752***
q_nuclear	-9.912***	-10.215***	-8.541***	-9.231***	-45.748***	-46.371***	-47.044***	-48.737***
q_coal	-13.519***	-13.531***	-7.692***	-7.742***	-39.002***	-39.008***	-38.855***	-38.859***
q_cc	-12.132***	-12.215***	-9.526***	-9.851***	-38.139***	-38.169***	-40.213***	-40.556***
q_fuelgas	-11.397***	-11.497***	-9.819***	-11.355***	-35.389***	-35.410***	-34.753***	-35.730***
brent	-1.299	-1.739	-1.299	-1.739	-1.283	-1.679	-1.283	-1.679
ttf_price	-2.683*	-2.895	-2.420	-2.664	-2.716*	-2.927	-2.571*	-2.784
uxc_price	-3.950***	-3.717**	-3.950***	-3.717**	-3.937***	-3.538**	-3.937***	-3.538**
eua_wprice	-1.840	-1.428	-1.840	-1.428	-1.819	-1.393	-1.819	-1.393
coal_index	-1.629	-1.624	-1.558	-1.550	-1.380	-1.390	-1.401	-1.412
d.brent	-42.031***	-42.027***	-42.031***	-42.027***	-42.031***	-42.027***	-42.031***	-42.027***
d.uxc_price	-10.626***	-10.711***	-10.626***	-10.711***	-42.803***	-42.867***	-42.803***	-42.867***
d.ttf_price	-26.921***	-26.922***	-26.921***	-26.922***	-43.701***	-43.694***	-43.701***	-43.694***
d.eua_wprice	-40.884***	-40.918***	-40.884***	-40.918***	-40.884***	-40.918***	-40.884***	-40.918***
precipitation	-18.188***	-19.004***	-4.120***	-4.449***	-21.449***	-22.324***	-29.968***	-30.019***
temperature	-4.023***	-3.991***	-4.023***	-3.991***	-4.649***	-4.623***	-4.649***	-4.623***
ind_prod	-1.128	-1.109	-1.128	-1.109	-1.126	-1.112	-1.126	-1.112
d.ind_prod	-30.222***	-30.224***	-30.222***	-30.224***	-42.714***	-42.713***	-42.714***	-42.713***

Null hypothesis: variable contains a unit root - level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2.B.2: Results for Unit Root Tests - Daylight

Chapter 3

The Effect of Intermittent RES-E on the Conventional Power Plant Mix - An Empirical Analysis of 18 European Countries

3.1 Introduction

Over the last decade, most of the electricity markets in the EU have experienced large penetrations of electricity generated by renewable energy sources (RES-E). In 2004 the share of renewable energy in gross final energy consumption in the EU was 8.3% and has increased to 15% until 2013 (Eurostat, 2015a). Given the EU target of 20% of gross final energy consumption having to be provided by RES-E by 2020, the amounts of RES-E that have to be integrated are likely to further increase in the coming years (Directive 2001/77/EC; since 2012 Directive 2009/28/EC). In order to reach the EU target, different national public support schemes have been implemented by the member states to incentivize the investment in RES-E. These are often combined with prioritized feed-in of the so-called green electricity. The EU's high priority of RES-E promotion stems not only from the wish to decarbonize the electricity sector but also to diversify, and thereby secure electricity supply.

However, a sustainable electricity generation by means of RES is not necessarily in accordance with a reliable supply of electricity. A large share of the renewable generation facilities are intermittent in their generation behavior if their main input factor is dependent on meteorological conditions. The most prominent examples are wind and solar PV installations, that are only able to produce when the wind is blowing or the sun is shining. This leads to an increase in an extremely fluctuating, partly stochastically, in-feed of electricity with marginal costs close to zero. The result is a considerable increase in uncertainty about the residual load that has to be covered by dispatchable, i.e. mainly conventional, power plants in each hour. In order to ensure security of supply, a flexible generation plant portfolio is needed that complements the intermittent RES installations. Such a flexible power plant mix is characterized by lower load factors of conventional plants and an increased demand for flexible peaking plants with relatively high marginal costs.

This paper aims at evaluating in an ex-post empirical analysis if and how the generation by intermittent RES-E has affected the conventional power plant mix in 18 European countries. By investigating the impact of the shares of RES-E generation on the shares of the capacities installed of the conventional generation technologies, this analysis aims at identifying the long-run effect. A panel data regression model is chosen with the share of intermittent RES-E generation as the explanatory variable of interest. In a second specification the electricity price, a possibly endogenous variable, is instrumented by the share of intermittent RES-E generation. It seems reasonable to assume that the share of generation by intermittent RES-E does not only have a direct effect on the composition of the conventional plant fleet but that this effect takes place via the electricity price, as the amount of RES-E generation directly effects the electricity price. This approach has the advantage that it allows to quantify the effect of RES-E generation on the conventional plant fleet through the price.

The remainder of the paper is structured as follows. Section two discusses the screening-curve model for the determination of the optimal long-term power plant mix when large amounts of intermittent RES-E enter the electricity market and gives a short overview over the findings of the relevant empirical literature. Section three begins with a description of the data followed by a correlation analysis. Then the empirical strategy is explained and the results are presented. Section four concludes on the findings.

3.2 Theoretical Background & Literature Review

To analyze the impact of RES-E on electricity prices as well as on the generation mix one has to distinguish between short- and long-run effects. In the short run, the stock of power plants is given, while, in the long-run, adjustments to the existing portfolio are possible. Hence, the short-run effect is a price effect only, while in the long-run alterations in the composition of the plant fleet might be observed.

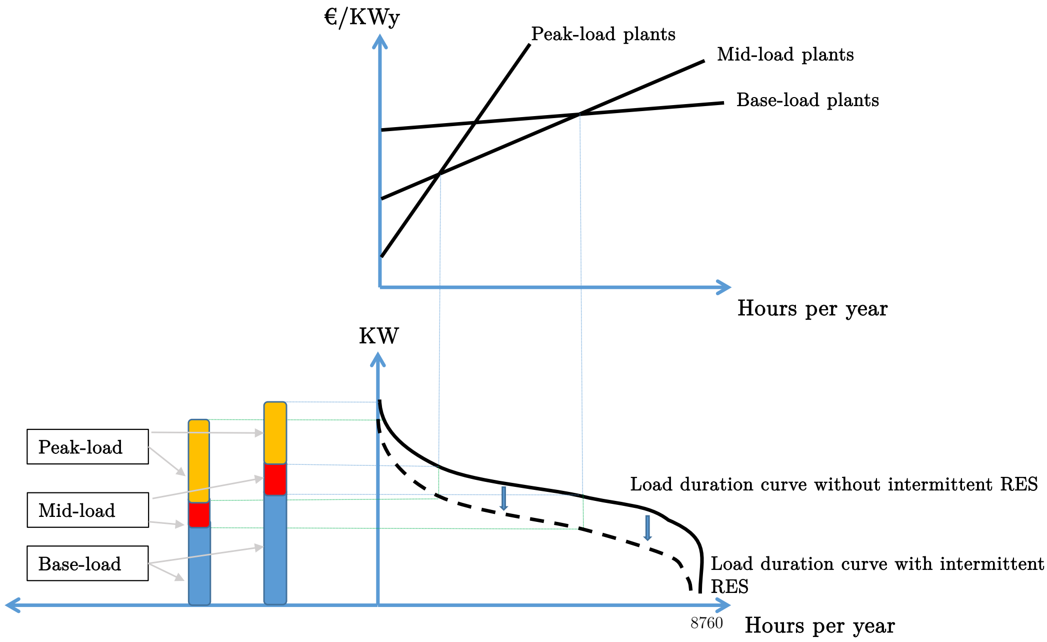
In the short run, where the generation mix is given, the feed-in of power generated by intermittent RES-E has only a price effect. Wind and solar power are usually produced at marginal cost close to zero and are often granted priority feed-in by the system operators. Therefore, they are dispatched and fed into the grid whenever they are available. This increase in power generated leads to a decrease in the residual load that has to be covered by the conventional power plants. Given a merit-order dispatch, the most expensive generation units are less often needed to meet the residual demand. Hence, the market price for electricity will decrease (see Weber and Woll, 2007 and Fürsch et al., 2012 for a more detailed discussion of the short-run merit-order effect).

Since this paper analyzes the effect of intermittent RES-E on the composition of the conventional generation mix, a long-term model that allows for adjustments in the power plant portfolio is needed. The screening and load-duration curve (LDC) analysis is well suited for this purpose. By minimizing the total annual generation costs while simultaneously taking into account that a certain electricity demand has to be covered, it allows for the determination of an optimal capacity mix consisting of different generation technologies (Lamont, 2008). Figure 3.1 displays the model graphically and also shows how the optimal composition of the generation mix changes when intermittent RES-E enter the electricity system.

First, the cost minimizing generation mix consisting of three different generation technologies without the generation by intermittent RES-E is determined. The upper part of Figure 3.1 shows the screening curves for base-load, mid-load and peak-load plants. A screening curve graphically depicts the annual revenue that is required for a power plant owner to cover its levelized cost of capital[1] as well as its variable cost of production depending on the hours

[1]The levelized cost of capital is the amortized overnight fixed life-cycle cost per MWh (see Joskow, 2011; Stoft,

of runtime, i.e. the capacity factor[2]. At the points of intersection of the screening curves a technology switch takes place in the sense that a different type of power plant becomes cost optimal to produce electricity (Stoft, 2002). Peak-load plants have low fixed but high variable costs, and therefore are optimal when runtimes are low (intersection of peak-load and mid-load plants). The opposite holds for base-load plants. These are usually characterized by high fixed and low variable costs. These types of plants are optimal when long runtimes are required that allow them to cover their fixed costs (intersection mid-load and base-load plants). Mid-load plants are located in between.



Source: Own Figure based on Fürsch et al., 2012 and Weber & Woll, 2007

Figure 3.1: The Impact of Intermittent RES-E on the Optimal Capacity Mix

In order to determine the optimal capacity mix, a LDC, that graphically depicts the electricity demand, is added to the model (see the lower part of Figure 3.1). For this purpose, the load at each hour of the year is measured and drawn beginning with the highest load level, i.e. the maximum load that occurs only for one hour a year. Therefore, the LDC is downward sloping ending at hour 8760, the point at which the lowest load observed during the year is measured. Mapping the points of intersection of the screening curves to the load-duration curve yields the optimal generation mix of base-, mid- and peak-load plants. The required capacity in gigawatt for each type of technology can then be read off the y-axis (see Green, 2006; Stoft, 2002). The RHS bar on the lower LHS of Figure 3.1 shows the composition of the generation mix for the given example without intermittent RES-E. Stoft (2002) argues that the resulting generation

2002).

[2]If the hours of runtime during a year are stated as a percentage of the total hours per year, i.e. 8760, this yields the capacity factor.

portfolio constitutes a long-run equilibrium as the LDC already contains the price effect on demand.

The impact of power in-feed by intermittent RES-E can be modeled as a downward shift in the LDC (see e.g. Sáenz de Miera et al., 2008; Fürsch et al., 2012; Weber and Woll, 2007). Since the generation by intermittent RES-E is weather-dependent, these plants cannot be dispatched. Their generation pattern is stochastic and can be interpreted as an exogenous shock to the conventional power plants. These are dispatchable and have to serve the residual load (the dashed line in Figure 3.1). The resulting residual LDC is steeper than the original LDC without intermittent RES-E. The need for base-load capacity is decreased while the need for peak-load capacity is increased. This is due to the fact that during many hours the load can be satisfied by the intermittent RES-E. As the hours of dispatch for the conventional plants decrease, a large share of the base- and some of the mid-load plants cannot cover their fixed costs any longer and are either mothballed or closed down for good. However, during hours of high load and low wind and solar energy there has to be sufficient conventional back-up capacity leading to increased capacities of peak-load plants (e.g. Fürsch et al., 2012; Nicolosi and Fürsch, 2009; Wissen and Nicolosi, 2007). The resulting generation portfolio with high shares of intermittent RES-E therefore consists of lower shares of power plants with high capital and low variable costs and higher shares of power plants with high capital and low variable costs (see the LHS bar on the lower LHS of Figure 3.1). However, when comparing the two scenarios, i.e. with and without intermittent RES-E, it is noticeable that the total installed capacity of conventional plants is only slightly lower in the case with intermittent RES-E than in the base case. Given the low capacity credit of intermittent RES-E only a small amount of conventional generation technologies can be substituted by intermittent generation devices (Nicolosi and Fürsch, 2009).

The expected price effect in the long-run equilibrium differs from the one in the short-run merit-order model. Contingent on the patterns of RES-E feed-in and demand for electricity, the residual load experiences an increasing volatility. This volatility gets more pronounced the more RES-E enters the power system translating into more volatile spot market prices (Nicolosi and Fürsch, 2009). However, in long-run equilibrium, when the power plant mix has fully adapted to the RES-E capacities, the average wholesale price for electricity depends solely on the combination of the costs of the different conventional generation plants. These costs, in turn, are independent of the shape of the residual LDC. Thus, the average spot market price with intermittent RES-E will be the same or at least similar to one without intermittent RES-E (Sáenz de Miera et al., 2008; Weber and Woll, 2007).

A drawback of the model is, that it does not account for possible ramping constraints of the different generation technologies. Yet, the increased volatility in the residual load pattern requires a more flexible plant portfolio. However, the least flexible technologies with respect to their ramping behavior are the base-load plants, while the most flexible ones are the peak-load plants. The model already predicts an increase in peak-load and a decrease in base-load technologies.

Fürsch et al. (2012) consider also the impacts of a sub-optimally adapted generation portfolio as well as of cross-border exchanges of electricity. In case of a larger expansion of intermittent RES-E than expected, there will be excess capacities of base-load plants and hours of peak load will be satisfied by mid-load plants. Thus, peak-load plants will not be dispatched and the spot market price will be lower since no scarcity prices will occur. The possibility of cross-border trade of electricity in the presence of intermittent RES-E leads to a lower reduction in the spot market price than otherwise. The low price due to the feed-in of RES-E leads to an increased demand by foreign countries. Thus, the domestic conventional generators face an increased residual demand and the spot market price rises.

Several studies have analyzed the short- as well as the long-run effect of large-scale integration of intermittent RES-E in the electricity market. As far as the short-run perspective is concerned, the studies find similar results, i.e. a reduction in the hourly spot market price for electricity. Gelabert et al. (2011) conduct an empirical study for the Spanish electricity market for 2005 to 2009. They find that an increase in electricity produced by intermittent RES-E and cogeneration of 1 GWh leads to a decrease in the electricity price of almost 2 €/MWh. A similar study for the Austrian-German region between July 2010 and June 2012 finds a reduction in the day-ahead electricity prices by roughly 1 €/MWh for every 1 GWh of RES-E added (Würzburg et al., 2013). Simulation based studies for Germany by Weber and Woll (2007) and Sensfuß et al. (2008) find also a price decreasing effect by renewable energy sources for the year 2006. Weber and Woll (2007) conduct a simulation analysis based on a simple merit order model, while Sensfuß et al. (2008) employ an agent-based model. Sáenz de Miera et al. (2008) identify the merit-order effect in Spain by simulating the merit order and the resulting price with and without wind generation. Taking the difference in the two prices, the authors also find a price reducing effect.

The findings of empirical studies on the long-term effect of intermittent RES-E on the optimal conventional capacity mix are in line with what the theoretical model discussed earlier in this paper predicts. The long-run equilibrium conventional generation portfolio, when large amounts of intermittent RES-E penetrate the market, consists of larger capacities of peaking plants with relatively low capital costs and fewer capacities of relatively capital intensive plants. The total amount of conventional capacities installed, however, stays about the same or decreases only slightly. The long-term price effect is also zero. A simulation study confirming this has been conducted by Lamont (2008) with Californian data of 2001. Green and Vasilakos (2011) employ a market equilibrium model for Great Britain, while Bushnell (2010) applies a similar model to several regions of the western US. He finds that new wind installations of at least 10 GW are required to be able to substitute 1 to 2 GW of conventional capacity. Fürsch et al. (2012)

use the Dispatch and Investment Model for Electricity Markets in Europe (DIME) to calculate the optimal power plant mix for Germany between 2015 and 2030. The authors endogenize cross-border electricity trade with other European countries, yet their findings are similar to those of the other studies. Additionally, including start-up costs and operating reserve and ramping constraints does not change the findings concerning the optimal conventional power plant portfolio (de Jonghe et al., 2011; Delarue et al., 2011; de Sisternes, 2011; Nicolosi, 2011). De Jonghe et al. (2011) show that the optimal capacity mix depends to a large extent on the ramp rates of base-load plants.

3.3 Empirical Analysis

3.3.1 Data

For the empirical analysis an unique dataset of 18 European countries covering the years 2000 to 2010 is constructed. Data on the installed capacities of conventional power plants are available by fuel type, i.e. hydro, nuclear, coal, gas and oil (Platts, 2011). For the intermittent RES-E the total yearly generation by solar PV and wind is used instead of its installed capacities (IEA, 2015). It is assumed that the actual generation by intermittent RES-E is more relevant to the operators of conventional power plants than the capacity installed given its low load factors. The choice of countries is determined by data availability. The set of countries consists of European OECD countries, since the Platts database is restricted to Europe and the focus on OECD countries ensures a good data coverage for the control variables.[3] Besides, these countries cover the entire range of different shares of intermittent RES-E generation, i.e. low, intermediate and high. In Table 3.1 the countries are grouped according to their share of the sum of wind and solar PV to the total power generation. Low levels of intermittent RES-E are observed for ten of the 18 countries with shares below 1.40%. With roughly 2% to 3.3% power generated by wind and solar PV, Austria, Luxembourg, the Netherlands and Greece have intermediate levels of fluctuating RES-E. High shares with 6.7% to almost 9.5% are realized in Germany, Portugal, Spain and Ireland.

Table 3.2 presents the descriptive statistics of the variables used in the analysis.[4] The dependent variable is the share of the capacity installed to the total conventional capacity installed. Three dependent variables are considered, namely the share of coal, gas- and oil-fired power plants of a country. In line with theory, countries with high and intermediate shares of RES-E have higher shares of gas-fired plants, 27.7% and 32.9% respectively, than countries with a low share of RES-E (18.6%).

[3]Denmark is missing due to unavailability of the price data.

[4]Tables with descriptive statistics for the three groups of countries separately are shown in the Appendix (see Tables 3.A.1 to 3.A.3).

Country	Share of wind & solar pv	Classification
Austria	3.18 %	intermediate
Belgium	0.56 %	low
Czech Republic	0.14 %	low
Finland	0.24 %	low
France	0.72 %	low
Germany	6.68 %	high
Greece	2.86 %	intermediate
Hungary	0.28 %	low
Ireland	6.94 %	high
Italy	1.30 %	low
Luxembourg	2.12 %	intermediate
Netherlands	3.30 %	intermediate
Norway	0.65 %	low
Poland	0.33 %	low
Portugal	8.59 %	high
Spain	9.20 %	high
Sweden	0.96 %	low
United Kingdom	1.33 %	low

Table 3.1: Share of Intermittent RES-E Generation to Total Generation in the Year 2007

Besides the variable of interest, i.e. the share of generation by wind and solar PV total generation, the share of the other conventional capacities, also including hydro and nuclear plants, one national and three electricity market indicators are controlled for. Except for the GDP long-term growth forecast, these variables are lagged three years to account for the time it takes to build a power plant. The GDP long-term growth forecast is used as a proxy for the expected development of electricity demand and controls for the expected future size of the market. The regulation variable is an indicator that summarizes the regulatory provisions in the electricity sector on a scale from zero to six. A value of six denotes an entirely regulated electricity sector. Given the better availability of data, the electricity price net of taxes and levies for industry consumers with an annual demand of 24000 MWh is chosen instead of the electricity wholesale price. The price is measured in €/MWh.

In this analysis, the countries' electricity markets are implicitly defined by national boundaries. This should be an appropriate assumption since the data set ends in 2010, and hence, market integration of the different countries' electricity markets should not yet be an issue. Efforts by the EU to enforce the integration of of the national electricity markets started, in particular, only in 2009 where the network access for cross-border exchanges was regulated (Directive 2009/72/EC and Regulation 714/2009/EC). Besides, market coupling among Austria, Belgium, France, Germany, Luxembourg, the Netherlands and the Scandinavian countries took place only in November 2010. Nevertheless, we control for the possibility of market integration. Following common practice in international trade economics, the sum of electricity exports and imports divided by the total electricity generation of a country is employed as a measure for the degree of that country's market integration.[5]

[5] In economics of international trade a country's degree of openness is usually measured by the total trade-to-GDP ratio (Alcalá and Ciccone, 2004).

	All Countries							
Variable	Variable Name	Obs	Mean	Std. Dev.	Min	Max	years	Source
Dependent Variable								
Inst. capacity (share)	share_*							
Coal (%)	share_coal	198	25.56	23.39	0[1]	91.88	2000-2010	PLATTS (2011)
Gas (%)	share_gas	198	23.80	19.60	0.34	76.08	2000-2010	PLATTS (2011)
Oil (%)	share_oil	198	8.60	8.12	0[2]	36.97	2000-2010	PLATTS (2011)
Independent Variables								
Other (%)	share_other	198	42.04	28.14	2.45	99.63	2000-2010	PLATTS (2011)
GDP growth forecast	gdpgfore_l	198	1.99	2.83	-9.34	9.63	2000-2010	OECD (2015a)
Regulation	regul_elec	198	2.59	1.00	0.87	5.63	2000-2010	OECD (2015b)
Industry price (€/MWh)	price	133[3]	53.11	14.68	23.25	108.00	2000-2007	Eurostat (2015b)
Total Generation (GWh)	gen_tot	198	175332.9	177444.6	1169	640578	2000-2010	IEA (2015)
Degree of market integration	integration	198	0.3757	0.685	0.01	6.14	2000-2010	IEA/OECD (2015)
Intermittent RES-E								
Solar PV generation (GWh)	gen_pv	198	269.44	1216.44	0	11729	2000-2010	IEA (2015)
Wind generation (GWh)	gen_wind	198	3950.84	8463.33	0	44271	2000-2010	IEA (2015)
Share RES-E (%)	share_resgen	198	2.09	3.10	0	17.37	2000-2010	IEA (2015)

1: No coal power plants in Luxembourg. 2: No oil-fired power plants in Norway.
3: Prices in Austria missing for 2000 to 2002, in Luxembourg for 2005 to 2006 and in the Netherlands for 2000 to 2004.

Table 3.2: Descriptive Statistics: All Countries

3.3.2 Correlation Analysis

To analyze whether the share of intermittent RES-E has an effect on the composition of the conventional power plant mix, first a correlation analysis is performed. Figures 3.1 to 3.3 show the evolution of the power plant mix for the countries with low, intermediate and high levels of RES-E generation, respectively, as well as the yearly generation patterns of power produced by wind and solar PV for the years 2000 to 2010. The stacked area displays the capacities installed of the conventional capacities. The lines plot the generation by wind and solar PV and the corresponding ordinate axis is on the right-hand side. Correlation coefficients for each of the three groups as well as for all countries are shown in Table 3.3. Correlation between the measures of wind and solar PV generation (separately and as a sum), the share of conventional capacities installed and the price are looked at. The price and the measures for wind and solar PV are lagged three years. To account for a possible trend in the data, the development of the correlation coefficients over time are shown in Figure 3.4.

The group of countries with low levels of wind and solar PV generation constitutes the largest group with ten countries. It is also the most diverse group with respect to the sizes of the electricity markets when comparing the total conventional capacities installed (see Figures 3.1 and 3.B.1).[6] France (107 GW) possesses the largest plant fleet while Hungary (8 GW) has the second smallest plant fleet in the dataset. Except for Italy (70 to 85 GW) and the United Kingdom (75 GW to 80 GW), the other countries' pant fleets range roughly between 15 and 30 GW. Regarding the composition of the plant fleet, it is notable that, except for Italy, Hungary, Norway and Poland, all countries dispose of significant capacities of nuclear power plants. Norway and Italy rely on hydro- as well as gas-fired plants, respectively. In terms of CO_2 emissions these three technologies are regarded as rather clean. This might partly explain the low shares of intermittent RES-E when thinking in terms of the achievement of the EU climate targets. Exceptions are the Czech Republic, Poland and the United Kingdom. Particularly, the former two are heavily relying on coal plants. In case of the United Kingdom, coal has been replaced by gas as the main fuel type in 2005.

The increase in the generation of intermittent RES-E started in the years between 2004 and 2006. However, this can mainly be attributed to wind generation, as the solar PV generation is often zero or only slightly above zero. Except for the United Kingdom and Italy, where the main fuel type switched to gas, no visible alterations in the mix of conventional plants took place.

[6]Given the large differences in the amounts of capacities installed among the countries, one should be aware that the scaling in the figures is not the same. This is to simplify readability.

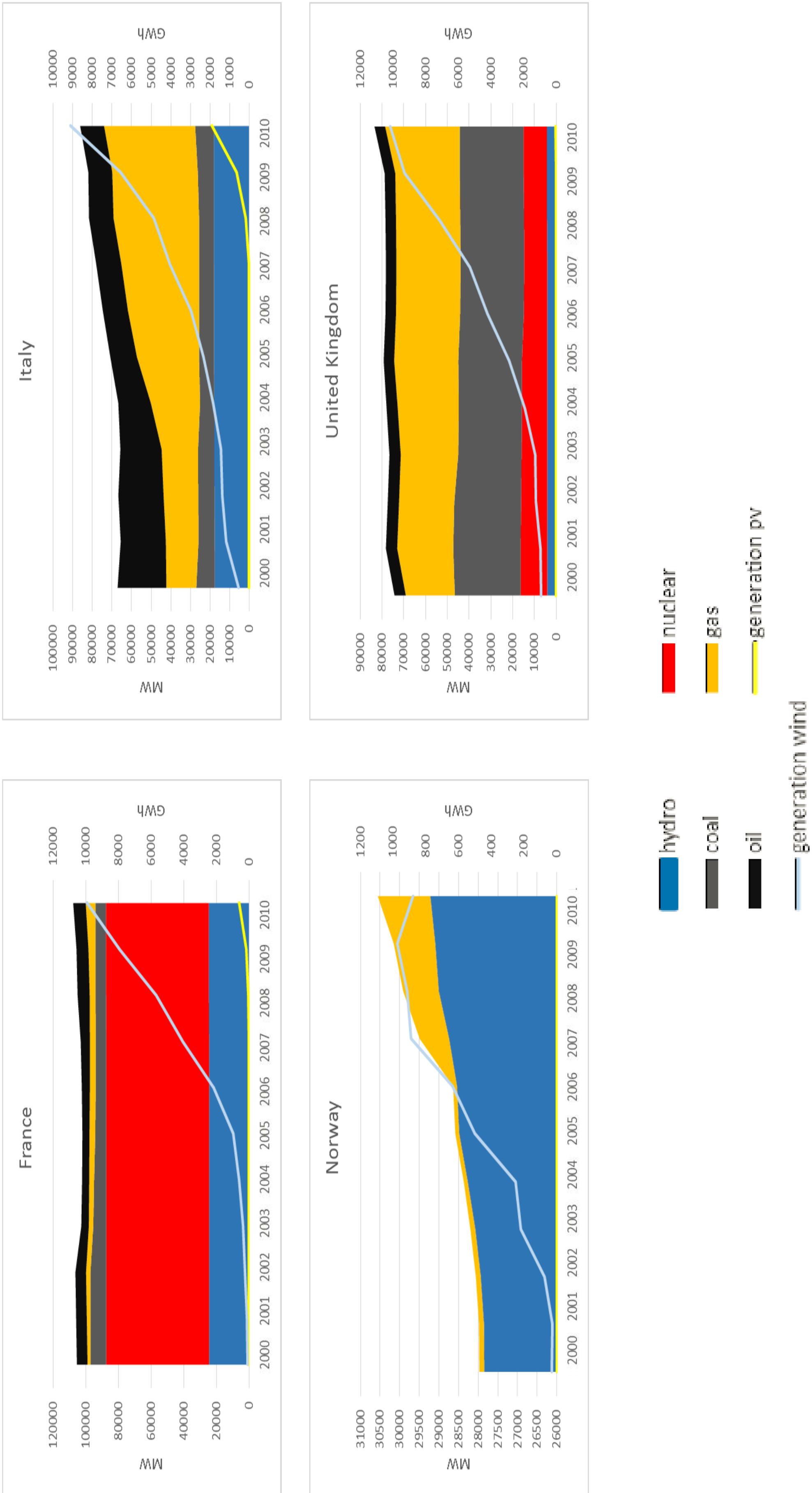


Figure 3.1: Power Plant Mix of Countries with Low Shares of RES-E

The group of countries with intermediate shares of intermittent RES-E is the most homogeneous group in the dataset when the size as well as the composition of plant fleets are considered (see Figure 3.2). With total conventional capacities installed in the range of 10 to 18 GW, these power markets are rather small. Except for Greece, the countries' main fuel types are either hydro or gas with shares of at least 70%. None of these countries disposes of any considerable amounts of nuclear power plant capacities.[7] Besides, Luxembourg does not have any coal- and hardly any oil-fired generation technologies and no changes in the composition of the plant fleet have been taken place in the observed period. A similar picture can be observed for the Netherlands. Except for a slight increase in gas-fired capacities in the last years of the sample and a drop in oil-fired technologies by 200 MW to 38 MW (0.22%), the plant mix remained unchanged. Austria experienced a slight increase in gas-fired technologies and a decrease in coal- and oil-fired plants. However, the capacities installed of these technologies account for less then 30% of the entire plant fleet.

In comparison to the first group of countries, the increase in wind generation started two to three years earlier, i.e. in 2002/2003. In the cases of Greece ($>$ 500 GWh), Luxembourg ($>$ 20 GWh) and the Netherlands ($>$ 800 GWh), these countries already started with a positive level of RES-E generation before a significant increase occurred where the generation almost doubled from one year to the next. However, these growth rates diminished in 2007, while the expansion in wind generation even came to hold in Austria and Luxembourg.

[7]The Netherlands have nuclear capacities of less than 500 MW.

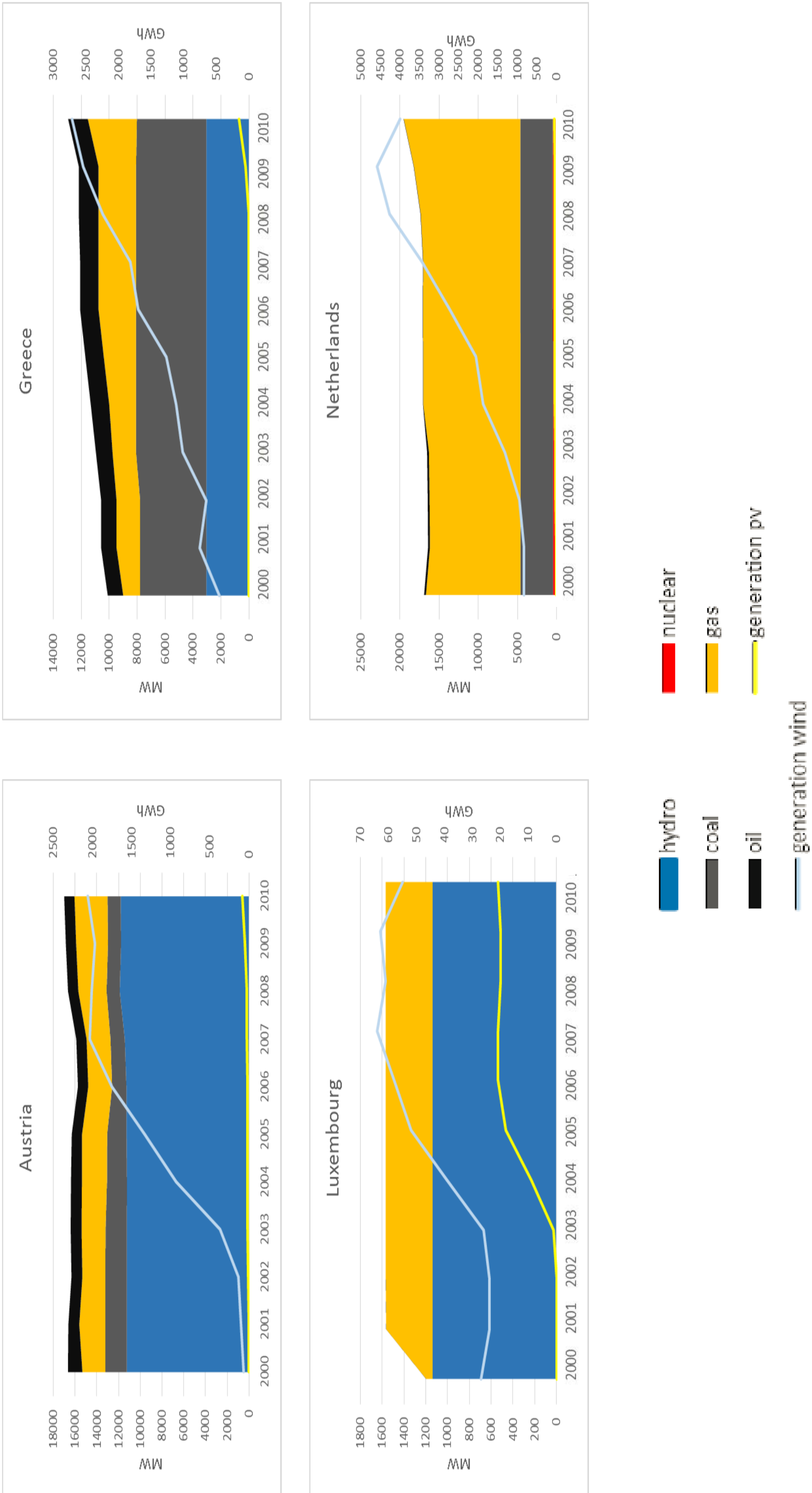


Figure 3.2: Power Plant Mix of Countries with Intermediate Shares of RES-E

As can be seen in Figure 3.3, the plant fleets of the four countries with the highest shares of wind and solar PV installations are also the most diverse. Except for Ireland and Portugal, that do not posses any nuclear power plants, all fuel types are deployed. With roughly 100 GW (Germany) and 50 to 70 GW (Spain) of conventional capacities installed, Germany and Spain belong to the largest power markets in the data set. The smallest plant fleet in the entire dataset has Ireland with roughly five to seven Gigawatt. While Ireland's capacities installed of hydro- and coal-fired plants stayed rather unchanged over time, it experienced a sharp increase in gas-fired technologies from 30.8% in 2000 to almost 60% in 2010. The share of oil-fired plants, however, halved in the same time period. Despite its small decrease of about 2 GW over the years, Germany's main fuel type is coal. On the other hand, the capacity installed of gas-fired plants has increased by almost 7.5 GW. In Spain, a change in the main fuel type has taken place over the course of the time. While hydro used to have the largest share of generation capacities, the massive deployment of gas-fired capacities had the effect that gas is the main fuel type since 2005. Spain also experienced a minor drop in oil-fired capacities, while the rest stayed constant. The evolution of the plant mix in Portugal is similar to the one in Spain. However, Portugal disposes of larger shares of hydro and oil-fired plants.

The increased generation by wind and solar PV in Germany and Spain started already in the 1990's and hence, significantly earlier than in the other countries of the sample. In Ireland and Portugal increased growth rates are observed since 2003/2004, which is about the same time as wind generation started to expand in the sample of countries with intermediate RES-E generation. Notably, the yearly generation of wind power in Germany has stayed more or less constant since 2007. Interestingly, the increase in gas-fired generation technologies in Ireland, Portugal and Spain seem to be parallel to the increase in generation by intermittent technologies, particularly wind power.

Overall, an expansion of the conventional capacities installed is observed for all countries in the sample. Thereby, the highest shares of capacities added are observed for gas-fired plants, especially in the countries with intermediate and high shares of RES-E. However, besides its favorable ramping behavior, gas is relatively cheap and plants are rather quick to build.

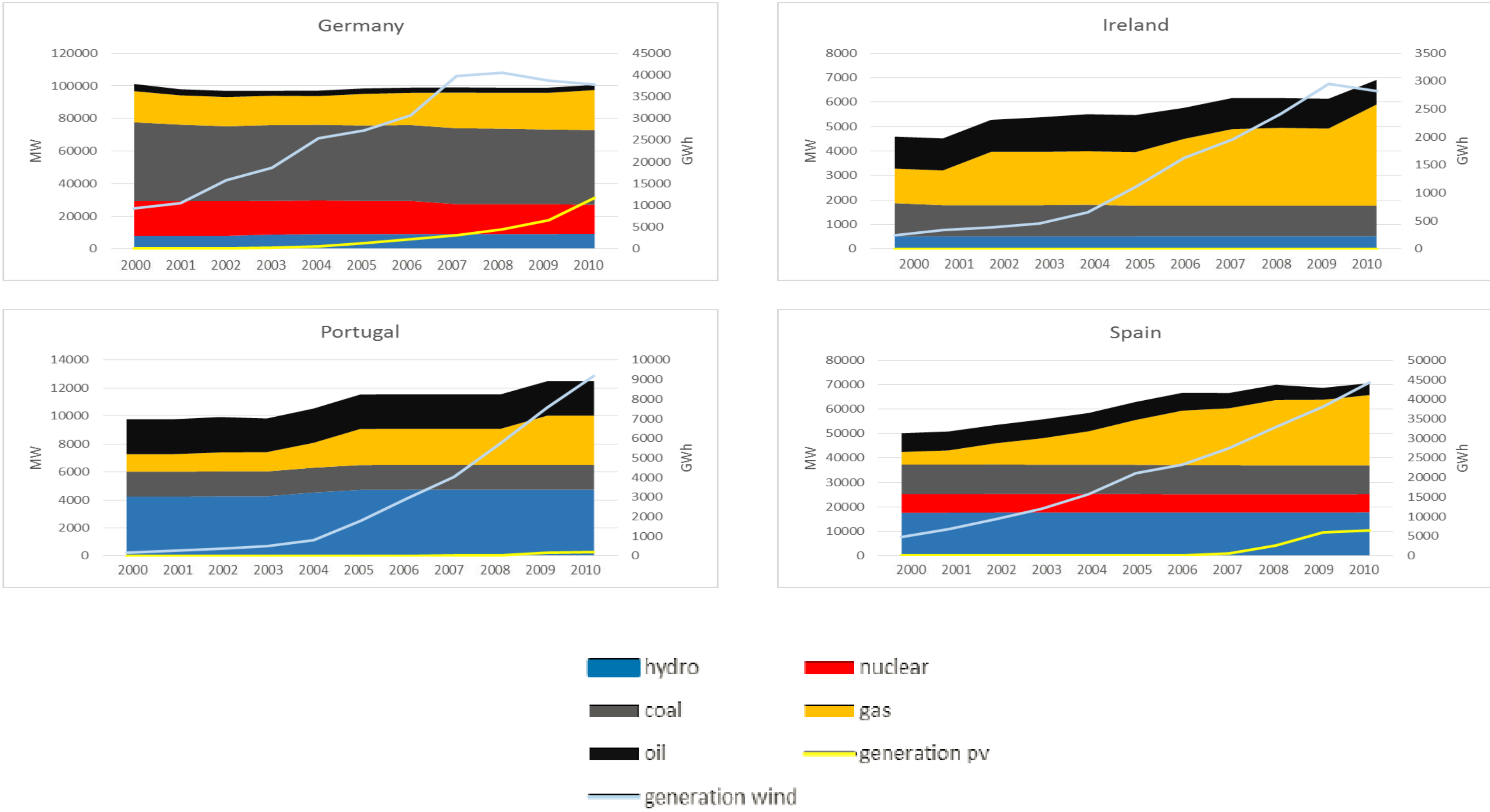


Figure 3.3: Power Plant Mix of Countries with High Shares of RES-E

	Low levels of RES-E			Intermediate levels of RES-E		
Variable	*generation pv (-3)*	*generation wind (-3)*	*generation RES-E (-3)*	*generation pv (-3)*	*generation wind (-3)*	*generation RES-E (-3)*
gen. pv (-3)	1			1		
gen. wind (-3)	0.70***	1		0.59***	1	
gen. RES-E (-3)	0.70***	1***	1	0.60***	1***	1
share hydro	-0.07	-0.05	-0.05	-0.28	-0.63***	-0.63***
share nuclear	-0.13	-0.08	-0.08	0.63***	0.53***	0.53***
share coal	-0.27**	-0.18	-0.18	-0.24	0.40**	0.40**
share gas	0.43***	0.32***	0.32***	0.61***	0.51***	0.51***
share oil	0.57***	0.27**	0.28**	-0.54***	0.08	0.07
price (-3)	0.69***	0.49***	0.49***	0.47**	0.90***	0.90***
	High levels of RES-E			**All countries**		
Variable	*generation pv (-3)*	*generation wind (-3)*	*generation RES-E (-3)*	*generation pv (-3)*	*generation wind (-3)*	*generation RES-E (-3)*
gen. pv (-3)	1			1		
gen. wind (-3)	0.77***	1		0.78***	1	
gen. RES-E (-3)	0.80***	1***	1	0.80***	1***	1
share hydro	-0.32*	-0.31*	-0.32*	-0.11	-0.16*	-0.16*
share nuclear	0.47***	0.76***	0.75***	0.04	0.03	0.03
share coal	0.57***	0.59***	0.60***	0.14	0.12	0.12
share gas	-0.21	-0.21	-0.21	0	0.09	0.08
share oil	-0.51***	-0.84***	-0.83***	-0.11	-0.08	-0.08
price (-3)	0.36**	0.10	0.11	0.28***	0.30***	0.30***

Level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.3: Correlation Coefficients by Country Classification

The results of the correlation analyses for the subsets of countries as well as for the entire sample do not display a clear-cut picture (see Table 3.3 and Figure 3.4). Table 3.3 shows the correlation coefficients for the generation by solar PV, wind and RES-E with the shares of the installed capacities of conventional power plants and the price for the entire time period of eleven years. The correlations between the share of capacity installed of gas-fired plants and the generation of both wind and solar PV are positive and highly significant for the first and the second group of countries. In line with theoretical predictions, the correlation coefficients are larger for the group of countries with intermediate shares of RES-E than those with low shares. Surprisingly, for the sample of countries with high shares of RES-E the respective correlation coefficients have a negative sign, yet are insignificant. This is in contrast to what the graphical analysis of the development of the composition of the conventional plant fleet has suggested. The negative correlation coefficients for the share of hydro and wind as well as RES-E generation can be explained by the expansion of gas-fired power plants, which increases the share of gas, thereby decreasing the share of hydro. The same holds for the negative correlation coefficients of oil and the share of wind as well as RES-E generation. The positive correlation for nuclear in the second group of countries is entirely driven by the Netherlands, as this is the only country in this group that has nuclear power plants installed. The positive correlation coefficients, particularly for the countries with high shares of RES-E generation, are surprising in the case of coal. However, the large share and only small decrease in Germany – together with fact that the amount of coal plants in Portugal and Spain have remained more or less unchanged – may explain this observation. The price correlations for the countries with high shares of RES-E generation are smaller in size when compared to the second group and statistically insignificant. The only exception is the price correlation with the capacity installed of solar PV. Given that the increased generation by intermittent RES-E started earlier in Germany and

Spain than in the countries with intermediate levels of RES-E, these countries might be already better adapted. Considering the correlation coefficients for the entire sample, except for the share of hydro, none of the shares of the conventional capacities installed displays a significant correlation coefficient with one of the RES-E measures. Correlations with the price are again positive and statistically significant.

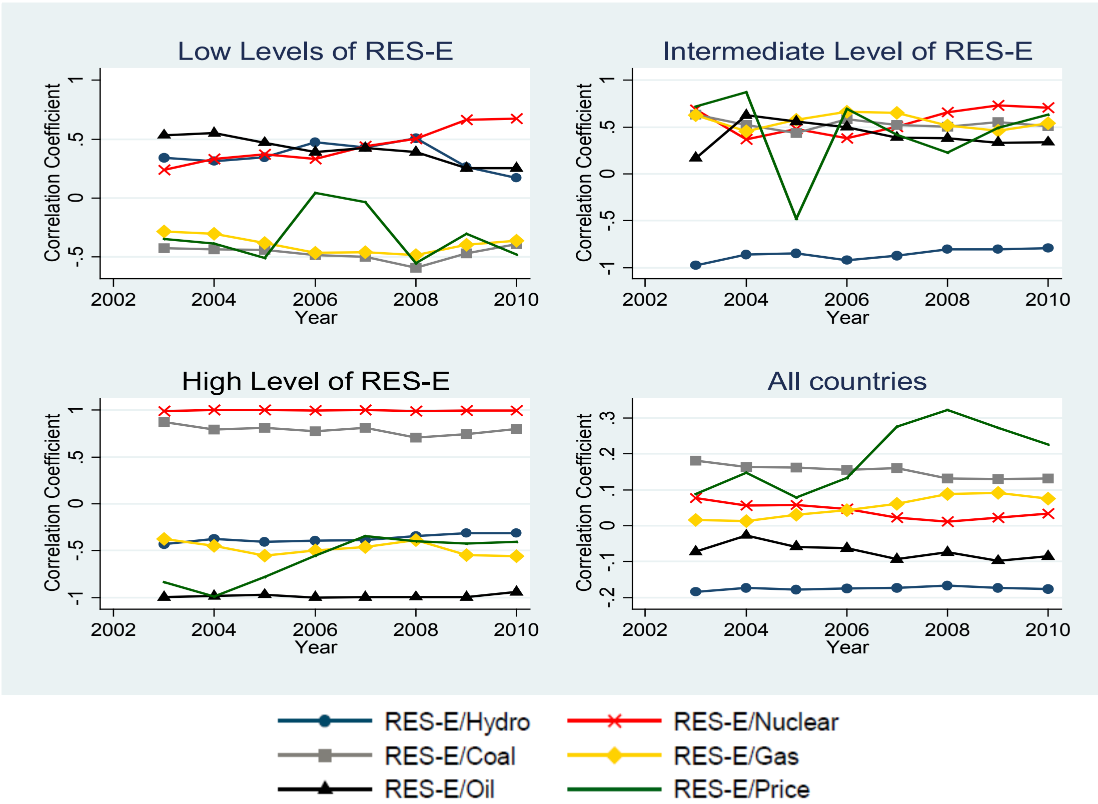


Figure 3.4: Development of Correlation Coefficients

The correlation coefficients in Table 3.3 are not detrended. However, when considering the graphical analysis one might suspect a trend in the data. Therefore, Figure 3.4 displays the development of the yearly correlation coefficients over time to see how they behave over the years.[8] When interpreting the results, one has to keep in mind that the correlation coefficients are not statistically significant, which is not surprising given the small number of observations. The results do not differ significantly from those of the previous correlation analysis. The coefficients are larger for the group of countries with intermediate shares of RES-E than for those with low shares. Considering the development of the coefficients over time, they seem to remain more or less constant. The only notable exceptions are the correlations between the RES-E generation and the price, which are nonconstant over time. While they are negative for countries with low and high shares of RES-E, they are positive for countries with intermediate shares of RES-E as well as for all countries. It seems that, not surprisingly, the generation

[8]For reasons of better readability, in these figures only the correlations with the RES-E generation are shown.

by RES-E has a price diminishing effect in particular for countries with large shares of RES-E. This is in line with what theory suggests for the short-term development (e.g. Weber and Woll, 2007; Fürsch et al., 2012) and several empirical studies (e.g. Green and Vasilakos, 2010; Sáenz de Miera et al., 2008; Gelabert et al., 2011) have found. However, the correlation coefficient is diminishing over time. Since we use industry instead of wholesale prices other price components might have increased the price for industrial consumers. Considering all countries combined (lower right panel), the correlation coefficients are rather small, i.e. between -0.2 and +0.3, and smaller than for the individual groups of countries. The correlation coefficients for gas are positive and slightly increasing over time, while the ones for oil are negative yet also getting stronger. These findings are in line with what theory predicts. However, the correlation coefficients are neither strong nor statistically significant. In addition, we observe hardly any development over time. This suggests that if we find an effect of RES-E generation on the composition of the power plant mix at all, it might be rather small.

3.3.3 Empirical Strategy

The goal of this empirical study is to examine the effects of RES-E on the composition of the conventional power plant mix, i.e. on the share of the capacities installed of coal-, gas- and oil-fired power plants, for the years 2000 to 2010 for 18 European countries. To identify its effects, we control for other factors that might have an impact on a country's power plant portfolio, namely the share of the capacity installed by fossil fuel types, the GDP long-term growth forecast, a measure for the degree of wholesale electricity market integration, the industrial electricity price and a measure for the degree of regulation in the electricity market. The shares of installed capacities (in percentage) - instead of its absolute capacities installed or the change in the installed capacities - is used, as it reflects changes in the composition of the plant fleets best. For example, it accounts for the fact that in case of an overall expansion in all fuel types, the share of a fuel type that undergoes a proportionately smaller increase will end up with lower overall shares in its capacity installed. The likelihood of omitted variable bias is reduced by making use of the panel structure of the dataset.

Thus, the following one-way error components model including a constant term is derived as the baseline specification:

$$C_{it} = \alpha_0 + \alpha_1 \mathbf{C}_{it-3} + \alpha_2 \mathbf{X}_{it-3} + \alpha_3 GDP + \alpha_4 RES_{it-3} + \eta_i + \epsilon_{it} \tag{3.1}$$

with

C_{it}	:	$(share\_coal$, $share\_gas$, or $share\_oil)$
$\mathbf{C}_{it-3}$	=	$(share\_coal$, $share\_gas$, $share\_oil$ $share\_other)$
$\mathbf{X}_{it-3}$	=	$(integration$, $electricity\ price$, $regulation)$
GDP	=	$(GDP\ long - term\ growth\ forecast)$
RES_{it-3}	=	$(share\_generation\_RES)$

The dependent variable, C_{it}, is the share of the capacity installed compared to the total conventional capacity installed, where i and t are the country and time subscripts, respectively. The generation technologies on the left-hand side are coal-, gas- and oil-fired plants, respectively. Hence, three individual equations are estimated separately.[9] $\mathbf{C}_{it-3}$ is a vector that contains the shares of the remaining conventional capacities lagged three years except for the dependent variable, i.e. we do not employ a dynamic model. The vector $\mathbf{X}_{it-3}$ summarizes the set of country-level energy statistics. These control variables are also lagged by three years to take account of the time lag between investment and grid connection. GDP denotes the trend long-term growth forecast of the gross domestic product (GDP) in real terms. The index is generated by an evaluation of the economic climate based on model-based as well as expert estimations (OECD, 2015a). The variable of interest, RES_{it-3}, is employed as the sum of the yearly electricity generation by wind and solar PV. As the observed correlation coefficients among the generation by wind and solar PV are high (see Table 3.3), including the measures for wind and solar PV individually might very likely lead to biased estimates, since the effect cannot be correctly assigned to the respective variable, as they measure more or less the same thing. This can result in small and insignificant and even incorrect signs for either the wind and/or the solar PV variable. Therefore, the sum of the two measures is taken to avoid any possible multicollinearity issues. The country-specific, time-invariant effects are denoted by η_i. The idiosyncratic error term is defined as ϵ_{it} and strict exogeneity is assumed, i.e. all explanatory variables are uncorrelated with the error term in every time period.

Since the data consists of cross-sectional and time-series data, it is tested if a random-error (RE) or fixed-effects (FE) specification should be employed. The Hausman (1978) specification test points towards a fixed effects model. Therefore, a within transformation approach is chosen to make use of the time dimension within the dataset to account for the influence of unobserved country-specific, time-invariant characteristics. These could be geographical features of a country that determine to a large extent the power plant mix. E.g. given the mountains and the lakes Austria installed a lot of pump storage plants, while Germany relies to a large extent on coal-fired generation facilities due to its large natural coal deposits. The time-invariant characteristics are erased from the estimation equation as the mean value of each variable gets deducted by the within transformation.

The presence of heteroskedasticity, serial correlation and/or cross-sectional dependence of the

[9] An alternative approach would be to estimate a seemingly unrelated regression (SUR) model. However, the reported correlation coefficients along with the SUR estimation output are too low, that endogeneity due to simultaneity should not be an issue.

error term will lead to biased standard errors. As these standard errors are used for computing test statistics, they will also be biased, when not corrected for (Wooldridge, 2010). The null hypotheses of the modified Wald test for groupwise heteroskedasticity (Baum, 2001) as well as of the Wald test for first order autocorrelation in the idiosyncratic error term suggested by Wooldridge (2002) have to be rejected.[10] The null hypothesis of cross-sectional independence in Pesaran's cross-sectional dependence test (2004) valid for samples with $N > T$ can be accepted. In order to correct for groupwise heteroskedasticity and first order autocorrelation, cluster-robust standard errors are computed, where clustering takes place on the country level. Yet, given the small cluster size in the sample at hand, the cluster-robust estimator might produce downward biased standard errors. Rogers (1994) states that "if no cluster is larger than 5% or so of the total sample, the standard errors will be not too far off". The size of the clusters in this analysis is around 6.5%. One could argue to expand the time series, yet without also expanding the number of cross sections, this does not help. Doing so will only aggravate the small cluster size problem, thereby worsening the bias in the standard errors (Donald and Lang, 2007). Instead, normal standard errors will be reported along with standard errors robust to heteroskedasticity and autocorrelation.

In order to check the robustness of the model, we estimate a second specification of equation (1) where the lags of the shares of the remaining conventional capacities installed, i.e. $\mathbf{C}_{it-3}$, will not be included in the regression (Model I-B). First, the shares of the conventional capacities are interdependent even if they enter into the regression with a three-year lag. Therefore, their explanatory power - in an economic sense - should be rather small. Second, the small size of the sample allows only for a restricted number of regressors in order not to use up too many degrees of freedom. By leaving out the variables for the shares of the remaining conventional technologies, the number of regressors reduces to a favorable number of five. For the same reason, it will be abstained from including a full set of year dummies.

So far, strict exogeneity of the regressors has been assumed. However, the price variable is suspected to suffer from correlation with the error term due to unobserved effects that vary over time. To remedy this potential endogeneity of the price an instrumental variable (IV) approach is taken (Model II). This also serves as a further robustness check. The two baseline specifications of equation (1), i.e. specifications (A) and (B) are estimated by two-stage least squares with the user-written Stata routine *xtivreg2* (Schaffer, 2010). The share of generation by intermittent RES-E lagged by four years is utilized as an instrument for the price lagged by three years.[11] An increased feed-in of power by intermittent RES-E leads to more volatile and, in the short run, lower wholesale prices that are also affecting the industrial electricity prices. Hence, the RES-E generation does not directly effect the change in the capacities installed, but

[10] The Wald test for first order autocorrelation in the idiosyncratic error term is implemented in Stata by the user-written command of Drukker (2003).

[11] No observations are lost by lagging the instrument variable by four years as it is also available for the year 1999.

it explains part of the price. Using the RES-E measure as an instrument has the advantage that the effect of intermittent RES-E on the dependent variable via the price can be quantified with the help of the first-stage regression results.[12]

3.3.4 Results

Table 3.4 reports the results for the within regression estimations (Models I-A and I-B). Estimations (1a) to (3a), i.e. Model (A), include the percentage shares of the remaining conventional capacities installed, while they are left out in the specifications (1b) to (3b), i.e. Model (B). The dependent variables in the estimations (1), (2) and (3) are the percentage share of coal-fired, gas-fired and oil-fired generation capacities, respectively. The asterisks indicating the significance level belong to the cluster-robust standard errors. When comparing the size of the normal and the cluster-robust standard errors, the latter ones are larger than the normal ones in about half of the cases. Exceptions are, in particular, the standard errors for the long-term GDP growth forecast coefficient as well as for the coefficients of the measure for the degree of market integration in all three estimations of both models. However, the differences are only small in size and, more importantly for Model B, do not affect the size of the significance level. Therefore, the risk of too small standard errors due to the small cluster size of the sample does not seem to be overly severe in Model B. At least, the cluster-robust standard errors do not lead to smaller levels of statistical significance than the normal standard errors. Yet, lower cluster-robust standard errors occur more often in the specifications including the share of the remaining conventional capacities, indicating that the downward bias in the standard errors is more severe here. But, except for the *share_coal* coefficient in estimation (3a), the significance levels stay the same for the first type of specifications (1a to 3a) also for cases where the cluster-robust standard errors are lower then the normal ones.

The coefficients for the percentage shares of the remaining installed capacities other than the dependent variable are always negative and statistically significant. This is as expected, as the shares of the conventional capacities are interdependent even if they enter into the regression with a three-year lag. Comparing the sizes of the coefficients of the two alternating specifications, they do not differ too much. Although, they are on average larger for specification (B), which is not surprising as the effects of the remaining conventional capacities is partly captured by the other control variables.

Neither the long-term GDP growth forecast, the measure of market integration nor the industry price have a statistically and economically significant impact on any of the three shares of

[12]As the price variable is the industrial electricity price, a dummy indicating whether the country employs a Feed-in Tariff (FIT) system as well as an index for the production by energy-intensive industries were also considered as instruments. Usually, the costs of the FITs are apportioned to the industrial consumers, and thereby being part of the electricity bill paid by these consumers. The industrial production acts as a demand-shifter. For example, an increase in the production of energy-intensive industries increases the demand for electricity, but does not directly effect the supply side, i.e. the capacities installed of the power plants. However, these measures did not proof to be good instrument variables.

Variables	(I-1a) share_coal	(I-2a) share_gas	(I-3a) share_oil	(I-1b) share_coal	(I-2b) share_gas	(I-3b) share_oil
Constant	36.37***	54.88***	46.00***	25.47***	24.53***	10.95***
	$(4.657)^a$	$(8.127)^a$	$(5.123)^a$	$(1.261)^a$	$(2.537)^a$	$(2.416)^a$
	(4.813)	(6.938)	(8.113)	(1.088)	(2.642)	(1.871)
L3.share_coal		-0.449***	-0.291***			
		$(0.152)^a$	$(0.084)^a$			
		(0.168)	(0.134)			
L3.share_gas	-0.226***		-0.489***			
	$(0.045)^a$		$(0.052)^a$			
	(0.064)		(0.066)			
L3.share_oil	-0.294***	-0.590***				
	$(0.051)^a$	$(0.122)^a$				
	(0.079)	(0.099)				
L3.share_other	-0.067	-0.366**	-0.372***			
	$(0.080)^a$	$(0.152)^a$	$(0.096)^a$			
	(0.071)	(0.112)	(0.109)			
gdpgfore_l	-0.008	0.071	-0.059	0.028	-0.005	-0.025
	$(0.024)^a$	$(0.056)^a$	$(0.043)^a$	$(0.027)^a$	$(0.062)^a$	$(0.051)^a$
	(0.029)	(0.076)	(0.051)	(0.029)	(0.090)	(0.062)
L3.integration	-2.156	1.576*	-0.517	-2.451	-0.449	0.161
	$(1.504)^a$	$(0.826)^a$	$(0.368)^a$	$(1.73)^a$	$(0.309)^a$	$(0.168)^a$
	(2.623)	(0.889)	(0.592)	(2.684)	(0.798)	(0.548)
L3.price_24	-0.008	0.031	-0.034	-0.003	0.040	-0.048
	$(0.013)^a$	$(0.026)^a$	$(0.023)^a$	$(0.015)^a$	$(0.056)^a$	$(0.043)^a$
	(0.011)	(0.029)	(0.020)	(0.012)	(0.036)	(0.025)
L3.regul_elec	0.673**	-0.441	-0.325	0.888***	-1.839**	0.567
	$(0.319)^a$	$(0.517)^a$	$(0.208)^a$	$(0.275)^a$	$(0.868)^a$	$(0.565)^a$
	(0.207)	(0.511)	(0.340)	(0.180)	(0.507)	(0.349)
L3.share_resgen	-0.185*	0.980**	-0.130	-0.398**	1.756**	-0.518
	$(0.103)^a$	$(0.349)^a$	$(0.180)^a$	$(0.160)^a$	$(0.646)^a$	$(0.299)^a$
	(0.101)	(0.253)	(0.168)	(0.085)	(0.260)	(0.179)
Observations	128	133	125	128	133	125
R-squared	0.613	0.723	0.593	0.546	0.576	0.318
Number of countries	17	18	17	17	18	17

a: Standard errors are robust to heteroskedasticity and autocorrelation. The asterisks indicating the significance level are based on these standard errors.
Level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.4: Results for Fixed-Effects Estimation

the installed capacities, i.e. coal, gas and oil. The effect of the index measuring the degree of regulation in the electricity sector, where a higher index value implies a larger degree of regulation, varies with the fuel type. An increase in the index by one leads to an increase in the share of coal plants by on average 0.67% (Model I-A) and 0.89% (Model I-B), respectively. The effect of a tighter regulation on the share of gas-fired generation technologies is negative and statistically significant only for Model B. It does not have a significant effect on the share of oil-fired power plants.

The effects of the variable of interest, the percentage share of RES-E generation to total generation, is as predicted by theory. As has been shown in Section 3.2, the share of peak-load plants is expected to increase and that of base-load generation technologies to decrease. An increase in the RES-E generation decreases the shares of coal- and oil-fired power plants, while it has a positive effect on gas-fired generation capacities. Yet, the effect on the oil plants is not statistically significant. An increase in the share of RES-E generation by 1% decreases the share of coal plants by on average 0.19% and increases the share of gas-fired power plants by on average 0.98% (Model I-A) or 1.76% (Model I-B). Base-load plants and to a certain extent 'dirty' peak-load plants are replaced by a more flexible, i.e. mid- to peak-load, generation technology.

The within regression results have shown that although its effect is partly statistically significant, the size of the effect is rather small. An explanation for this finding might be that the effect of RES-E generation on the shares of the conventional generation plants are already reflected in the electricity price. Along with the estimation and the first-stage regression results for the IV specification (Model II), Table 3.5 also reports the results of the weak identification test by Kleibergen-Paap. As only one instrument is employed, the model is just identified, and hence, there is no need to test for overidentification. Again, normal standard errors are reported along with the cluster-robust standard errors and small-sample statistics are used. Regarding the possible downward bias in the cluster-robust standard errors, the pattern of cluster-robust standard errors being lower than the normal standard errors is very similar to the one in the first FE estimations of Table 3.4. The asterisks indicating the significance level belong to the cluster-robust standard errors.

Variables	(II-1a) share_coal	1^{st} stage L3.price	(II-2a) share_gas	1^{st} stage L3.price	(II-3a) share_oil	1^{st} stage L3.price	(II-1b) share_coal	1^{st} stage L3.price	(II-2b) share_gas	1^{st} stage L3.price	(II-3b) share_oil	1^{st} stage L3.price
L3.price	-0.059***		0.275***		-0.066		-0.113**		0.514**		-0.188*	
	(0.015)^a		(0.090)^a		(0.048)^a		(0.046)^a		(0.235)^a		(0.094)^a	
	(0.023)		(0.068)		(0.036)		(0.025)		(0.092)		(0.045)	
L3.share_coal			-0.385	-0.127	-0.285***	0.346						
			(0.270)^a	(0.657)^a	(0.091)^a	(0.649)^a						
			(0.220)	(0.555)	(0.133)	(0.673)						
L3.share_gas	-0.212***	0.016			-0.475***	0.502*						
	(0.057)^a	(0.657)^a			(0.058)^a	(0.283)^a						
	(0.071)	(0.559)			(0.070)	(0.323)						
L3.share_oil	-0.313***	-0.640	-0.480***	-0.493								
	(0.057)^a	(0.733)^a	(0.137)^a	(0.284)^a								
	(0.083)	(0.682)	(0.133)	(0.319)								
L3.share_other	-0.023	0.925	-0.513**	0.860*	-0.337***	1.374*						
	(0.094)^a	(0.642)^a	(0.209)^a	(0.491)^a	(0.100)^a	(0.512)^a						
	(0.078)	(0.601)	(0.127)	(0.382)	(0.105)	(0.661)						
gdpgfore_l	-0.039	-0.599**	0.223*	-0.619**	-0.078	-0.597**	-0.042	-0.593**	0.311	-0.638**	-0.115	-0.620**
	(0.025)^a	(0.225)^a	(0.112)^a	(0.224)^a	(0.051)^a	(0.228)^a	(0.048)^a	(0.233)^a	(0.229)^a	(0.234)^a	(0.092)^a	(0.238)^a
	(0.034)	(0.242)	(0.105)	(0.241)	(0.055)	(0.247)	(0.045)	(0.235)	(0.165)	(0.235)	(0.080)	(0.240)
L3.integration	-0.222	40.26**	2.399**	-4.687*	-0.630*	-4.731*	1.283	37.97**	-0.439	0.031	0.159	0.052
	(1.845)^a	(14.01)^a	(1.024)^a	(2.564)^a	(0.315)^a	(2.576)^a	(3.448)^a	(13.78)^a	(0.563)^a	(0.802)^a	(0.227)^a	(0.800)^a
	(3.055)	(22.14)	(1.058)	(2.970)	(0.556)	(3.010)	(3.717)	(21.72)	(1.285)	(2.156)	(0.623)	(2.185)
L3.regul_elec	0.551	-2.389*	0.466	-3.762*	-0.442	-3.725*	0.415	-4.105**	0.609	-5.131***	-0.153	-5.166***
	(0.336)^a	(1.946)^a	(0.858)^a	(2.070)^a	(0.235)^a	(2.063)^a	(0.410)^a	(1.677)^a	(1.899)^a	(1.547)^a	(0.870)^a	(1.548)^a
	(0.227)	(1.760)	(0.671)	(1.634)	(0.352)	(1.653)	(0.275)	(1.418)	(1.003)	(1.281)	(0.488)	(1.299)
L4.share_resgen		5.338***		5.344***		5.306***		4.747**		4.691**		4.664**
		(1.528)^a		(1.511)^a		(1.518)^a		(1.683)^a		(1.684)^a		(1.682)^a
		(0.967)		(0.935)		(0.947)		(0.727)		(0.727)		(0.737)
Observations	128		133		125		128		133		125	
R-squared	0.537		0.555		0.583		0.173		-0.111		0.110	
Number of countries	17		18		17		17		18		17	
Kleibergen-Paap rk Wald F statistic	12.211	(30.482)	12.500	(32.649)	12.210	(31.417)	7.957	(42.637)	7.757	(41.646)	7.686	(40.066)
Endogeneity test	6.374**	(5.138**)	8.367***	(15.242***)	1.011	(0.640)	3.410*	(22.616***)	2.634	(36.742***)	1.753	(8.580***)

a: Standard errors are robust to heteroskedasticity and autocorrelation. The asterisks indicating the significance level are based on these standard errors.
Level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Stock-Yogo weak ID test critical values: 10% max. IV size: 16.38; 15% max. IV size: 8.96; 20% max. IV size: 6.66; 25% max. IV size: 5.53. Test values in parentheses are based on normal standard errors.

Table 3.5: Results for Fixed-Effects IV Estimation with Small Sample Size Correction

Overall, the size and the signs of the coefficients in the instrumented estimations do not differ widely from the first estimations. The coefficients of the remaining installed capacities are again negative and mainly statistically significant. The GDP long-term growth forecast has a statistically significant effect only on the share of gas-fired power plants in Model (II-A). The positive sign is as expected. An expected increase in the GDP growth is an indicator for a future increase in economic output, which requires an increased amount of power. The degree of power market integration has a positive effect on the share of gas-fired but a negative effect on the share of oil-fired power plants. This implies the more integrated a country's electricity market the higher is the share of gas-fired and the lower the share of oil-fired generation technologies. As before the degree of regulation in the electricity sector are statistically insignificant in all of the specifications. The coefficients for the instrumented price variable are strongly significant and the signs are according to what theory predicts. When compared to the results of the first estimations (see Table 3.4), the coefficients have the same sign, yet the effects are larger in size.

By multiplying the coefficients of the share of intermittent RES-E generation of the first stage with the price coefficient of the second stage, one can quantify the effect of the share of intermittent RES-E generation on the shares of the conventional generation technologies via the price. An increase in the share of wind- and solar-generated power by 1 % leads to a decrease in the share of coal-fired power plants installed of on average 0.31% (Model II-A) and 0.54% (Model II-B), respectively. The same increase in the share of intermittent RES-E generation results in an increase of on average 1.47% (Model II-A) and 2.41% (Model II-B), respectively. Their effect on the share of oil plants is again negative. A 1% increase results in a decrease of on average 0.35% (Model II-A) and 0.88% (Model II-B).

When interpreting the results of the IV estimations, one has to be aware that the share of RES-E generation is not a very strong instrument for the price. The F-statistics of the Kleibergen-Paap Wald test for the cluster-robust estimations are either between the 15% and the 10% critical values of the Stock-Yogo weak identification test for Model A and in the case of Model B even slightly below the level of the 15% critical value. A test statistic that is at least as high as the 15% critical value is desirable. In the cases of the non-cluster-robust estimations the instrument can be considered as strong, however. The endogeneity tests state that the price is exogenous in the estimations with the share of oil-fired plants as the dependent variable as well as with the share of of gas-fired plants in specification II-2b. Irrespective of the quality of the instrument, the first stage regression can nevertheless be considered as a reduced-form estimation, that measures the effect of the share of intermittent RES-E generation on the price. As has been shown, this effect is apparent and one can say that the effect of RES-E on the composition of the plant fleet is partly explained by its effect through the price.

Overall, the analysis has shown that the effect of the share of intermittent RES-E generation on the composition of the conventional plant fleet is as predicted by theory, i.e. an increase in mid-, and particularly peak-load plants and a decrease in base-load technologies.[13] A disproportionate increase in the share of gas-fired power plants is found, while the shares of coal- and oil-fired power plants are found to decrease less than proportionately. The decreasing effect is more than offset by the increase in gas-fired plants. This finding supports the general expectation that only a small amount of conventional power plants can be substituted by intermittent generation technologies (Nicolosi and Fürsch, 2009).

Since the data set ends in 2010, by lagging the share of RES-E generation by three years, this reflects the generation level of 2007. Yet, substantial expansions in the shares of intermittent RES-E generation have particularly taken place in recent years and adjustments in the conventional plant fleet usually take time to become effective and visible. Therefore, it would be interesting to repeat the analysis with a larger sample including also the developments of the last five years. In order not to aggravate the potential downward bias in the cluster-robust standard errors when expanding the time series for a fixed cluster size, one should also widen the data set by increasing the number of countries. Employing the day-ahead spot-market wholesale price for electricity instead of the industrial electricity price will be an interesting robustness check as the spot market price is more directly affected by the amount of RES-E generation. Since these prices are only available from 2004 onwards for a larger set of countries, using these prices is not well applicable with the short panel of this analysis.

3.4 Conclusion

This paper analyzes the long-run effect of intermittent RES-E generation on the composition of the conventional plant fleet. The underlying panel data consists of 18 European countries for the years 2000 to 2010. Three fixed effects models are estimated separately with the share of coal-, gas- and oil-fired power plants as the dependent variables. In a second specification the electricity price, a possibly endogenous variable, is instrumented by the share of intermittent RES-E generation. It has the advantage, that this approach allows for the quantification of the effect of RES-E generation on the conventional plant fleet through the price.

The effect of the share of intermittent RES-E generation on the composition of the conventional plant fleet is as predicted by theory. An increase in the share of RES-E generation decreases the shares of coal- and oil-fired power plants, while it has a positive effect on the share of gas-fired generation capacities. An increase of 1% in the share of wind and solar PV generated power decreases the share of coal plants by on average 0.19% to 0.54% and the share of oil-fired

[13] To check the robustness of these results, we replace the variable measuring the degree of market integration by a country's yearly net-import of electricity. As market integration does not seem to be an issue given the data set ends in 2010 and its coefficients are for the majority of the specifications not statistically significant this seems to be feasible. With the net-import of electricity, defined as total electricity imports minus total exports, a measure for the energy dependence of a country is included, that controls for the trade in electricity taking place among countries rather than its integration. The estimation results remain quantitatively and qualitatively unchanged (see Tables 3.C.1 to 3.C.3 in the Appendix).

plants by on average 0.13% to 0.88%. The effect on the share of oil-fired plants, however, is not statistically significant. The share of gas-fired generation technologies increases by on average 0.98% to 2.41%, given a 1% increase in the share of intermittent RES-E generation.

When interpreting the results one has to be aware that the cluster-robust standard errors might suffer from a small downward bias given the small cluster size. Besides, the quality of the instrument in the IV regression is not as good as would be desirable. Yet, the first stage regression of the price on the share of intermittent RES-E generation still serves as a valid reduced form approach to analyse the effect of the intermittent RES-E generation on the electricity price. Thereby, this effect is an indicator for how much of the effect of intermittent RES-E on the conventional plant fleet is already captured in the price mechanism.

Since the dataset ends in 2010, it would be interesting for further research to expand the panel dataset to include the developments of the recent years as well as a broader set of countries. The effects should become more pronounced as the deployment of, and hence generation by intermittent RES-E has expanded tremendously in the recent years. Expanding the sample should also help in reducing or getting rid of the downward bias in the cluster-robust standard errors.

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Appendix

3.A Descriptive Statistics

	Countries with low levels of RES-E							
Variable	Variable Name	Obs	Mean	Std. Dev.	Min	Max	years	Source
Dependent Variable								
Inst. capacity (share)	share_*							
Coal (%)	share_coal	110	27.66	28.28	0.03	91.88	2000-2010	PLATTS (2011)
Gas (%)	share_gas	110	18.59	18.50	0.34	53.73	2000-2010	PLATTS (2011)
Oil (%)	share_oil	110	7.57	7.30	0[1]	36.97	2000-2010	PLATTS (2011)
Independent Variables								
Other (%)	share_other	110	46.18	30.28	5.99	99.63	2000-2010	PLATTS (2011)
GDP growth forecast	gdpgfore_l	110	2.02	2.72	-9.34	6.74	2000-2010	OECD (2015a)
Netimport (GWh)	netimport	110	-305.27	25235.24	-77034	50968	2000-2010	IEA (2015a)
Regulation	regul_elec	110	2.67	0.96	1.17	4.96	2000-2010	OECD (2015c)
Industry price (€/MWh)	price	80	53.11	14.68	23.25	108.00	2000-2007	Eurostat (2015b)
Total Generation (GWh)	gen_tot	110	196164.5	160895.5	33708	576210	2000-2010	IEA (2015)
Intermittent RES								
Solar PV generation (GWh)	gen_pv	110	50.86	214.16	0	1906	2000-2010	IEA (2015)
Wind generation (GWh)	gen_wind	110	1336.62	2257.01	0	10180	2000-2010	IEA (2015)
Share RES-E (%)	share_resgen	110	0.56	0.68	0	3.65	2000-2010	IEA (2015)

1: No oil-fired power plants in Norway.

Table 3.A.1: Descriptive Statistics: Low Shares of RES-E - Belgium, Czech Republic, Finland, France, Hungary, Italy, Norway, Poland, Sweden, United Kingdom

	Countries with intermediate levels of RES-E							
Variable	Variable Name	Obs	Mean	Std. Dev.	Min	Max	years	Source
Dependent Variable								
Inst. capacity (share)	share_*							
Coal (%)	share_coal	44	19.28	16.49	0[1]	46.92	2000-2010	PLATTS (2011)
Gas (%)	share_gas	44	32.89	23.79	4.93	76.08	2000-2010	PLATTS (2011)
Oil (%)	share_oil	44	4.46	4.55	0.51	11.65	2000-2010	PLATTS (2011)
Independent Variables								
Other (%)	share_other	44	43.37	30.53	2.45	95.00	2000-2010	PLATTS (2011)
GDP growth forecast	gdpgfore_l	44	2.07	2.91	-5.92	7.76	2000-2010	OECD (2015a)
Netimport (GWh)	netimport	44	6398.73	6058.56	-1368	21459	2000-2010	IEA (2015a)
Regulation	regul_elec	44	2.87	0.89	1.75	5.63	2000-2010	OECD (2015c)
Industry price (€/MWh)	price	21[2]	49.83	8.67	36.7	66.1	2000-2007	Eurostat (2015b)
Total Generation (GWh)	gen_tot	44	57281.32	35891.74	1169	118140	2000-2010	IEA (2015)
Intermittent RES								
Solar PV generation (GWh)	gen_pv	44	22.34	28.44	0	158	2000-2010	IEA (2015)
Wind generation (GWh)	gen_wind	44	1282.09	1240.64	24	4581	2000-2010	IEA (2015)
Share RES-E (%)	share_resgen	44	2.07	1.16	0.11	5.00	2000-2010	IEA (2015)

1: No coal power plants in Luxembourg.
2: Prices in Austria missing for 2000 to 2002, in Luxembourg for 2005 to 2006 and in the Netherlands for 2000 to 2004.

Table 3.A.2: Descriptive Statistics: Intermediate Shares of RES-E - Austria, Luxembourg, Netherlands, Greece

	Countries with high levels of RES-E							
Variable	Variable Name	Obs	Mean	Std. Dev.	Min	Max	years	Source
Dependent Variable								
Inst. capacity (share)	share_*							
Coal (%)	share_coal	44	26.56	12.47	14.22	47.96	2000-2010	PLATTS (2011)
Gas (%)	share_gas	44	27.74	12.52	10.25	59.89	2000-2010	PLATTS (2011)
Oil (%)	share_oil	44	15.32	8.93	3.18	29.00	2000-2010	PLATTS (2011)
Independent Variables								
Other (%)	share_other	44	30.38	13.70	7.46	50.18	2000-2010	PLATTS (2011)
GDP growth forecast	gdpgfore_l	44	1.82	3.06	-6.84	9.63	2000-2010	OECD (2015a)
Netimport (GWh)	netimport	44	-957.84	7077.94	-20100	9998	2000-2010	IEA (2015a)
Regulation	regul_elec	44	2.13	1.08	0.87	4.28	2000-2010	OECD (2015c)
Industry price (€/MWh)	price	32	62.08	14.41	42.75	108	2000-2007	Eurostat (2015b)
Total Generation (GWh)	gen_tot	44	241305.4	239830.9	23977	640578	2000-2010	IEA (2015)
Intermittent RES								
Solar PV generation (GWh)	gen_pv	44	1062.98	2415.72	0	11729	2000-2010	IEA (2015)
Wind generation (GWh)	gen_wind	44	13155.14	14221.26	168	44271	2000-2010	IEA (2015)
Share RES-E (%)	share_resgen	44	5.93	4.53	0.39	17.37	2000-2010	IEA (2015)

Table 3.A.3: Descriptive Statistics: High Shares of RES-E: Germany, Ireland, Portugal, Spain

3.B Power Plant Mix of Countries with Low Shares of RES-E II

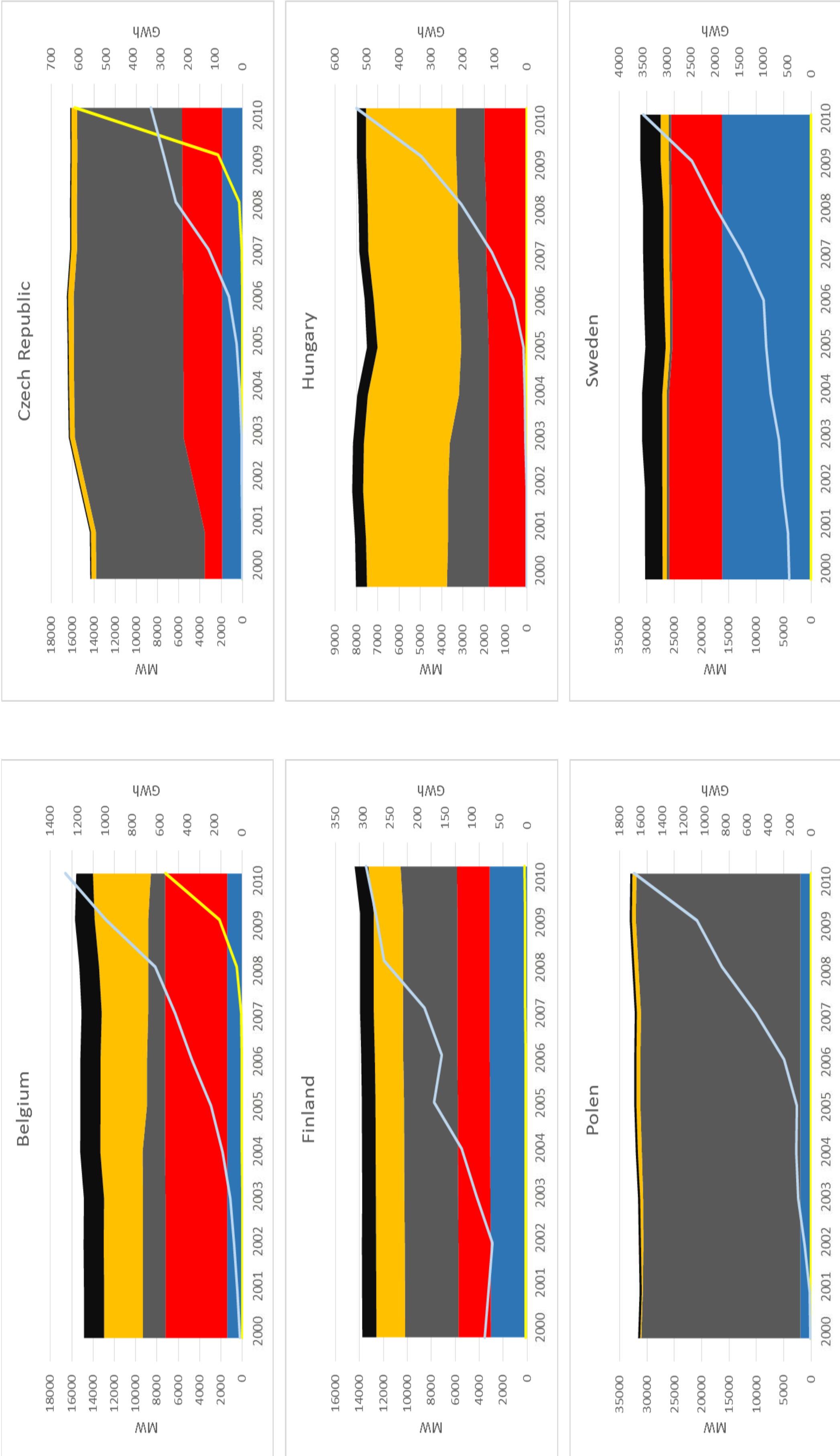

Figure 3.B.1: Power Plant Mix of Countries with Low Shares of RES-E II

3.C Estimation Results: Robustness Check

Variables	(I-1a) share_coal	(I-2a) share_gas	(I-3a) share_oil	(I-1b) share_coal	(I-2b) share_gas	(I-3b) share_oil
Constant	36.18***	48.75***	48.49***	24.92***	24.37***	11.12***
	$(4.57)^a$	$(8.061)^a$	$(5.146)^a$	$(1.190)^a$	$(2.472)^a$	$(2.294)^a$
	(4.805)	(6.043)	(7.553)	(0.878)	(2.651)	(1.893)
L3.share_coal		-0.406**	-0.310***			
		$(0.177)^a$	$(0.097)^a$			
		(0.168)	(0.132)			
L3.share_gas	-0.229***		-0.495***			
	$(0.045)^a$		$(0.053)^a$			
	(0.064)		(0.065)			
L3.share_oil	-0.306***	-0.610***				
	$(0.049)^a$	$(0.125)^a$				
	(0.078)	(0.099)				
L3.share_other	-0.069	-0.236*	-0.418***			
	$(0.078)^a$	$(0.130)^a$	$(0.079)^a$			
	(0.070)	(0.083)	(0.092)			
gdpgfore_l	-0.009	0.053	-0.056	0.028	0.003	-0.031
	$(0.023)^a$	$(0.062)^a$	$(0.045)^a$	$(0.027)^a$	$(0.063)^a$	$(0.050)^a$
	(0.029)	(0.076)	(0.051)	(0.030)	(0.089)	(0.062)
L3.netimport	$-1.49 \cdot 10^{-5}$	$5.07 \cdot 10^{-5}$	$-4.05 \cdot 10^{-5}$	$-7.98 \cdot 10^{-6}$	$2.52 \cdot 10^{-5}$	$-2.95 \cdot 10^{-6}$
	$(1.12 \cdot 10^{-5})^a$	$(5.01 \cdot 10^{-5})^a$	$(6.62 \cdot 10^{-5})^a$	$(1.16 \cdot 10^{-5})^a$	$(6.78 \cdot 10^{-5})^a$	$(7.36 \cdot 10^{-5})^a$
	$(1.62 \cdot 10^{-5})$	$(4.35 \cdot 10^{-5})$	$(3.45 \cdot 10^{-5})$	$(1.18 \cdot 10^{-5})$	$(5.44 \cdot 10^{-5})$	$(4.53 \cdot 10^{-5})$
L3.price_24	-0.010	0.026	-0.034	-0.005	0.041	-0.050
	$(0.013)^a$	$(0.029)^a$	$(0.022)^a$	$(0.014)^a$	$(0.056)^a$	$(0.043)^a$
	(0.011)	(0.030)	(0.020)	(0.012)	(0.036)	(0.025)
L3.regul_elec	0.722**	-0.383	-0.355	0.941***	-1.861**	0.566
	$(0.307)^a$	$(0.535)^a$	$(0.223)^a$	$(0.271)^a$	$(0.855)^a$	$(0.544)^a$
	(0.196)	(0.517)	(0.341)	(0.169)	(0.504)	(0.348)
L3.share_resgen	-0.193	1.165**	-0.192	-0.402**	1.753**	-0.521
	$(0.113)^a$	$(0.402)^a$	$(0.181)^a$	$(0.166)^a$	$(0.655)^a$	$(0.305)^a$
	(0.101)	(0.236)	(0.155)	(0.086)	(0.260)	(0.179)
Observations	128	133	125	128	133	125
R-squared	0.614	0.723	0.592	0.544	0.576	0.319
Number of countries	17	18	17	17	18	17

a: Standard errors are robust to heteroskedasticity and autocorrelation. The asterisks indicating the significance level are based on these standard errors.
Level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.C.1: Results for Fixed-Effects Estimation - Robustness Check (net-import)

Variables	(II-1a) share_coal	1^{st} stage L3.price	(II-2a) share_gas	1^{st} stage L3.price	(II-3a) share_oil	1^{st} stage L3.price
L3.price	-0.063***		0.358***		-0.093*	
	$(0.012)^a$		$(0.124)^a$		$(0.050)^a$	
	(0.023)		(0.083)		(0.041)	
L3.share_coal			-0.274	-0.293	-0.310***	0.127
			$(0.339)^a$	$(0.658)^a$	$(0.105)^a$	$(0.607)^a$
			(0.258)	(0.552)	(0.136)	(0.663)
L3.share_gas	-0.211***	0.065			-0.468***	0.454
	$(0.055)^a$	$(0.667)^a$			$(0.0610)^a$	$(0.262)^a$
	(0.072)	(0.567)			(0.073)	(0.324)
L3.share_oil	-0.315***	-0.468	-0.468***	-0.441		
	$(0.054)^a$	$(0.720)^a$	$(0.158)^a$	$(0.270)^a$		
	(0.083)	(0.686)	(0.155)	(0.321)		
L3.share_other	-0.016	1.067	-0.340	0.440	-0.372***	0.911*
	$(0.090)^a$	$(0.637)^a$	$(0.219)^a$	$(0.364)^a$	$(0.096)^a$	$(0.512)^a$
	(0.080)	(0.606)	(0.116)	(0.276)	(0.098)	(0.454)
gdpgfore_l	-0.043*	-0.634**	0.251*	-0.572**	-0.091	-0.570**
	$(0.024)^a$	$(0.219)^a$	$(0.134)^a$	$(0.212)^a$	$(0.057)^a$	$(0.209)^a$
	(0.034)	(0.245)	(0.124)	(0.242)	(0.059)	(0.248)
L3.netimport	$-2.02 \cdot 10^{-5}$	$-2.86 \cdot 10^{-5}$	$6.27 \cdot 10^{-5}$	$-3.69 \cdot 10^{-5}$	$-3.89 \cdot 10^{-5}$	$-1.69 \cdot 10^{-4}$
	$(1.66 \cdot 10^{-5})^a$	$(2.02 \cdot 10^{-4})^a$	$(9.14 \cdot 10^{-5})^a$	$(2.12 \cdot 10^{-4})^a$	$(6.14 \cdot 10^{-5})^a$	$(2.61 \cdot 10^{-4})^a$
	$(1.78 \cdot 10^{-5})$	$(1.41 \cdot 10^{-4})$	$(6.36 \cdot 10^{-5})$	$(1.40 \cdot 10^{-4})$	$(3.76 \cdot 10^{-5})$	$(1.72 \cdot 10^{-4})$
L3.regul_elec	0.539	-3.516*	0.897	-3.941*	-0.583*	-3.943*
	$(0.320)^a$	$(2.007)^a$	$(1.143)^a$	$(2.205)^a$	$(0.293)^a$	$(2.187)^a$
	(0.224)	(1.674)	(0.780)	(1.649)	(0.365)	(1.662)
L4.share_resgen		5.515***		4.661***		4.477***
		$(1.435)^a$		$(1.447)^a$		$(1.347)^a$
		(0.986)		(0.862)		(0.876)
Observations	128		133		125	
R-squared	0.531		0.396		0.556	
Number of countries	17		18		17	
Kleibergen-Paap rk Wald F statistic	14.761	(31.269)	10.38	(29.227)	11.05	(26.117)
Endogeneity test	6.819***	(5.799**)	7.164***	(24.075***)	2.48	(1.988)

a: Standard errors are robust to heteroskedasticity and autocorrelation. The asterisks indicating the significance level are based on these standard errors.
Level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Stock-Yogo weak ID test critical values: 10% max. IV size: 16.38; 15% max. IV size: 8.96; 20% max. IV size: 6.66; 25% max. IV size: 5.53. Test values in parentheses are based on normal standard errors.

Table 3.C.2: Results for Fixed-Effects IV Estimation with Small Sample Size Correction - Robustness Check (net-import) 1

Variables	(II-1b) share_coal	1^{st} stage L3.price	(II-2b) share_gas	1^{st} stage L3.price	(II-3b) share_oil	1^{st} stage L3.price
L3.price	-0.117**		0.524**		-0.200**	
	$(0.046)^a$		$(0.224)^a$		$(0.088)^a$	
	(0.026)		(0.095)		(0.049)	
gdpgfore_l	-0.048	-0.626**	0.329	-0.640***	-0.133	-0.644***
	$(0.046)^a$	$(0.225)^a$	$(0.216)^a$	$(0.222)^a$	$(0.0827)^a$	$(0.215)^a$
	(0.046)	(0.238)	(0.168)	(0.234)	(0.084)	(0.240)
L3.netimport	$-1.94 \cdot 10^{-5}$	$-1.29 \cdot 10^{-5}$	$6.00 \cdot 10^{-5}$	$-1.93 \cdot 10^{-5}$	$-5.52 \cdot 10^{-5}$	$-1.48 \cdot 10^{-4}$
	$(2.98 \cdot 10^{-4})^a$	$(2.04 \cdot 10^{-4})^a$	$(1.35 \cdot 10^{-4})^a$	$(2.05 \cdot 10^{-4})^a$	$(8.12 \cdot 10^{-5})^a$	$(2.52 \cdot 10^{-4})^a$
	$(2.35 \cdot 10^{-5})$	$(1.43 \cdot 10^{-4})$	$(8.56 \cdot 10^{-5})$	$(1.41 \cdot 10^{-4})$	$(5.27 \cdot 10^{-5})$	$(1.74 \cdot 10^{-4})$
L3.regul_elec	0.349	-5.154***	0.653	-5.136***	-0.222	-5.21***
	$(0.427)^a$	$(1.560)^a$	$(1.825)^a$	$(1.499)^a$	$(0.834)^a$	$(1.489)^a$
	(0.282)	1.306)	(1.015)	(1.273)	(0.505)	(1.286)
L4.share_resgen		4.778**		4.672***		4.502**
		$(1.674)^a$		$(1.617)^a$		$(1.593)^a$
		(0.754)		(0.738)		(0.755)
Observations	128		133		125	
R-squared	0.148		-0.137		0.083	
No. of countries	17		18		17	
Kleibergen-Paap rk Wald F statistic	8.141	(40.168)	8.351	(40.074)	7.986	(35.593)
Endogeneity test	3.662*	(22.921***)	2.904*	(37.209***)	2.012	(9.017***)

a: Standard errors are robust to heteroskedasticity and autocorrelation. The asterisks indicating the significance level are based on these standard errors.
Level of Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Stock-Yogo weak ID test critical values: 10% max. IV size: 16.38; 15% max. IV size: 8.96; 20% max. IV size: 6.66; 25% max. IV size: 5.53. Test values in parentheses are based on normal standard errors.

Table 3.C.3: Results for Fixed-Effects IV Estimation with Small Sample Size Correction - Robustness Check (net-import) 2

Chapter 4

The Effects of High-Level Competitive Sports Participation on Later Job Success*

*This chapter is based on a paper co-authored by Ralf Dewenter.

4.1 Introduction

Participation in sports is widely acknowledged to have positive effects on individual health and general well-being. Moreover, physical activities are also assumed to exert a positive impact on labour market success. While most studies focus on either leisure activities or college sports, little has been said about the impact of professional and elite sports on athletes' later job success, after their athletic career. In comparison to leisure activities and college sports, professional sports is much more time consuming and therefore assumed to be a closer substitute to education and vocational training. However, professional sports may also result in the development or enhancement of positive personal characteristics such as endurance, commitment and discipline.

When analysing job market outcomes of athletes one can identify at least four different channels through which participation in elite sports may contribute to later job market success. The contribution can be either positive or negative, i.e. can be beneficial or detrimental to a professional career. First, while the theory of human capital is applicable, it does not allow an unambiguous assessment of professional sports and its impact on a later labour market outcome: Following Becker (1965) one might argue that the allocation of time to other activities than schooling and vocational training directly leads to a lower level of human capital and therefore to lower productivity. As participation in elite sports is extremely time consuming, this may result in a much less intensive education. The resulting diminished academic activity might then be detrimental to a business career. By this reasoning the participation in elite sports will result in limited careers and lower individual incomes.

However, considering human capital as a multidimensional object leads to different results. Apart from positive effects on health and individual well-being (see Lechner, 2009), elite athletes are often supposed to show certain skills and personal characteristics such as commitment, discipline, self-confidence and a high stress tolerance, that may also be helpful for a professional business career. Particularly the combination of these characteristics may provide benefits for the former athletes that can facilitate their professional success (Schmidt and Saller, 2013). Put differently, athletes are supposed to develop or enhance certain positive character traits which can also be beneficial for a successful business career.

Steger (2002) shows that productive consumption, i.e. activities that cannot be classified as labour, will indirectly contribute to the income, increases the stock of human capital as well as the efficiency of labour. Concerning elite sports one can talk about productive consumption if by the participation in top sports certain skills and personal properties are gained or enhanced and if these properties are also relevant and valuable in the later working life or in other non-sporting areas. These properties are named transferable skills or life skills (see Danish et al., 2007 and 1993; McKnight et al., 2009). These skills include inter alia "learning to set and develop plans to reach goals" (Danish and D'Augelli, 1983), "high self-confidence and expectations of success", "focus on the present task", "viewing difficult situations as challenging and exciting" as well as "strong determination and commitment" (Krane and Williams, 2006). In addition, Danish et al. (1993) mention further skills such as the ability to perform under pressure, to communicate with others, to accept responsibility for ones behaviour, to accept criticism and feedback in order to learn, to evaluate oneself, and to build self-control as well as self-motivation.

Second, there are also social networking effects: on the one hand, an extreme commitment into elite sports may lead to the development of character disorders and antisocial behaviour. Elite athletes may therefore, intentionally or not, invest less in education and social competences, which may result in a less successful professional career. Ogilvie and Tutko (1971), e.g., argue that the participation in elite sports leads to character disorders instead of building character. The promotion of competitive rivalry prohibits the development of pro-social character traits. As a consequence, antisocial behaviour can have a negative impact on the professional career and thus, on income.

On the other hand, elite sports may well stimulate pro-social character traits. Especially in team sports, team work abilities or at least team compatibility is an important requirement for sporting success. By this means, pro-social behaviour can also be developed with respect to private or professional life. Furthermore, athletes may then benefit from elite sports participation. This may be the case if attributes such as team work abilities are decisive for the recruitment or promotion decision.

As a third channel, participation in elite sports may serve as a signaling device. Potential employers may assume that beside showing other positive characteristics, former athletes are also highly motivated (see Lechner, 2009). Furthermore, in connection with higher education, athletes also signal a high performance and assertiveness.

A fourth channel may simply be induced by former athletes' prominence. Given that an employer can choose between two otherwise identical candidates, he might opt for the prominent one.

The rest of the paper is organised as follows. Next, we briefly discuss the findings of other studies on the impact of sports participation on the labour market success. In the third chapter, we describe the data and provide some descriptive statistics. We then use an unique data set to analyse if and to which extent former elite athletes, which were formerly sponsored by the German Sports Aid Foundation (Stiftung Deutsche Sporthilfe), are more successful in their later working lives than non-athletes. The occupational success is measured by the monthly income net of taxes. Put differently, we address the question if former athletes earn a higher average net monthly income than similar persons, that have not participated in elite sports. To deal with a possible selection problem, we employ covariate nearest-neighbour matching (CVM) and control for several factors influencing the size of the labour income. To the best of our knowledge, this study is the first analysis on the effects of participation in elite sports on later job success.

4.2 Literature Review

A number of studies exist which analyse the impact of high school and college athletic participation as well as of physical activities on different measures such as grades, health, well-being and labour market success.

A qualitative analysis among 616 former successful German Olympic athletes, for example, shows that 65% have a school degree that allows for studies at a university or polytechnic. This rate is 40% above national average. More than 50% of former athletes hold a university degree. With respect to their professions, the authors find that the former Olympic athletes are more often employed in jobs that have a high reputation than the national average. They typically work in management positions or academic professions and less often in the fields of trade and craft (Conzelmann and Nagel, 2003).

A study among twelve to sixteen year old students in the Netherlands by Jonker et al. (2011) compares the level and importance of self-regulatory skills among teenage top athletes and non-athletes in the pre-university and in the pre-vocational school system. In total, six self-regulatory skills are being tested, i.e. planning, self-monitoring, evaluation, reflection, effort and self-efficacy. The authors find that students in the pre-university system had higher scores in five of the self-regulatory skills than in the pre-vocational system. Comparing the youth athletes with the non-athletes within their respective school systems the athletes outscored the non-athletes on three skills.

Schmidt and Saller (2013) compare job-related personality features of top athletes supported by the German Sports Aid Foundation with students at the European Business School as well as qualified employees and managers. The top athletes obtained above average results in the categories commitment, discipline and steadiness. However, the athlete must be aware of the skills she gained or enhanced by participating in elite sports in order to be able to transfer them to non-sporting settings. Additionally, it must be known that these competences are also valuable in other areas of life (Danish et al., 2007). Besides, having been an elite athlete may serve as a signaling device. It can benefit recruitment and promotion processes if potential employers value this as a signal that a person is highly ambitious, dedicated or loyal to the team (Long and Caudill, 1991).

Long and Caudill (1991) find that ten years after having been freshmen former male college athletes realise a four percent higher annual income than their fellow students. However, they do not find a positive income effect for former female college athletes. Ewing (1995) confirmed most of these results, analysing former high school athletes. Moreover, in a different study

Ewing (1998) provides evidence that former high school athletes more often hold jobs with better labour market outcomes.

Barron et al. (2000) use longitudinal survey data to analyse the impact of high school athletic participation on labour market outcomes. Overall, they find evidence for positive effects on wages and educational attainment. Similarly, Ewing (2007) finds also higher wages for former high school athletes. Athletes are, moreover, also more likely to receive fringe benefits such as retirement, medical insurance, dental insurance and paid vacation.

Lechner (2009) analyses the impact of individual leisure sport activities on labour market variables as well as on health and subjective well-being. Using individual data from the German Socio-Economic Panel study (GSOEP), the author finds significant effects with respect to income. Active sports participation increases income by about €1200 per year. The returns on sports activities are comparable to those from one additional year of schooling. As Lechner (2009) also uses matching techniques for identification matters, this paper is closest to our analysis.

4.3 Empirical Analysis

4.3.1 Identification

When analysing the effect of participation in elite sports on salary only realized income is observable. However, to measure the exact effect one has to compare the actual income with the income the same person would have earned if she had not executed any top sports. As naturally such a counterfactual situation does not exist we use information on a control group to approximate respective incomes. For each former athlete, we identify up to four control group members of non-athletes by using covariate nearest-neighbour matching (CVM). We then compare the salaries of persons of the treatment group, i.e. former athletes, with those of the control group, i.e. non-athletes, that posses the same probability to be successful in the labour market. The difference in salaries of treatment and control group members across all matches yields the sample average treatment effect (SATT).

Job success is measured by the monthly income net of taxes. We distinguish between married and unmarried individuals to account for differences in income tax rates. Sex is included to account for a possible gender wage gap (see Antonczyk et al., 2010). A dummy variable East Germany (Old Lander) indicates whether a workplace is located in East (West) Germany and controls for possible differences in income (see Ragnitz, 2012). As a person who is still on job training typically receives a lower salary than a completely qualified person, we include a dummy variable stating whether someone is still in training. We also control for full-time and part-time employment.

To identify adequate matching partners, we use several personal characteristics which are supposed to have an impact on income, such as gender, marital status, labour market experience, workplace location (East or West Germany), level of training, job position, character traits and attitude towards life. Related to the Mincer wage equation, we include a measure for the job market experience, the number of years being employed as well as an instrument for the educational attainment (Mincer 1974, and 1958).[1]

The level of educational attainment may to some extent be endogenous when athletes expect elite sports to be more compatible with studies than it would be with a job. For this reason, we use the professions of the respondents‘ parents when the latter were teenagers, as a proxy variable for the respondents‘ highest level of education. This is supposed a valid approximation as there exists some kind of path dependence between parents‘ occupation and their kids‘ level of education (see Eccles and Davis-Kean, 2005). Children whose parents have university degrees show a higher probability to become university graduates themselves.[2]

Former athletes may earn higher incomes because of the possession of certain character traits that are also beneficial to a career on the job market. If they possess these qualities irrespective of their athletic background, they may have experienced the same job market career even without having been an elite athlete. To prevent a self-selection bias we assess measures of the respondents‘ character traits and attitudes towards life and future in the matching process.

4.3.2 Nearest neighbour matching

In order to compose the control group of non-athletes we calculate the vectors of covariates to find the shortest distance to an observation in the treatment group. The distance is formally denoted as $d_M(i) = \|z - x\|_V$, where x indicates the covariate values for an observation i from the treatment group of former athletes, while z are the covariate values for its potential match from the group of non-athletes. Depending on the number of matching partners M, the set of indices that are at least as close as the Mth match are subsumed under $\tau_M(i)$ (see Abadie et al., 2004).

As the SATT score will be biased if the matching is not exact we use the bias-corrected matching estimator for the average treatment effect of the treated by Abadie et al. (2004) and Abadie and Imbens (2002):

$$\tau^{sample,t} = \frac{1}{N_1} \sum_{i:W_i=1} \left\{ Y_i - \tilde{Y}(0) \right\}, \tag{4.1}$$

[1]Using the year of birth would be an insufficient measure for the job market experience. Former athletes may enter into working life later than non-athletes due to the double burden of top sports (see Aquilina, 2013).

[2]The coding of the former athletes parents’ occupation is done by the StaBua 1992 job classification which is in accordance with the GSOEP data.

where Y_i represents the actual salary of a former elite athlete. The income of a former elite athlete if she had not been an elite athlete, indicated by $\tilde{Y}(0)$, is unobserved, and hence has to be predicted.

$$\tilde{Y}(0) = \frac{1}{\tau_M(i)} \sum_{l \in \tau_M(i)} \{Y_l + \hat{\mu}_0(X_i) - \hat{\mu}_0(X_l)\}, \tag{4.2}$$

where l indicates an observation of the control group and X_i and X_l are the matrices of covariate values of an observation of the treatment and control group, respectively. The bias correction is made by an adjustment of the differences within the matches for the differences in its covariate values. It is based on the regression function for the controls approximated by a linear function, i.e. $\hat{\mu}_0(x) = \hat{\beta}_{00} + \hat{\beta}'_{01}x$. The observations are weighted by $K_M(i)$, denoting the number of times an observation of the control group is used as a match.

The bias correction is only implemented for covariates that do not possess a good matching quality. The matching quality is tested with the Wilcoxon matched-pairs signed-rank test. For every covariate that has a test statistic smaller than 5 % significance level at least twice within each specification, we correct for the possible bias. Following Abadie and Imbens (2002), one specification includes three estimations since we vary the number of matching partners, i.e one, two and four matching partners. The bias corrected variables will be indicated in the regression tables. The test statistics of the Wilcoxon matched-pairs signed-rank test are shown in the Appendix (see Tables 4.A.1 to 4.A.6).

In determining SATT scores, we estimate various specifications to evaluate the robustness of our results. While, in a first specification, we include only the fathers' profession as a matching covariate and in a second specification, we also consider the profession of both parents. Furthermore, we vary the covariates to achieve exact or at least as exactly as possible matches. As a further robustness check, following Abadie and Imbens (2002), we vary the number of matching partners up to four different partners. Finally, we also determine the impact of team and individual sports as well as of gender on the average treatment effect.

4.3.3 Data

The data used in this study is extracted from two different sources. While information on the treatment group has been collected through a survey among former elite athletes, information on the control group is observed from the German Socio-Economic Panel (sozio-oekonomisches Panel, GSOEP, 2012).[3] The GSOEP is a representative survey of 20,000 individuals in 11,000 households. Since 1984 the persons are surveyed yearly on income, work, education and health

[3] Of course, we cannot rule out that the GSOEP does not include any (former) elite athletes. However, given the small percentage of top-level athletes in Germany, we do not consider it to be a problem. After all, matching two top-level athletes will result in a downward bias and not in an overestimation of the effect.

(Wagner et al., 2008). The database allows to construct the courses of education as well as the professional career paths of the individuals used for the control group.[4]

Data on the treatment group has been collected via an online questionnaire among athletes who were formerly supported by the German Sports Aid foundation.[5] Therefore, we can make use of the special characteristic that the kind of sports executed by these athletes are mainly amateur sports. Professional sports, that generally cover the cost of living or may even generate an extremely high income, are not represented in the data set. The funding criteria of the German Sports Aid Foundation are aligned such that the size of the granting are not only tied to the athlete's performance. The expenses caused by the execution of the sport and the social situation of the athletes are also taken into account (Sports Aid Foundation, 2014). This offers the advantage, that the former top athletes in our data set are obliged to enter into a professional vocational career at the latest once they have retired from top sports.

The survey took place in January and February 2013. In total, 1,346 members of the alumni association *emadeus* as well as about 4,500 formerly supported athletes have been requested by email to fill in the questionnaire. Overall, 938 former athletes (460 *emadeus* members and 478 non-members) responded to the request. However, given that some of the individuals have either not responded questions on income or are not yet employed, we ended up with a treatment group of 259 former athletes. In total, the online survey consists of 41 questions. Seven questions are aimed at the athletic career. The remaining 34 questions cover the socio-economic background of the respondents. These are in style of the GSOEP survey.

Asking for the exact income often has a deterrent effect and may thus result in a lower response rate. We therefore asked individuals to state their income by choosing a respective income category out of eleven income categories. While the lowest category covers monthly salaries in the range from zero to €500, the highest category contains salaries of at least €5,000 and above. The increase in the income categories takes place in steps of €500. As the GSOEP questionnaire asks for the exact income we had to assign persons in the control group to their respective income category for matters of comparability.

Table 4.1 displays the distribution of the monthly income net of taxes within the two groups, i.e. the treatment and the control group. While the majority of non-athletes fall within the lower and middle income brackets, the former athletes realize salaries primarily in the middle and upper brackets. A comparison of the average income of the two groups shows a similar result. Former athletes earn on average €3,046 net of taxes a month. The average income of the non-athletes is €812 lower. Regarding the median of athletes, it falls in income category five, i.e. €2,000 up to €2,500, thereby being one category above those of the non-athletes.

[4] The extraction and manipulation of the GSOEP data is conducted by the help of PanelWhiz (Haisken-DeNew and Hahn 2010).

[5] To achieve comparability of both surveys, we adapted the wording from the GSOEP questionnaires for the survey among former athletes.

The descriptive statistics of the variables used in the analysis are shown in Tables 4.1 to 4.4. The treatment group consists of 259 observations, while the pool of non-athletes from which the observations for the control group are drawn covers 4,292 individuals. The distributions within the two groups of athletes and non-athletes are approximately identical with respect to sex and the location of the workplace.

	Athletes		Non-athletes	
monthly income net of taxes in €	#	%	#	%
0 - < 500	4	1.54%	231	5.38%
500 - < 1000	10	3.86%	585	13.63%
1000 - < 1500	19	6.56%	897	20.90%
1500 - < 2000	54	20.85%	865	20.15%
2000 - < 2500	48	18.53%	586	13.65%
2500 - < 3000	28	10.81%	358	8.34%
3000 - < 3500	28	10.81%	280	6.52%
3500 - < 4000	19	7.34%	174	4.05%
4000 - < 4500	11	4.25%	109	2.54%
4500 - < 5000	8	3.09%	63	1.47%
≥ 5000	32	12.36%	144	3.36%
Total	*259*		*4292*	
Ø	*3046 €*		*2234 €*	
Stand. Dev.	*1323 €*		*1176 €*	
Median	*2000 - < 2500 €*		*1500 - < 2000 €*	

Table 4.1: Distribution of the Monthly Income Net of Taxes

Differences in the distribution between the two groups can be observed with respect to the professional status. While the majority of non-athletes works as employees (57.06%) and workers (22.16%), the former athletes work mostly as employees (67.95%) and civil servants (15.06%). The share of workers among the athletes is only 8.11% and, hence considerably below the one of the control group. The proportion of self-employed and interns does not vary between the two groups. The same holds for the share of people that are currently in training. Among the non-athletes about 66.08% are married which is considerably higher than in the treatment group (49.03%). Also, the average job market experience differs between the two groups (see Table 4.3). Job market experience is measured by the number of years a person has been active on the job market since her first employment.

The questionnaires contain also questions on the character traits as well as the attitudes towards life and the future of the respondents. Regarding the GSOEP survey, the questions concerning the character traits were last asked in 2009, while the questions on the attitudes towards life and future were asked the last time in 2005. Since these personal attributes are not likely to vary much over the time (particularly not for adults) we use this information in our analysis. We consider this important in order to control for the impact characteristics, such as commitment and self-motivation, have on success, and therefore also on income. Attributes like beauty, height and health are also found to have a positive effect on income (see e.g. Harper, 2000;

	Athletes		Non-athletes	
	#	%	#	%
No. of observations	259		4292	
Team sports	85	32.82%	-	-
Individual sports	174	67.18%	-	-
Sex				
Men	146	56.37%	2291	53.38%
Women	113	43.63%	2001	46.62%
Fed. State of workplace				
West Germany	220	84.94%	3499	81.52%
East Germany	39	15.06%	793	18.48%
Job position				
Worker	21	8.11%	951	22.16%
Self-employed (0)[1]	12	4.63%	203	4.73%
Self-employed (9)[2]	9	3.47%	179	4.17%
Self-employed (9+)[3]	7	2.70%	37	0.86%
Intern	1	0.39%	33	0.77%
Employee	176	67.95%	2449	57.06%
Clerk	39	15.06%	434	10.11%
Marital status				
Married	127	49.03%	2836	66.08%
Single	132	50.97%	1456	33.92%
Currently in training				
Yes	16	6.18%	178	4.15%
No	243	93.82%	4114	95.85%
Type of employm. status				
Full-time	229	88.42%	3207	74.72%
Part-time	30	11.58%	1085	25.28%
Profession of Parents				
Profession of father	259	100.00%	4292	100.00%
Profession of mother	243	93.82%	2941	68.52%

1: 0 employees, 2: 1-9 employees, 3: more than 9 employees.

Table 4.2: Explanatory Variables I

Athletes					
Variable	Ø	Std. Dev.	Min	Max	Median
No. years in job	11.80	9.50	0	45	9
Non-athletes					
Variable	Ø	Std. Dev.	Min	Max	Median
No. years in job	27.09	11.13	2	55	28

Table 4.3: Explanatory Variables II

Rashad 2008; Hübler, 2009). Besides, these attributes may as well be positively correlated with selection into competitive sports. Not accounting for this, we might misattribute this effect to the participation in elite sports and overestimate the income premium. Unfortunately, we do not have the respective data to also control for that. However, beauty, height and health may also be positively correlated with the character traits and general attitudes. A taller, more beautiful and healthier person may also have a more positive attitude towards life and future. Therefore, matching former athletes and non-athletes with similar personal characteristics should diminish the self-selection problem.

Table 4.4 shows the statements according to which the respondents should assess themselves as well as the respective descriptive statistics. Regarding the character trait the respondents were asked to state on a scale from one to seven to what extend they agree to the given statements. Thereby, "1" indicates "does not apply at all" and "7" indicates "applies totally". In total, the respondents were inquired on five character traits. Concerning the attitudes towards life and future the respondents got two statements they are, again, asked to evaluate on a scale from one to seven according to its personal applicability. Similarly, "1" indicates "does not agree at all" and "7" indicates "agree totally". In both categories the extent to which the respondents agree to the statements is higher among former athletes than among non-athletes.

	Athletes					
Variable	Description	Ø	Stand. Dev.	Min.	Max.	Median
Character Traits; I am	... communicative, talkative (1)	5.69	1.19	1	7	6
(Scale: 1-7)	... inventive, contributing new ideas (2)	5.00	1.35	1	7	5
	... rather lazy (3)	2.13	1.46	1	7	2
	... easily getting nervous (4)	2.90	1.56	1	7	2
	... completing tasks efficiently & effectively (5)	6.04	1.00	1	7	6
Attitude in life	The way my life progresses depends on me. (1)	5.90	0.89	3	7	6
(Scale: 1-7)	Success has to be earned. (2)	6.04	1.02	2	7	6
	Non-athlete					
Variable	Description	Ø	Stand. Dev.	Min.	Max.	Median
Character Traits; I am ...	... communicative. talkative (1)	5.45	1.35	1	7	6
(Scale: 1-7)	... inventive. contributing new ideas (2)	4.66	1.34	1	7	5
	... rather lazy (3)	2.44	1.54	1	7	2
	... easily getting nervous (4)	3.46	1.63	1	7	3
	... completing tasks efficiently & effectively (5)	5.90	1.01	1	7	6
Attitude in life	The way my life progresses depends on me. (1)	5.56	1.24	1	7	6
(Scale: 1-7)	Success has to be earned. (2)	6.00	1.09	1	7	6

Table 4.4: Explanatory Variables III

4.3.4 Results

Nearest-neighbour matching

To identify the effect of participation in elite sports on later job success we estimate the sample average treatment effect. Tables 4.5 and 4.6 summarize the results from our initial regressions. The first column displays the number of matching partners and the second column contains the SATT score, i.e. the amount a former athlete earns on average more or less than a non-athlete. As monthly income is stated in categories of €500, the SATT score has to be interpreted in the following way: a score of, say, 1.500 means that a former athlete has an on average 1.5 times one income category – or €750 higher monthly income net of taxes – than a non-athlete. The average treatment effect in Euros are given in column four. The size of the treatment group is shown in column five and the size of the control group after the matching has been taken place in column six.[6] The total number of observations of both groups that can be drawn from for the matching is stated in column seven. Column eight shows the percentage of exact matches.

	Model I (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.38***	.176	688.00	259	199	4551	78.76
2	1.50***	.170	750.00	259	354	4551	76.06
4	1.45***	.167	724.50	259	607	4551	69.79
	Model I (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.51***	.224	753.50	243	181	3184	74.89
2	1.56***	.203	777.50	243	311	3184	71.60
4	1.50***	.182	751.50	243	513	3184	66.05

Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, Standard errors are robust to heteroskedasticity. Observations for the control group are drawn from the group of non-athletes with replacement.
biasadj: Model I (a): job position, fed. state workpl., character trait 1, character trait 3, character trait 4, profession father, no. of years in job, marital status
biasadj: Model I (b): job position, character trait 3, character trait 4, no. of years in job, marital status

Table 4.5: Results Model I

For all of our regressions, we find a positive income effect for the participation in elite sports. While for Model I (a) matching is carried out by using each covariate given in Tables 4.2 and 4.4, Model I (b) additionally includes the mother's profession. In both models the variable number of years in job is required to be matched as exactly as possible. Depending on the number of matching partners, former athletes receive a monthly income net of taxes that is on average €688 to €750 above that of comparable non-athletes for Model I (a). In Model I (b) the observed income effect is higher by about €40 (see Table 4.5). The results are statistically significant at the 1 percent level of confidence. Given the small variation in the SATT scores as well as the high percentage of exact matches, the results seem to be quite robust.

[6] The lower number of observations in the control group compared to the treatment group can be attributed to the fact that we match with replacement.

Model II expands the analysis with respect to the number of variables on which an exactly as possible match is conducted. Not only the number of years in job, but also the types of profession and the marital status are forced to be matched as exactly as possible. Again, we find a positive and statistically significant income effect for the participation in elite sports. The measured SATT scores are persistently above those of Model I. On average, the determined income effect exceeds that of Model I by roughly 10%. Surprisingly, comparing the results of Model II with the raw mean difference in incomes from Table 4.1 (€812), the matched difference exceeds this value four of six times. One would expect it rather to be below the raw mean difference. However, not every observation in the control group is matched to a treated observation. Comparing the measures of the matching quality, Model I performs much better than Model II. Lower income effects therefore allow for a more conservative interpretation of the results.[7]

	Model II (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.53***	.177	763.50	259	200	4551	67.18
2	1.56***	.165	781.50	259	360	4551	64.86
4	1.65***	.164	826.50	259	600	4551	56.66
	Model II (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.69***	.194	844.50	243	172	3184	64.61
2	1.84***	.175	920.00	243	313	3184	59.67
4	1.52***	.172	761.50	243	508	3184	51.75

Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, Standard errors are robust to heteroskedasticity. Observations for the control group are drawn from the group of non-athletes with replacement.
biasadj: Model II (a): job position, character trait 1, character trait 3, character trait 4, profession father, no. of years in job
biasadj: Model II (b): job position, character trait 3, character trait 4, profession mother, no. of years in job

Table 4.6: Results Model II

An analysis of box plot charts allows some inference about the influence of the single covariates on the measured income effect. Figure 4.1 summarizes plots for twelve of the variables used in Model I(a) with two matching partners. The x-axis indicates the income difference for each observation in the treatment group and its respective match and the y-axis gives the respective covariates. On average, the participation in elite sports leads to a positive income difference for more or less all variables. Nonetheless, some covariates show a considerably larger positive income spread than others.

An inspection of the distributions of full-time and part-time employed former athletes reveals that the positive income effect is clearly driven by full-time employed. Turning to gender, the income effect is bigger for men than for women, yet nonetheless positive for both groups. The same can be observed for the marital status, married former athletes realise incomes which are higher by about two income categories, on average, unmarried athletes ascend only one

[7] As a kind of robustness check, we performed nearest-neighbour CVM, where we corrected all matching variables for possible biases. However, the results remain qualitatively as well as quantitatively unchanged.

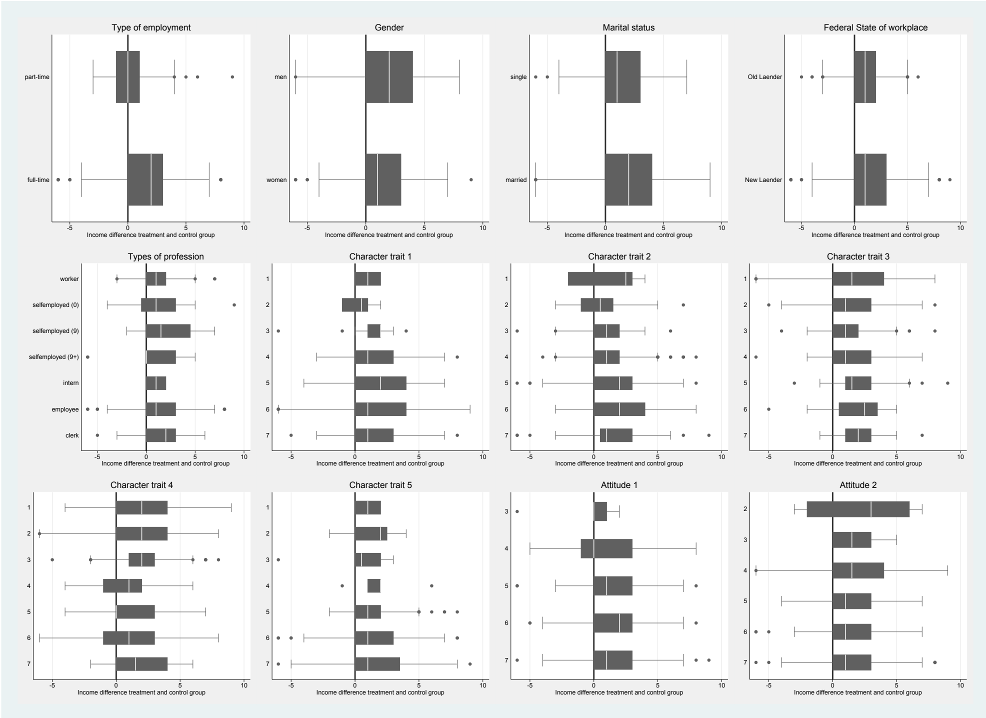

Figure 4.1: Box Plot Charts of the Matching Variables

category. Whether the workplace is situated in West or East Germany has no (or at least no significant) impact on income premiums.

Among the types of profession, the largest positive income differences are observed for self-employed former athletes with up to nine employees as well as for individuals that work in the civil service (*clerk*). About 20% of all employees in the civil service are middle grade civil servants. While the majority of non-athletes (44.0%) works in the higher intermediate civil service, the majority of former athletes (43.6%) works in the higher civil service, which is surely an explanation for the premiums.

Regarding the distributions of the character trait measures, the results are somewhat ambiguous. Similar median income premiums can be achieved irrespective of either a strong agreement or a strong disagreement to some of the given character trait statements. This applies, for example, for character trait 2. The largest positive median income spread is realized for former athletes who ranked themselves either “1” or “5” or “6”. A further surprising result can be observed for character trait 3. The biggest income premium is realized by individuals which assess themselves as rather lazy. Yet, the second largest median income spread is attained by respondents disagreeing with this statement. Similarly, respondents that rank themselves rather low to intermediate in completing tasks efficiently and effectively realise the highest median income premium. It is, of course, not clear whether these distributions result from distorted self-perceptions or just from some kind of superiority. Even lazy individuals can be successful at work when they are at the same time highly intelligent and creative. Turning to measures for attitudes, a general view that success has to be earned does not seem to be very important for a higher income premium. Respondents ranking themselves low to medium in this respect, realize the highest median income difference. However, personal responsibility ("The way my life progresses depends on me.") coincides with a high median difference in income. But, again, when interpreting the box plot charts for the character-trait and attitude-towards-life measures, one has to bear in mind that these values are based on a subjective self-assessment.

Extensions and robustness checks

As we are aware of several characteristics of both, treatment group and the control group members, our data allows for a number of extensions and robustness checks.

Job market experience Some variables like part-time versus full-time employment may partly be determined by the participation in competitive sports. This may be the case if athletes decide to work part-time to ensure the reconciliation of their professional life with top sports. As a robustness check, we consider only former athletes whose job market experience are at least five and ten years, respectively. If the decision to work part-time was driven by the sport, the former athlete will most probably change to full-time after her career. The regression results for at least five years of job market experience are shown in Table 4.B.1 in the Appendix.[8] The magnitude of the income premium stays quantitatively and qualitatively unchanged. This can also be interpreted in light of the signaling hypothesis. First, former athletes may start in their working life at a higher age and employers may be willing to pay a wage premium simply because they are more mature. Second, former athletes may be paid a higher wage because employers believe them to be more committed, disciplined and diligent. If this is the case, after a few years on the job, the income lead should shrink. The age advantage becomes less important and if the former athlete cannot fulfill the expectations, the advance laurels will be eaten up with time.

Team sports vs. individual sports Analysing former athletes that participated in team sports and those that performed individual sports separately, one still finds a positive and statistically significant income effect for both groups (see Table 4.B.2 and Table 4.B.3 in the Appendix). While former athletes in team sports receive a labour income net of taxes that is on average about €745 to up to almost €905 higher than that of comparable non-athletes (Specification Team I(a) and I(b)), the income premium of athletes in individual events is lower (€715 to €782). Possible reasons for this finding can be a greater capacity for teamwork or a greater willingness to work in a team on part of the former team athletes. These are properties that are often beneficial in a professional life. However, when interpreting the results one should

[8]The results for at least ten years of employment remain qualitatively and quantitatively unchanged and are available upon request.

notice that the number of observations in the group of former team athletes is quite low, i.e. 85 and 80. Yet, the results are statistically significant and the matching quality, measured by the percentage of exact matches, is high. Therefore, it can reasonably be concluded from these results that the participation in team sports generates a higher positive income effect, when compared to individual sports.

Gender-wage gap Splitting the analysis according to gender, we find a positive and statistically significant income effect for both, women and men, within their respective gender groups (see Tables 4.B.4 and 4.B.5 in the Appendix). The average income effect of women is a bit lower than that of men. On average, former female athletes earn €560 to €635 more a month than their peers, who have not participated in elite sports (Specification Women I(a) and I(b)). Performing the same analysis among the group of men, we estimate a positive average income effect of about €800 to €928 (Specification Men I(a) and I(b)). Comparing the income distributions of former female and male athletes, female former athletes have a peak at €1,500 to €2,500 and the distribution is skewed to the right. The distribution of the male incomes is double-peaked at €1,500 to €3,000 and at least €5,000 with the majority falling into the largest income category. One possible explanation for this income spread observable in the data is the share of full-time and part-time employment among females and males. While almost 97% of the male former athletes work full-time, this is true for only 78% of the female former athletes.

Comparing the income of former female athletes with men, who did not participate in elite sports, there is no definite result observable (see Table 4.B.6 in the Appendix). The SATT scores are consistently positive, yet they are rather small in size and, except for one estimation, none is statistically significant. Former female athletes earn the same monthly income net of taxes than non-athlete males. This finding is in so far interesting as usually women receive on average a lower income than men for similar works (Antonczyk et al., 2010). It seems that the participation in elite sports helps in closing the gender-wage gap.

Propensity score matching Apart from CVM, we also used two types of propensity score matching to evaluate the effect of elite sports participation. In the PSM we use the same set of variables we also include in the CVM. At first, propensity scores are estimated using the variables on character traits, attitudes towards life, and parents' professions by means of probit and logit techniques. The remaining set of variables are used as covariates in the actual matching process. Overall, the estimates remain qualitatively and quantitatively unchanged in comparison to CVM. We interpret these results such that our estimates are robust to changes in the specification and in the method used.[9]

Overall, our findings indicate that the positive effects attributed to the participation in elite

[9]Results are available upon request.

sports with respect to a later professional career prevail. The estimated SATT scores for the income effect of former athletes are consistently positive and statistically as well as economically significant. Besides, the results prove to be robust with regard to variations in the specification and estimation method. This seems to support the theory of productive consumption. Since we control for the existence of certain character traits, that are also beneficial to a professional career, the participation in elite sports appears to enhance these character traits. A further explanation for the findings may be a signaling effect. The very fact that one has participated in elite sports may induce employers to assign the former athlete with these characteristics (Long and Caudill, 1991). Former athletes seem to benefit especially if they are not easily getting nervous and if they believe that personal responsibility is important. Moreover, the positive income effect can in particular be observed for former athletes working in the civil service.

4.4 Conclusion

This paper analyses the effect of participation in elite sports on the later success in professional careers using a unique dataset. We estimate SATT scores for former elite athletes by covariate nearest-neighbour matching. This allows to quantify the average difference in the monthly net income of formerly by the German Sports Aid Foundation supported athletes and non-athletes, that have the same probability to be professionally successful. As matching covariates we use socio-demographic variables as well as measures of personal qualities and attitudes. By varying the number of matching partners and covariates, we verified the robustness of the results. We also estimate the SATT scores for different groups and analyse the general tendencies of the influence of the covariates on the income effect with the help of box plot charts.

Our findings seem to support the theory of productive consumption and signaling. We find a positive and statistically as well as economically significant effect for the participation in elite sports on the later job success. On average, former athletes receive a monthly net income that exceeds the income of non-athletes by about €690 to €780. The effect is even larger for former athletes that have participated in team sports. The premium attributed to team sports can be rationalized by a possible greater capacity for teamwork or a greater willingness to work in a team. This suggests that a certain importance concerning the income, is actually attached to the ability to work in teams.

The separate study of men and women shows that both male and female former athletes receive an income premium when compared to non-athletes. Male athletes earn on average about €850 more than male non-athletes. The income difference for female athletes when compared to non-athletes of the same gender is smaller, yet also positive and significant. Most interestingly, participation in elite sports results in a closing of the gender-wage gap. Thus, female former athletes receive about the same monthly net income than male non-athletes.

To sum up, our estimates prove to be robust and significant. We identify relatively strong positive income effects, that can be attributed to the former participation in elite sports. Our findings suggest that practicing top-level sports generates welfare beyond the mere positive effect on the society. In addition to the establishment of role models and the conveyance of character traits that are commonly regarded as positive, such as fair play, team spirit and commitment, it creates economic benefits on part of the former athletes itself. Further, when debating about the level and the scheme of elite sports funding, this long-term effect should also be taken into account.

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Appendix

4.A Tables Signranktest

	Model I (a)			Model I (b)			Model II (a)			Model II (b)		
Variable	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
Marital status	.0013	.0000	.0000	.0001	.0000	.0000	.	.	.	.	.	.
Full-time/Part-time	.4054	.3304	.5176	.6171	.5271	1.0000	.6698	.3452	.6467	.6831	.7576	.7833
Sex	.4233	.6117	.5879	1.0000	.7055	.4730	.2673	.5807	.3726	.8997	.3543	.7349
# years in job	.0013	.0003	.0000	.0003	.0009	.0000	.0073	.0000	.0000	.0003	.0000	.0000
Profession	.0747	.0046	.0000	.1717	.0070	.0000	.0253	.0016	.0000	.0253	.0016	.0000
Apprentice y/n	.	.3173	.0833	.3173	1.0000	1.0000	1.0000	.4669	.6473	.0956	.5316	.4533
Fed. state workpl.	.1336	.0222	.0233	.6698	.5716	.9251	.0116	.0039	.0084	.5637	.8137	.1250
Profession father	.0130	.0064	.0001	.2639	.3012	.3352	.0000	.0001	.0000	.1914	.1299	.0206
Profession mother	-	-	-	.3095	.1252	.0016	-	-	-	.0157	.0001	.0000
Character trait 1	.1440	.0187	.0127	.3546	.4682	.2682	.1221	.0310	.0220	.6326	.8977	.6277
Character trait 2	.1693	.0905	.0900	.0534	.1076	.0061	.5334	.1526	.0630	.1208	.2426	.0073
Character trait 3	.0371	.0001	.0000	.0008	.0000	.0000	.0011	.0000	.0000	.0000	.0000	.0000
Character trait 4	.1707	.0037	.0000	.2041	.0012	.0000	.1268	.0087	.0000	.0142	.0016	.0000
Character trait 5	.7659	.9729	.3111	.5415	.9330	.3049	.8769	.6735	.3683	.2547	.9120	.1921
Attitude 1	.7694	.9034	.4786	.1761	.4957	.1132	.8072	.2980	.0252	.2648	.2743	.1201
Attitude 2	.7592	.6026	.1930	.2639	.2149	.0027	.1620	.6735	.6626	.7367	.4845	.2225

Table 4.A.1: Matching Variables - Signranktest - Model I and Model II

	Model I (a)			Model I (b)			Model II (a)			Model II (b)		
Variable	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
Marital status	.1025	.0032	.0000	.0164	.0004	.0000	.	.	.	.	.	.
Full-time/Part-time	.3173	1.0000	.4328	.1797	.6171	.4652	.7389	.3711	.0782	.7389	.5930	.6219
Sex	.4386	.3841	.1281	.4386	.2230	.0339	.1573	.1228	.0051	.2513	.2482	.0312
# years in job	.1628	.0031	.0002	.0103	.0021	.0006	.2646	.0131	.0000	.0842	.0034	.0000
Profession	.0254	.0827	.0285	.0455	.0960	.0254	.0833	.0143	.0005	.0833	.0143	.0005
Apprentice y/n	.	.	.	.	.	.	.3173	.3173	1.0000	.1573	.5637	.5637
Fed. state workpl.	.6547	.5637	.2568	.1573	.0707	.0236	.5637	.7815	.3841	.6547	.1083	.0094
Profession father	.0260	.0271	.0080	.1614	.2619	.3110	.0008	.0009	.0027	.2794	.1910	.4645
Profession mother	-	-	-	.1592	.0220	.0206	-	-	-	.0748	.0009	.0000
Character trait 1	.4824	.0739	.3624	.6971	.8580	.5277	.3570	.1229	.0993	.8241	.9637	.6217
Character trait 2	.3828	.4260	.2989	.2539	.3174	.1051	.8441	.6494	.5734	.7744	.7440	.1718
Character trait 3	.5416	.3010	.0025	.1084	.0158	.0346	.1027	.0373	.0024	.0229	.0078	.0090
Character trait 4	.7390	.4037	.0253	.2566	.0546	.0004	.6757	.1889	.0246	.3041	.0584	.0046
Character trait 5	.7692	.8443	.4225	.4795	.6959	.8521	.8295	.8816	.4244	.9426	.3169	.4212
Attitude 1	.3784	.0457	.2968	.4148	.0878	.3242	1.0000	.1433	.1517	.5987	.1580	.9266
Attitude 2	.1749	.3139	.1938	.6113	.9030	.0213	.5953	.7152	.3056	.8482	.6989	.0032

Table 4.A.2: Matching Variables - Signranktest - Model I and Model II - Team sports

	Model I (a)			Model I (b)			Model II (a)			Model II (b)		
Variable	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
Marital status	.0047	.0022	.0000	.0090	.0000	.0000	.	.	.	.	.	.
Fuul-time/Part-time	1.0000	.4328	.3096	1.0000	.6949	.5413	.5930	.5050	.8273	.4386	1.0000	.6662
Sex	.4328	.8997	.8033	.6310	.2159	.6971	.6121	.7290	.4634	.6547	.0294	.5467
# years in job	.0045	.0138	.0053	.0050	.0498	.0021	.0094	.0004	.0011	.0008	.0007	.0000
Profession	.5493	.0109	.000	.5535	.0326	.0001	.1573	.0455	.0047	.1573	.5127	.0047
Apprentice y/n	.	.3173	.0833	.	.5637	1.0000	.5637	.6171	.5164	.2568	.5127	.4838
Fed. state workpl.	.0348	.0010	.0007	.1967	.0956	.0997	.0124	.0004	.0002	.3938	.6858	.9287
Profession father	.1122	.0679	.0044	.5349	.5680	.7991	.0092	.0164	.0002	.4088	.3632	.0539
Profession father	-	-	-	.7341	.6507	.0690	-	-	-	.0897	.0128	.0002
Character trait 1	.1944	.1071	.0291	.3101	.6246	.4769	.2714	.1153	.1009	.7671	.8629	.9075
Character trait 2	.3254	.1675	.2134	.2195	.2556	.0277	.4249	.1745	.0702	.1586	.2992	.0137
Character trait 3	.0308	.0002	.0000	.0087	.0000	.0000	.0059	.0000	.0000	.0001	.0000	.0000
Character trait 4	.1114	.0048	.0000	.0172	.0104	.0000	.1199	.0157	.0001	.0312	.0104	.0001
Character trait 5	.8847	.7436	.4693	.2187	.7926	.2500	.7365	.5794	.5286	.1813	.7422	.3615
Attitude 1	.3432	.1570	.7686	.3010	.7661	.1474	.7683	.7486	.1273	.3205	.7030	.0617
Attitude 2	.9637	.8073	.3717	.1293	.2663	.0406	.1708	.1326	.2507	.6549	.1843	.6810

Table 4.A.3: Matching Variables - Signranktest - Model I and Model II - Individual Sports

	Model I (a)			Model I (b)			Model II (a)			Model II (b)		
Variable	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
Marital status	.0495	.1655	.0043	.0330	.0094	.0065	.	.	.	.	.	.
Full-time/Part-time	.8273	.3763	.0348	.3938	.3865	.0359	.6949	.3270	.0656	1.0000	.7681	.0542
# years in job	.2244	.3212	.5132	.5485	.3806	.9383	.9280	.3679	.0013	.6684	.0206	.0001
Profession	.3417	.0022	.0000	.0147	.0004	.0000	.1573	.0455	.0047	.1573	.0455	.0047
Apprentice y/n	.	.3173	.0455	.	.3173	.1797	.4142	.4913	.6394	.2059	.4669	.4349
Fed. state workpl.	.6547	.1336	.2059	.5271	.8348	.6803	.1797	.2253	.6171	.0184	.1573	.0116
Profession father	.1201	.0089	.0001	.1235	.1007	.0709	.0113	.0001	.0000	.0247	.0365	.0041
Profession mother	-	-	-	.3578	.1196	.0934	-	-	-	.0318	.0497	.0005
Character trait 1	.8857	.7241	.4339	.8369	.3648	.1215	.8244	.7663	.2177	.9733	.5661	.1191
Character trait 2	.6113	.9096	.9284	.6697	.7712	.8212	.6892	.8641	.8309	.3985	.9393	.9307
Character trait 3	.0208	.0025	.0000	.0287	.0086	.0000	.0052	.0001	.0000	.0047	.0000	.0000
Character trait 4	.6832	.4853	.0155	.4527	.1557	.0002	.4960	.3059	.0003	.5003	.0260	.0000
Character trait 5	.0923	.0069	.0000	.1684	.0205	.0000	.0593	.0222	.0000	.0496	.0035	.0000
Attitude 1	.4223	.7408	.8205	.4230	.7695	.8552	.4657	.7575	.0815	.2230	.0255	.0020
Attitude 2	.4522	.5795	.2197	.0939	.0131	.0001	.3256	.1560	.9195	.7274	.7286	.1001

Table 4.A.4: Matching Variables - Signranktest - Model I and Model II - Women vs. Women

	Model I (a)			Model I (b)			Model II (a)			Model II (b)		
Variable	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
Marital status	.0012	.0000	.0000	.0001	.0000	.0000	.	.	.	.	.	.
Full-time/Part-time	.0455	.0143	.0002	.0455	.0339	.0290	.3173	.1573	.0116	.1797	.2059	.2752
# years in job	.0029	.0000	.0000	.0000	.0000	.0000	.0009	.0000	.0000	.0000	.0000	.0000
Profession	.5301	.0026	.0000	.7370	.2430	.0006	.0833	.0143	.0005	.0833	.0143	.0005
Apprentice y/n	.3173	.0833	.0047	.1573	.1797	.0124	.5637	.2059	.2382	.3173	.2850	.3841
Fed. state workpl.	.7389	.2568	.0801	.3458	.3763	.8292	.1088	.1824	.1730	.6698	.7773	.6188
Profession father	.0516	.0356	.0073	.5427	.8001	.7512	.0903	.2419	.0241	.7904	.6727	.7763
Profession mother	-	-	-	.0615	.0486	.0024	-	-	-	.0122	.0000	.0000
Character trait 1	.0135	.0264	.0005	.1625	.2493	.0428	.0640	.0648	.0171	.4625	.5186	.6735
Character trait 2	.4422	.1298	.0404	.2422	.0515	.0005	.4437	.1194	.0306	.1584	.1258	.0017
Character trait 3	.0856	.0009	.0000	.0003	.0000	.0000	.0006	.0000	.0000	.0000	.0000	.0000
Character trait 4	.0376	.0001	.0000	.0005	.0000	.0000	.0600	.0008	.0000	.0044	.0003	.0000
Character trait 5	.0797	.0791	.1382	.0423	.4334	.5995	.3607	.4618	.1668	.3974	.8374	.5644
Attitude 1	.7291	.8059	.5283	.3715	.3723	.1575	.7844	.3618	.7115	.8576	.7316	.9848
Attitude 2	.2644	.9425	.5409	.7861	.8508	.3801	.2635	.2993	.2734	.2722	.2637	.5831

Table 4.A.5: Matching Variables - Signranktest - Model I and Model II - Men vs. Men

	Model I (a)			Model I (b)			Model II (a)			Model II (b)		
Variable	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
Marital status	.0278	.0223	.0010	.1441	.1521	.0080	.	.	.	.	.	.
Full-time/Part-time	.0016	.0000	.0000	.0005	.0000	.0000	.0008	.0000	.0000	.0001	.0000	.0000
# years in job	.4194	.3914	.0769	.0648	.0199	.0162	.2369	.3357	.0147	.0344	.0002	.0000
Profession	.2040	.0135	.0000	.5370	.0194	.0000	.1573	.0455	.0047	.1573	.0455	.0047
Apprentice y/n	.	.3173	.0455	.3173	.1573	.0082	.0455	.0196	.3657	.0253	.6547	.3961
Fed. state workpl.	.2059	.3711	.4458	.7630	.5127	.8927	.1088	.2087	.4855	.4913	.8694	.6662
Profession father	.1929	.4588	.4913	.0763	.0978	.1481	.5882	.7791	.7850	.5994	.6509	.9699
Profession mother	-	-	-	.0027	.0002	.0149	-	-	-	.2209	.1741	.6224
Character trait 1	.0107	.0001	.0000	.0058	.0000	.0000	.0038	.0000	.0000	.0039	.0000	.0000
Character trait 2	.7895	.3173	.8215	.8387	.8652	.7533	.3255	.4611	.8310	.3275	.7079	.8420
Character trait 3	.0001	.0000	.0000	.0008	.0000	.0000	.0000	.0000	.0000	.0007	.0000	.0000
Character trait 4	.7208	.9638	.7099	.6345	.9187	.7389	.6048	.1178	.9117	.6134	.5848	.5530
Character trait 5	.0179	.0032	.0000	.0039	.0001	.0000	.0455	.0009	.0000	.0035	.0000	.0000
Attitude 1	.7203	.9641	.8628	.4769	.1488	.0339	.3227	.0681	.0910	.3063	.2728	.1516
Attitude 2	.4591	.1027	.0200	.0627	.0516	.0055	.4313	.5134	.4997	.9134	.6033	.4994

Table 4.A.6: Matching Variables - Signranktest - Model I and Model II - Women vs. Men

4.B Results: Extensions and Robustness Checks

	5 years experience I (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.37***	.240	685.00	183	155	4326	93.44
2	1.59***	.221	795.00	183	283	4326	90.71
4	1.56***	.215	780.00	183	509	4326	86.07
	5 years experience I (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treatment	# Control	N	% exact matches
1	1.55***	.267	775.00	175	141	3005	88.00
2	1.56***	.237	780.00	175	258	3005	86.00
4	1.51***	.230	755.00	175	443	3005	81.00
	5 years experience II (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treatment	# Control	N	% exact matches
1	1.57***	.235	785.00	183	155	4326	80.87
2	1.60***	.214	800.00	183	288	4326	77.05
4	1.55***	.209	775.00	183	503	4326	69.13
	5 years experience II (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treatment	# Control	N	% exact matches
1	1.87***	.259	935.00	175	141	3005	76.57
2	1.61***	.222	805.00	175	262	3005	71.43
4	1.73***	.214	865.00	175	447	3005	62.00

Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$,Standard errors are robust to heteroskedasticity. Observations for the control group are drawn from the group of non-athletes with replacement.
biasadj: Model I (a): job position, fed. state workpl., character trait 1, character trait 3, character trait 4, profession father, no. of years in job, marital status
biasadj: Model I (b): job position, character trait 3, character trait 4, no. of years in job, marital status
biasadj: Model II (a): job position, character trait 1, character trait 3, character trait 4, profession father, no. of years in job
biasadj: Model II (b): job position, character trait 3, character trait 4, profession mother, no. of years in job

Table 4.B.1: Results 5 Years of Labour Market Experience

	Team I (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.52***	.280	759.50	85	80	4377	71.76
2	1.74***	.267	868.00	85	142	4377	72.35
4	1.49***	.270	744.00	85	257	4377	68.24
	Team I (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treatment	# Control	N	% exact matches
1	1.67***	.319	835.00	80	73	3021	70.00
2	1.81***	.286	905.00	80	131	3021	73.12
4	1.58***	.288	792.00	80	228	3021	67.81
	Team II (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treatment	# Control	N	% exact matches
1	1.78***	.294	891.50	85	76	4377	62.35
2	1.82***	.269	908.50	85	142	4377	61.76
4	1.73***	.255	865.50	85	250	4377	54.71
	Team II (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treatment	# Control	N	% exact matches
1	1.96***	.321	982.00	80	68	3021	61.25
2	2.09***	.268	1048.50	80	125	3021	60.00
4	2.11***	.265	1054.00	80	218	3021	52.81

Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$,Standard errors are robust to heteroskedasticity. Observations for the control group are drawn from the group of non-athletes with replacement.
biasadj: Team I (a): job position, profession father, no. of years in job, marital status
biasadj: Team I (b): job position, character trait 3, profession mother, no. of years in job, marital status
biasadj: Team II (a): job position, character trait 3, profession father, no. of years in job
biasadj: Team II (b): job position, character trait 3, profession mother, no. of years in job

Table 4.B.2: Results Team Sports

	Individual I (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.43***	.217	715.00	174	148	4466	83.33
2	1.45***	.211	725.50	174	268	4466	78.74
4	1.56***	.195	782.00	174	473	4466	72.56
	Individual I (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.52***	.243	761.00	163	130	3104	77.25
2	1.42***	.244	707.50	163	233	3104	69.76
4	1.49***	.211	745.00	163	403	3104	63.62
	Individual II (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.67***	.219	832.50	174	146	4466	70.69
2	1.54***	.205	772.00	174	271	4466	66.95
4	1.63***	.204	812.50	174	474	4466	58.76
	Individual II (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.87***	.237	932.50	163	127	3104	66.87
2	1.54***	.224	767.50	163	235	3104	61.66
4	1.50***	.217	750.50	163	404	3104	53.07

Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, Standard errors are robust to heteroskedasticity. Observations for the control group are drawn from the group of non-athletes with replacement.
biasadj: Individual I (a): job position, fed. state workpl., character trait 3, character trait 4, no. of years in job, marital status
biasadj: Individual I (b): job position, character trait 3, character trait 4, no. of years in job, marital status
biasadj: Individual II (a): job position, fed. state workpl., character trait 3, character trait 4, profession of father, no. of years in job
biasadj: Individual II (b): job position, character trait 3, character trait 4, profession mother, no. of years in job

Table 4.B.3: Results Individual Sports

# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
	Women I (a)						
1	1.18***	.255	590.00	113	84	2114	76.11
2	1.17***	.234	587.00	113	146	2114	74.78
4	1.12***	.215	560.00	113	250	2114	67.92
	Women I (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.27***	.246	635.00	111	76	1550	74.77
2	1.14***	.235	568.50	111	134	1550	69.82
4	1.15***	.223	572.50	111	216	1550	62.39
	Women II (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.37***	.256	685.00	113	81	2114	63.72
2	1.44***	.252	718.00	113	147	2114	59.29
4	1.22***	.237	612.00	113	248	2114	49.56
	Women II (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.42***	.278	707.50	111	71	1550	55.86
2	1.27***	.268	633.00	111	132	1550	51.80
4	1.31***	.244	652.50	111	220	1550	40.99

Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, Standard errors are robust to heteroskedasticity. Observations for the control group are drawn from the group of non-athletes with replacement.
biasadj: Women I (a): job position, character trait 3, character trait 5, profession father, marital status
biasadj: Women I (b): job position, character trait 3, character trait 5, attitude in life 2, marital status
biasadj: Women II (a): job position, character trait 3, character trait 5, profession father
biasadj: Women II (b): job position, fed. state workpl., character trait 3, character trait 4, character trait 5, attitude in life 1, profession father, profession mother, no. years in job

Table 4.B.4: Results Women

	Men I (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.60***	.223	800.50	146	117	2437	72.60
2	1.85***	.219	924.50	146	210	2437	72.95
4	1.67***	.213	834.00	146	357	2437	66.10
	Men I (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.86***	.296	928.00	132	105	1634	72.73
2	1.81***	.256	905.50	132	188	1634	69.32
4	1.86***	.235	928.50	132	298	1634	63.64
	Men II (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	1.84***	.208	919.50	146	116	2437	60.96
2	1.82***	.198	908.00	146	215	2437	57.88
4	1.74***	.198	872.00	146	357	2437	49.49
	Men II (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	2.29***	.253	1146.00	132	97	1634	59.09
2	1.96***	.231	980.00	132	183	1634	53.79
4	2.07***	.240	1036.00	132	303	1634	44.51

Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, Standard errors are robust to heteroskedasticity. Observations for the control group are drawn from the group of non-athletes with replacement.
biasadj: Men I (a): job position, character trait 1, character trait 3, character trait 4, profession father, no. of years in job, marital status, full-/part-time
biasadj: Men I (b): character trait 3, character trait 4, character trait 5, profession mother, no. of years in job, marital status, full-/part-time
biasadj: Men II (a): job position, character trait 3, character trait 4, no. of years in job
biasadj: Men II (b): job position, character trait 3, character trait 4, profession mother, no. of years in job

Table 4.B.5: Results Men

	Women vs. Men I (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	.040	.345	20.00	113	79	2404	71.68
2	.283	.296	141.50	113	139	2404	66.37
4	.381	.261	190.50	113	249	2404	61.94
	Women vs. Men I (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	.164	.415	82.00	111	73	1613	71.17
2	.149	.359	74.50	111	131	1613	61.26
4	.544**	.265	272.00	111	215	1613	61.26
	Women vs. Men II (a)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	.696**	.278	348.00	113	80	2404	63.72
2	.467*	.272	233.50	113	137	2404	54.42
4	.275	.255	137.50	113	227	2404	46.24
	Women vs. Men II (b)						
# Matches	SATT	Std. Dev.	in Euro	# Treat.	# Control	N	% exact matches
1	.480*	.285	240.00	111	70	1613	59.46
2	.430	.293	215.00	111	121	1613	53.15
4	.605**	.274	302.50	111	194	1613	41.22

Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, Standard errors are robust to heteroskedasticity. Observations for the control group are drawn from the group of non-athletes with replacement.
biasadj: Women vs. Men I (a): job position, character trait 1, character trait 3, character trait 5, marital status, full-/part-time
biasadj: Women vs. Men I (b): job position, character trait 1, character trait 3, character trait 5, profession mother, no. of years in job, full-/part-time
biasadj: Women vs. Men II (a): job position, apprentice, character trait 1, character trait 3, character trait 5, full-/part-time
biasadj: Women vs. Men II (b): job position, character trait 1, character trait 3, character trait 5, no. of years in job, full-/part-time

Table 4.B.6: Results Women vs. Men

Chapter 5

Concluding Remarks

This thesis presented three papers in empirical economics in the fields of energy and sports economics. In the first two papers the short- and long-term effects of intermittent electricity generation by wind and solar PV on the conventional generation and plant fleet were studied. The last paper dealt with the relationship between former competitive sports participation and the later job success.

Chapter 2, constituting the first paper, has analysed the short-run effect of power generated by wind and solar PV on the wholesale electricity prices and the conventional generation in Spain for the years 2008 to 2012. Using the merit order as the underlying structure and assuming the generation by wind and solar PV to be exogenous, we estimated a structural vector autoregressive model. We found a negative effect of wind and solar PV power on the wholesale price as well as on the quantities generated by conventional power plants, whereby the negative effect is largest for mid-merit plants, such as CCGTs. The effect can mainly be attributed to wind power. For further research it would be interesting to conduct this analysis for a panel of different – e.g. European – countries to see if the implications of the renewables expansion are persistent in the European electricity market. Using more recent years will also show if the effects become more pronounced.

In the third chapter, the long-run effect of renewables has been examined by investigating the change in the shares of the capacities installed of the conventional generation technologies in response to the feed-in by intermittent generation. Fixed effects as well as fixed effects instrumental variable models were applied to a panel of 18 European OECD countries. The results suggest that an increase in the share of RES-E generation decreases the shares of coal- and oil-fired power plants, while it has a positive effect on the share of gas-fired generation capacities. The results of the first stage of the fixed effects regression can be interpreted as a valid reduced form approach to analyse the effect of the intermittent RES-E generation on the electricity price. It suggests that a substantial part of the effect of intermittent RES-E on the conventional plant fleet is already captured in the price mechanism. As the data was only available until 2010, further research should use an expanded panel to include more countries as well as the developments of the recent years to reduce the downward-bias in the cluster-robust standard errors. Besides, using wholesale electricity prices should be an improvement to the analysis, since this price is more directly influenced by the amount of renewable generation.

Chapter 4 quantifies the income effect for former elite athletes in their later working lives compared to non-athletes. Applying covariate nearest-neighbour matching to survey data, we find a positive income premium for former elite athletes. This premium is even larger for team sports and male athletes. Most interestingly, comparing the income of former female athletes with male non-athletes, participation in elite sports closes the gender-wage gap. Overall, our findings suggest that practicing top-level competitive sports generates welfare beyond the mere positive effect on society, but also on part of the former athletes itself. This long-term effect should be taken into account when debating about the scheme and level of elite sports funding. A further interesting topic of research would be to investigate the income effect for different levels of sporting success. One might expect to find an inverted U-shape regarding accomplishments in sports and the later job success. Up to a certain level participation in elite sports has a positive effect on the later income, as the positive aspects of competitive sports prevail. Once that level has been crossed being an international top-level athlete might result in diminished academic activities and hence, limited careers and lower individual incomes.

Eidesstattliche Erklärung

Ich, Frau Leonie Giessing, versichere an Eides statt, dass die vorliegende Dissertation von mir selbständig und ohne unzulässige fremde Hilfe unter Beachtung der *Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Heinrich-Heine-Universität Düsseldorf* erstellt worden ist.

Düsseldorf, der 09. Juni 2016