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A Vision of the European Energy Future? The Impact of the German Response to the Fukushima Earthquake

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Abstract

The German response to the Fukushima nuclear power plant incident was possibly the most significant change of policy towards nuclear power outside Japan, leading to a sudden and very significant shift in the underlying power generation structure in Germany. This provides a very useful natural experiment on the impact of increasing proportions of renewable compared to conventional fuel inputs into power production, helping us to see how changed proportions in future as a result of policy moves in favour of renewables are likely to impact. We find through quasi-experimental exploration of a modified demand-supply framework that despite the swift, unpredicted change, the main impact was a significant increase in prices, partly caused by more frequent situations with unilateral market power. The price impact was also most significant in off-peak hours, leading to changed investment incentives. There were no appreciable quantity effects on the market, such as power outages, contrary to some views that the impacts would be significant. Furthermore, we find the sudden and unilateral phase-out decision by the German government has significantly affected electricity prices and thus competitiveness in neighbouring countries.

Keywords: Electricity markets; Atomausstieg; German power market; nuclear outages; renewables.

JEL-codes: L51; L94; Q41; Q48; Q54

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1 Introduction

The German "Atomausstieg" decision to have a nuclear moratorium following the Fukushima nuclear disaster in Japan in March 2011 was sudden, unexpected and significant internationally (Joskow and Parsons, 2012). We examine its impact on Germany and its neighbouring markets in terms of potential disruption to supply and in terms of price movements following the decision, using a quasi-experimental framework. Germany was heavily dependent on nuclear power; in 2010 over 22% of its power was from nuclear sources, but this decreased to less than 16% in 2012 (BDEW, 2011), mainly as a result of the immediate closure for testing in March 2011 followed by permanent shutdown by end- May 2011 of 6 of the 17 plants producing nuclear energy (as well as two that were offline at the time). We document the impact of this decision on the German and European power market. Others have suggested its significance. The *Frankfurter Allgemeine Zeitung* (31 May 2011), for example, estimated that the decision will cost the German people two billion euros per year and significantly reduce the stability of the system (quoted from Presseurop, 2011). In addition, as the International Energy Agency has pointed out, one plausible impact is that carbon emissions increase due to increased burning of dirty coal (*Guardian*, 16 June 2011).

Clearly, the Atomausstieg decision could have had a significant disruptive influence, leading to blackouts and selective supply reductions (though Kemfert and Traber, 2011, suggest this is unlikely). Additionally, a tighter demand-supply balance and change in fuel mix leading to greater variance in supply (given greater reliance on intermittent sources, Ketterer, 2012) may have impacted wholesale prices for power, which again would have a wider effect on costs, not only in Germany but also in the markets most closely integrated with it. We aim to provide convincing estimates and evaluation of these alternatives within Germany (plus Austria) using a demand-supply framework, modified to incorporate potential market power, exports and imports, using a quasi-experimental methodology (Shadish et al., 2002) to test for effects following the earthquake. In doing so, we make allowance for the particularities of the German market. In order to examine the wider European impact on prices, we include a VAR analysis to check for interactions with and impact on Germany's neighbouring countries.

To preview results, although there is no evidence that equilibrium quantity was negatively impacted by the sudden decision[1], there is a clear significant impact on price - a movement up the supply curve, other things equal, resulting from the use of higher cost fuel sources. We estimate an average price increase of around 7% and calibrate the net impact on Germany at approximately 1.5Bn Euro per year.[2] Our estimates find the price increase to be partly driven by increased market power: scarcity price markups become more common, in addition to a general leftward shift in the merit order[3]. Furthermore, the

[1] If there had been selective disconnection or "brown-outs" then we would expect to see these in the empirical estimates for load through a reduction in expected load given exogenous parameter values. There is no hard evidence that they occurred.

[2] The nearness of this estimate to that from the *Frankfurter Zeitung* quoted earlier is coincidental. They focus on a different calculation of magnitude, relating to tax revenues and government expenditure on renewables and climate measures. Our estimate of the price impact is larger than in Kemfert and Traber's (2011) simulations

[3] In energy economics the term merit order describes the supply schedule. Therefore, the available generating capacity is ranked in ascending order of the short-term marginal costs of production.

closure of the 6GW nuclear capacity was partially absorbed by cross-border trade but this had negative externalities in the sense of price increases in neighbouring countries. Our result contributes to the ongoing debate on whether electricity prices would have been lower with extended nuclear plant life spans (Nestle, 2012).

What may initially be more surprising is that the most significant impact on prices is in the off-peak periods. The intuition, confirmed by estimation, is that a reduction in the nuclear fleet implies a cut in cheap baseload provision. Times when baseload could be supplied by nuclear or lignite as marginal technology disappear, meaning that higher cost plant comes into operation especially in the quietest periods, while such technology jumps are better absorbed in peak hours as long as the replacement of baseload plants by renewables also includes solar generation. Alongside the rise in prices, this episode casts indirect light on the underlying mechanisms that will come into play as other European countries move to increased renewable provision. Over the period we examine, Germany moved from higher to lower biddable baseload capacity and, at the same time, to increased unbiddable intermittent renewable supply, a situation that will face most other countries in the EU. Thus, beyond the rise in prices, in our opinion this policy decision is one with significantly wider ramifications. We can view the sudden change in German policy as an experiment. It caused a quicker than anticipated move to a structure for power supply based on resources that are far more intermittent in nature, in which Germany is playing a key role (Figure 1). It therefore provides some pointers to the nature and scale of the much wider effects that may be anticipated in future as a result of a Europe- and world-wide move to greater reliance upon renewable resources over the next decades (Schmalensee, 2013, Huenteler et al., 2012). Moreover it also has implications for the impact of an individual country's policies on its neighbours' energy costs and the European policy on interconnection.

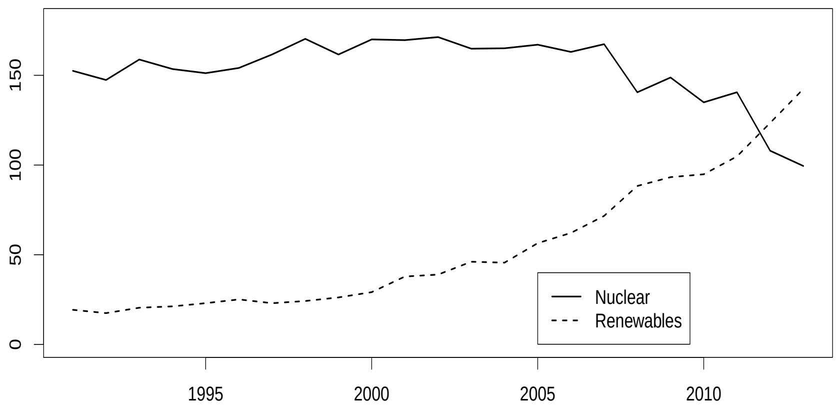

Figure 1: Gross electricity production from nuclear and renewable sources in Germany 1991-2013 (TWh). Renewables include wind power, renewable hydropower, biomass, photovoltaic. Data from BMWi (2014).

Our plan in the paper is as follows. We first describe the event (section 2) and the literature to date relevant to our model (section 3). Then in section 4 we develop our theoretical model of the German system. In section 5 we describe our variables and develop the estimation strategy. We then present and discuss the results in section 6. We extend the analysis to consideration of Germany's neighbours through a VAR analysis in section 7. Finally, section 8 has some concluding remarks.

2 German reaction to the Fukushima earthquake in context

Angela Merkel, the German Chancellor, had prior to the Fukushima earthquake been an advocate of nuclear power. A previous plan from 2002 under Gerhardt Schroeder to phase out nuclear plants entirely by 2022 had been delayed in 2010 against Red-Green opposition, with the lives of some plants extended until 2036 at the latest. However, following a dramatic change of mind by Merkel, the Fukushima accident resulted in all the eight pre-1981 plants being closed down permanently (hence, this has been described as an "Ausstieg vom Ausstieg vom Ausstieg", the first decision being the previous 2022 moratorium, the second the Merkel extension, the third the Merkel U-turn!). Clearly, this final decision was unexpected (opposed to the 2010 extension) and equally clearly, if Fukushima had not happened, the decision to close pre-1981 plants immediately would not have been made. Hence, this is a natural experiment- we measure the outcome of a completely unexpected event. It was an event of some significance: 6.3GW of capacity, around 4% of total capacity and 7% of conventional capacity, was permanently removed from the system at a stroke, with significant impacts on nuclear plant output, as shown in Figure 2.[4]

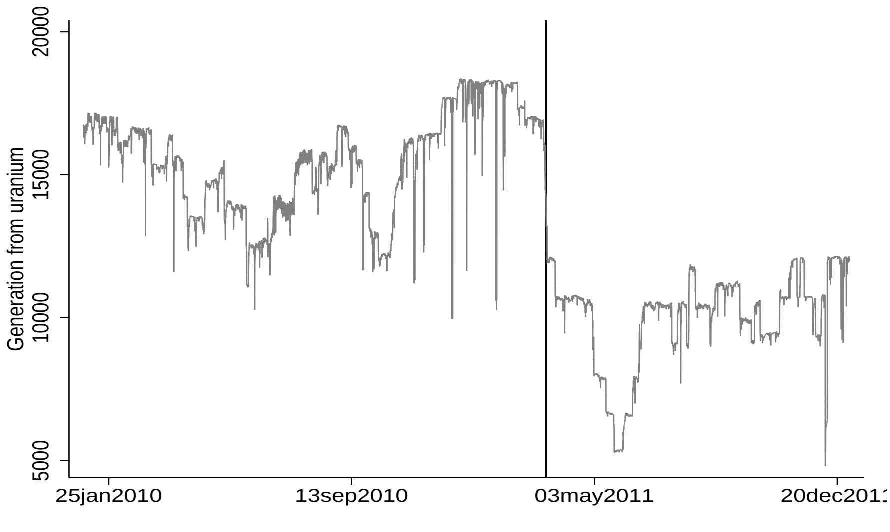

Figure 2: Generation from nuclear power plants before and after the Fukushima decision

Germany is one of the world's pioneers in renewable energy from wind and solar sources (Borenstein, 2012). Capacity in these areas has been growing rapidly, boosted by significant subsidies.[5] Wind capacity at end 2011 reached almost 30GW and photovoltaic power capacity reached 25GW, out of a total system

[4]We should note that two of the eight plants were not in production at the time of the decision. Considering these two plants increases capacity removed to 8.4GW.

[5]Here a key decision regarding the "Energiewende" came in September 2010, prior to the Fukushima earthquake, with the publication of a German Government strategy document (BMWi, 2010) on development of a renewable energy system.

listed capacity of 175GW (Source: BMWi, 2014). As a result, between end 2010 and end 2011, more capacity had been added through renewables (wind, 1.9GW, solar, 7.5GW) than had been removed by the Ausstieg. Capacity is one thing; clearly wind and photovoltaic capacity figures are potentially misleading in two senses- first these sources are nowhere near being used as intensively as conventional sources, nor are they "biddable" in the same way that coal, gas and pumped hydro plant is (Joskow, 2011). Thus whilst on average thermal plant provides around 50% of its total theoretical capacity over a year, wind hovers around 20% and photovoltaic only around 11%.[6] Taking average utilisation of nuclear plant conservatively to be around 75%, the 6.3GW of capacity that closed as a result would have produced 41TWh over a typical year. The increased capacity in wind and photovoltaic, on the other hand, would on average produce only just over 10.5TWh over the year. Thus in terms of production, there is a big net loss across these fuels and Germany is more likely to be on the upward sloping part of the supply schedule, despite the increased capacity.[7]

Examining these patterns in more detail, we should also take into account the "must-take" nature of wind and solar (under current conventions).[8] Hence, it becomes of importance what impact wind and solar plants have on the remainder of the system (Lechtenböhmer and Samadi, 2013). Here there is some positive impact- German demand is characterised by a high point in the middle of the day (particularly in summer; winter months have a high again around 19.00) which is nicely matched to the high point of solar production, as shown in the example for July 2012 in the first panel of Figure 3. However, there is also bad news: in the period after the Earthquake, the standard deviation of the remainder of the German load has increased, particularly in winter, as compared with the same period in 2010, whether measured by daily average or hourly average. In other words, the task required of the conventional generators is more variable, which is likely to add to costs. Because the power supply schedule is convex to the origin, a combination of 50% x units plus 50% $y(> x)$ units is more expensive than a constant $(x + y)/2$ units, for example.

Figure 3, panels 2 and 3, examines the variability of the residual load (load minus generation from volatile renewables) before and after 2011, using the data to be defined more precisely below. They consider the standard deviation of residual load across hours of the day within each month. Specifically, we calculate the standard deviation of residual load across, for example, 1$^{\text{st}}$-31$^{\text{st}}$ January for the hour between midnight and 1am, then for the hour between 1 and 2am, etc, for 2010 and 2012. These are the data points plotted in the second panel. As can be seen, in the winter months, plus early spring and late autumn, the standard deviation rises sharply in 2012 compared with 2010, whereas for the remainder of the year, as a result of the solar effect, this is not the case. The third panel provides a different cut of

[6] Authors' calculations from Bundesministerium (2012), comparing theoretical maximum output given capacities with actual output produced.

[7] This is not a complete comparison: Biomass production, which is rather intensively used, grew a little between these years, as did Brown Coal capacity. Overall, however, the gross additions of conventional generation over our period are certainly modest by comparison with the fall in nuclear capacity and the growth in renewable capacity, amounting in total over the three years to around 1.5GW (source, Bundesnetzagentur power plant list).

[8] We will discuss properties of the German EEG (*Erneuerbare Energien Gesetz*; translated Renewable Energy Act) in some more detail later.

the data. It examines the standard deviation in daily load across the days of the month. Thus, all the residual loads across the day are summed, and the standard deviation calculated across days. Standard deviation increases somewhat between 2010 and 2012, with a particularly stark increase in the winter months. Both forms of variance will require conventional generators to be more flexible and be used less intensively than previously where the 2012 figure is higher. By implication, prices will be higher in such cases.

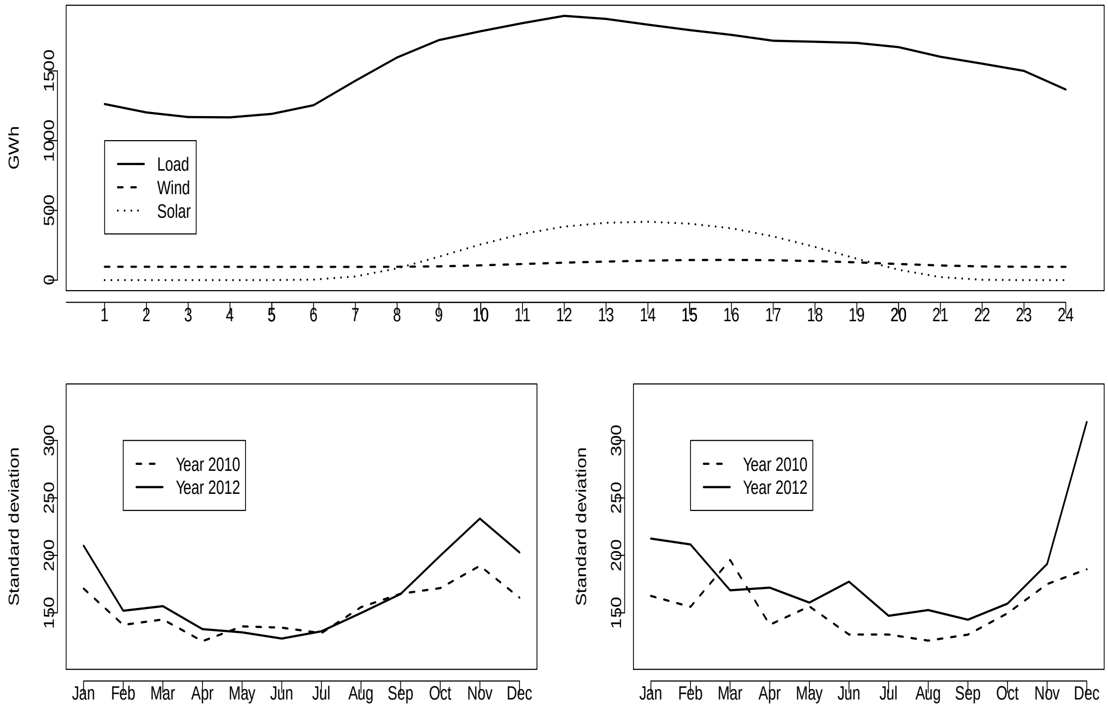

Figure 3: (1) Comparison of demand and unbiddable supply for July 2012, total hourly data, (2) residual load variability across hours within the day and (3) residual load variability across days within the month

Distributions of hourly electricity prices before and after the earthquake are compared in Figure 4. The histograms are overlapped to highlight the differences between the two distributions. As can be seen, the distribution of prices before the earthquake has larger frequencies in the left tail and around the mean (positive differences are in light grey), while the frequencies of the distribution after the earthquake are higher in the right tail (positive differences are in black). Descriptive statistics of the distributions depicted in Figure 4 are reported in Table 1. Mean and median prices are both higher after the earthquake. Whilst the standard deviation computed over the whole distribution is slightly higher in the first period, we obtain the opposite conclusion if we focus only on the central part of the distribution considering values between the first and third quartiles. Both distributions show a positive skewness, which is larger after the earthquake.

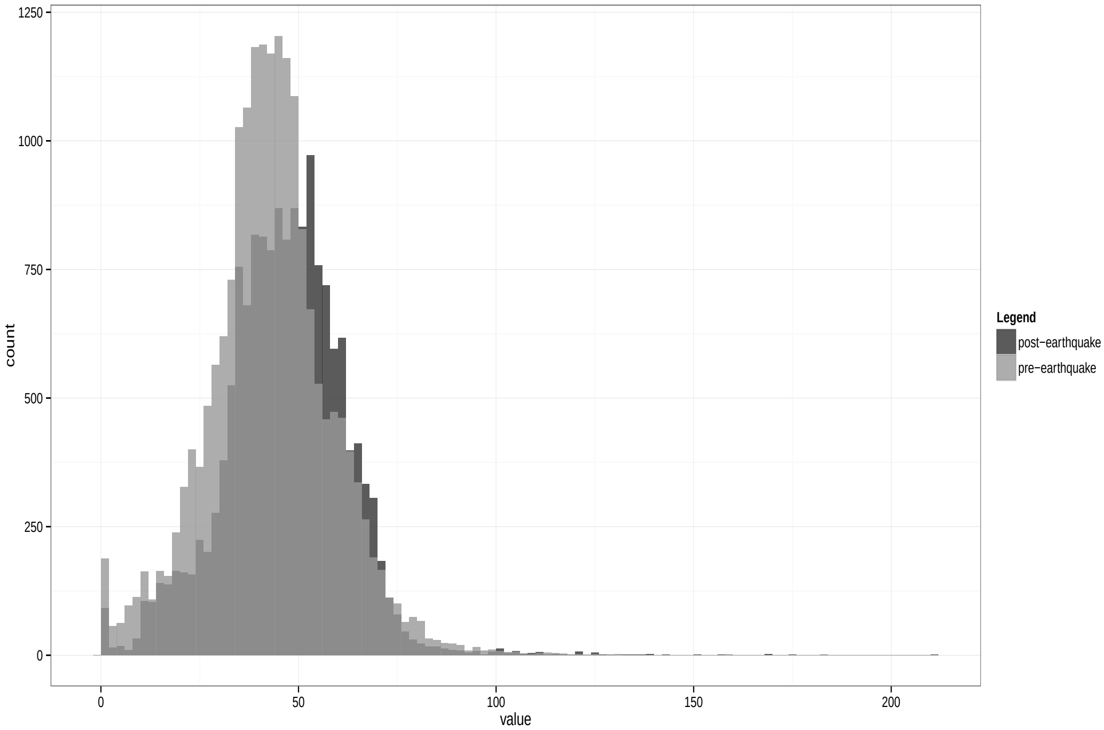

Figure 4: Empirical frequency distributions of spot prices before (light grey) and after (black histograms) the earthquake. The dark grey histograms show the overlapping area of the two distributions. For the sake of clarity the 154 hours with negative prices are not displayed.

Table 1: Summary statistics of pre- and post-earthquake distributions.

	Pre-earthquake			Post-earthquake		
	all hours	peak	off-peak	all hours	peak	off-peak
Median	42.56	48.31	35.93	47.00	53.08	40.10
Mean	42.58	49.64	34.24	46.33	52.38	39.19
Std.dev.	17.12	14.38	16.34	17.09	14.79	16.88
Std.dev. (central distr.)	4.76	4.77	4.63	5.43	4.51	4.16
I Quartile	33.99	40.50	26.81	37.26	44.31	33.08
III Quartile	51.27	58.08	43.35	56.18	61.05	47.91
# Observations	19344	10478	8866	15720	8515	7205

3 Impact of nuclear disaster on energy markets: A literature review

Environmental regulators and policy makers may take decisions which act in conflict with private companies' short run interests because they increase production costs, restrict production, or otherwise constrain the actions of firms (Bushnell et al., 2013). For instance, the decision to shut down nuclear plants after nuclear accidents could have negative effects on the community in terms of higher electricity prices. Most similar to our work is a very recent paper (Davis and Hausman, 2014) that examines the sudden unexpected closure of a nuclear power plant in California which had an impact on Californian generation capacity of similar magnitude to the German decision on German capacity. As is the case in our paper, a natural experimental approach is adopted. However, the details differ significantly: German policy has focused significantly on the subsidised development of renewables, so that wind and solar power (and consequently unbiddable generation) play a significantly larger part in generation. Germany is significantly better connected electrically with surrounding countries than California is with surrounding states. Therefore, whilst the cost of transmission constraints is a major focus of Davis and Hausman, interesting aspects of our paper lie particularly in tracing the impact of the increased variance in supply on prices and in the impact of the German decision on other European countries. Although California is somewhat larger in surface area than Germany, the German population is more than twice that of California, and its GDP is nearly double California's. Hence it is unsurprising that we find the magnitude of the impact of closure through prices to be much larger in Germany.

There is a rich literature in finance which studies the impact of nuclear disasters on stock prices, starting from the seminal paper by Brown and Warner (1985) where the event study methodology was firstly applied to study the effect of an exogenous event on the US stock exchange market. The most dramatic nuclear accidents in the last decades happened at Three Mile Island in March 1979, at Chernobyl in April 1986 and, most recently, at Fukushima in March 2011. The consequences of Three Mile Island disaster on the financial US market were studied by Bowen et al. (1983), Hill and Schneeweis (1983) and Barrett et al. (1986). The effects of the Chernobyl nuclear disaster have been analysed by many papers, amongst them, Fields and Janjigian (1989) and Kalra et al. (1993).

Although the Japanese earthquake is quite a recent event, a number of papers deal with the statistical evaluation of its economic and financial consequences. The main focus of this recent literature is, as with the previous nuclear accidents, on the influence on stock prices using mostly the event study methodology.

The paper by Ferstl et al. (2012) implements an event study experiment to assess the effect of the Fukushima disaster and consequent governments' decision in four countries: Japan, Germany, France and United States. The effect on stock prices in France and Germany was very quickly absorbed, meaning that the expectations of the market operators are towards a gradual shift from nuclear to alternative energies.

Betzer et al. (2013) studies the shareholder wealth effects on electricity companies in Germany and in other European countries in the few days after the Fukushima nuclear disaster using the event study technique. The main findings are of a wealth transfer from nuclear energy companies to renewable companies.

Finally there are various scenario studies that simulate the longer-term impact on electricity prices (e.g Kemfert and Traber, 2011, Knopf et al., 2014, and Fürsch et al., 2012). However, their outcomes are highly sensitive to the assumptions adopted; these models can be very complex and additionally they are not disclosed in detail due to business- and trade secrets (Nestle, 2012). Furthermore, what all these electricity market models have in common is the assumption of perfectly competitive markets.

4 Modelling the German electricity market

Our model of the German day-ahead power market, the market we study, is as follows.[9] Load and price are determined simultaneously in the market through the bids received by the system operator for each hour of the day. Any shortfalls or potential over-supply are handled through the shorter-term mechanisms within the day itself, which we do not consider. Thus what matters to load, and price, in this market are forecasts of values for the next day, not the actual values, which will instead impact on the intra-day activities. We model load in a conventional manner, the only additional element being an allowance for the potential impact of the Ausstieg, through for example load-shedding.

Factors influencing electricity demand are, for the most part, well known. Temperature is a key influence: low temperatures call forth demand for space heating power, whilst high temperatures may increase load due to the requirement for cooling. Lack of daylight also increases demand for lighting purposes. The level of industrial production has a positive impact on load. In addition to daylight, we allow demand to vary according to hour, day, month and season. Indirect effects on energy demand through an increase of final consumer prices resulting from the adjustments of the EEG-Umlage (EEG surcharge)[10] as well as direct effects through improved energy efficiency are captured by a trend variable. Finally, we allow for the Ausstieg decision to have an impact, through a gap between desired/anticipated demand, given underlying endogenous demand factors, and actual load. Absent that effect, we assume that demand equals supply equals load at all times. Several of the factors affecting the supply schedule are somewhat more novel, others more routine. We actually model supply bids into the market. Therefore, to the extent that "must-take" (forecast) wind and solar power are concerned, these reduce the anticipated residual load at the times they are forecast, and therefore reduce the clearing price of bids into the system. Coal, gas and carbon prices are all likely to impact positively on the prices bid in - gas is the most obvious since it is bought nearer to consumption, but the others may also have a significant effect. This effect is also possibly non-linear, because at higher load levels less efficient plant will be bid into operation. The other main variable input[11] into power production is water for cooling purposes, which will have an effect if river levels are low, or if temperatures are too high, because operation may need to be curtailed. Furthermore, river levels are good proxies for generation from run-of-river plants. After

[9] There is also some impact on the year-ahead futures market, which shows an initial overshoot, then a correction, but we do not investigate this in detail here.

[10] The Renewable Energies Act (EEG) is a promotion tool for renewable energy technologies which equips suppliers of renewable energies with a 20-year fixed feed-in tariff and unlimited priority feed-in into the grid. In other words maximum possible generation from renewables will be produced regardless of actual demand and the fixed feed-in tariff is paid instead of a market-based spot price. The system operators manage the process of selling renewables at the spot market and bid forecasted renewables into the day-ahead spot market at the lowest price (which can be zero or negative). The clearing system is via uniform-price which system operators receive for each kW from renewables. The EEG surcharge is a result of this process and is calculated on a yearly basis. It is primarily calculated as the forecasted yearly difference between expected revenues from renewables at the spot market and expected expenditures from the fixed feed-in-tariff payments (e.g. forecasted revenues from renewables in 2013 were 3.1 billion Euro and forecasted expenditures were 22.9 billion Euro) plus the error from the last year's calculation. These costs build the basis of the EEG surcharge and a price per kWh is calculated which is to be paid by the end-consumers as a component of the retail price. Thus, EEG surcharge is likely to have an indirect effect on electricity demand at the wholesale level. Electricity-intensive industries are essentially exempted from the EEG surcharge.

[11] We are assuming that labour acts largely as a fixed input in the short run; plant is of course assumed to be predetermined. Uranium is such a low element of costs in the nuclear industry that it can be ignored.

some experimentation, we included a (low) River Level variable and (high) River Temperature variable in the estimations. Again, we allow for a full set of calendar dummies to impact on supply, although some are unlikely to be important (for example, days of the week as within weekdays).

We should allow for market power to impact upon the price at which supply equals demand. Here, some authors (e.g. Graf and Wozabal, 2013) have concluded that recently there is little abuse of market power in the German market, but nevertheless we should test for its impact, which will in theory be to increase prices when loads are high and several studies have proven its relevance for other countries (Wolfram, 1999, Borenstein et al., 2002, Wolak, 2003). A conventional approach (e.g. Genesove and Mullin, 1998) takes the view that the adjusted Lerner index is an appropriate market power measure. However, in investigating electricity markets, it is commonly found that this does not work particularly well, and Newbery (2008) for example, has argued that the Residual Supply Index (RSI) is more appropriate. He justifies this through use of a Cournot-type model in which the strategic players have contracted some part of their capacity forward prior to the day-ahead bid process. Therefore, this contracted power is not a part of the manipulable supply and hence should not be considered as influencing price for a given load. He shows that under plausible assumptions, the RSI is an appropriate measure. In addition, however, there is an alternative justification for the RSI, based upon a Bertrand model with limited capacity. This model is sketched out in Appendix A to the paper.

The RSI is in general defined as[12]

$$RSI_i = \frac{Total\ Capacity \text{ less } i's\ Relevant\ Capacity}{Total\ Demand} = \frac{\sum_{j \neq i}(k_j - x_i)}{D} \tag{1}$$

where: *Total capacity* is the total regional supply capacity plus total net imports, *Company j's Relevant Capacity* is company i's capacity, k_j, less company i's contract obligations taken as x_i, and *Total Demand, D,* is metered load plus purchased ancillary services.

Whether the RSI or an adjusted Lerner index, is more appropriate as a measure of market power, there is a significant negative correlation between them which was first observed by Sheffrin (2002) and later theoretically derived by Newbery (2008). Furthermore, in the EU Sector Inquiry, London Economics (2007) found statistically highly significant relationships between RSI, Lerner Index and Price-Cost-Mark-Ups in the German Market. In sum, we assume the RSI to be an appropriate measure for market power.

Germany is by no means an electrical island. There are interconnectors with the countries that surround it, but these are capacity limited. If the interconnectors operate below capacity, then it may be expected that anticipated high prices in Germany will call power from other countries through arbitrage operations, whilst the reverse will happen if German prices lie below those of other countries. Of course, if for operational or other reasons interconnectors are congested, this import/ export activity will be curtailed. Thus, if German prices are relatively high, but the import facilities are congested, prices will

[12] E.g. Newbery (2008) or Twomey et al. (2005).

not be moderated by additional imports, and vice versa for export facilities.

Finally, our discussion in section 2 suggests that the Ausstieg event potentially has effects both due to the impact of lower capacity and due to the impact of increased variance. This latter effect leads to a lower level of baseload via nuclear power and a higher level of "must-take" intermittent power. Let us examine the increased variance issue in more detail. Consider it in simple terms as follows. Assume the supply schedule is convex, with the upper part (beyond baseload) strictly convex. We commence with an endowment N of baseload nuclear capacity that, for simplicity, provides a constant flow nt of power. This endowment is reduced exogenously at a point in time, A, to θN with the flow reducing to θnt. Assume that nt is the lowest value taken by load. The lost endowment is replaced at A by an endowment R of must-run renewable generation capacity providing a flow rt of power. Assume that $E(rt) = (1-\theta) \cdot nt$, and that rt is symmetrically and uniformly distributed between 0 and $2 \cdot (1-\theta) \cdot nt$. Thus the total baseload plus must-run supply is distributed symmetrically and uniformly between $\theta \cdot nt$ and $nt + (1-\theta) \cdot nt$, and the mean of this distribution is nt. Supplying the lowest value of load, nt, is on average more expensive after time A than before, because of the strict convexity of the supply schedule. By an extension of the same argument reliant on (non-strict) convexity, supplying any load greater than nt is also no less expensive in expected value terms after time A. Clearly, this argument makes a number of simplifying assumptions, but the key assumption, convexity of the supply schedule above some low level, is well-established empirically, for nations with many power plants. This suggests that the impact of the Ausstieg will differ depending upon the location of the intersection of demand along the supply curve. Therefore, in order to capture the effect of the Ausstieg, we explore both a dummy that has a constant impact following the initial decision, and dummies that separate this effect into different impacts across different seasons and peak and off-peak times. To summarize then, our basic estimation model takes on the following form:

$$D = D(P, IP, T, DL, Cal, Trend, D^{Fuk}; \varepsilon) \tag{2}$$

$$S = S(P, RSI, RE, CoalP, GasP, CarbP, Imp, Exp, RivT, RivLev, Cal, D^{Fuk}; \varepsilon) \tag{3}$$

$$S = D = L \tag{4}$$

where D is demand, P is spot price and L is Load. Furthermore, IP is an industrial production index, T is temperature, DL is a dummy for peak daylight hours, Cal is a set of calendar dummies, D^{Fuk} is a dummy for the Ausstieg event. S is supply, RSI is our market power index, RE is the forecast of production from Wind and Solar, AAP is the price of AA (AA = Coal, Gas or Carbon), Imp and Exp refer to import and export interconnector availability, $RivT$ and $RivLev$ refer to (low) average river levels and (high) temperatures for the major rivers. All these variables are defined more completely in the data section. Since we assume supply equal to demand equal to load, we can rewrite the system in terms of the two key endogenous variables, load and price, as follows:

$$\begin{aligned} L &= L(P, IP, T, DL, Cal, Trend, D^{Fuk}; \varepsilon) && (5) \\ P &= P(L, RSI, RE, CoalP, GasP, CarbP, Imp, Exp, RivT, RivLev, Cal, D^{Fuk}; \varepsilon) && (6) \end{aligned}$$

It is this system (5) and (6) that we estimate below. Load and price are endogenous. We treat the weather/ natural variables as exogenous, we take European prices for coal, gas and carbon in order to view them as essentially exogenous given the extensive market, and we view the import and export capacities variables as predetermined in the short run. We also assume that temperature does not influence supply, save through any indirect effects on *River Levels* and *River Temperature*. We view this as non-controversial.[13] RSI is potentially endogenous and we therefore instrument for it as well as instrumenting for load and price. As both equations are in principle (over) identified - the load equation excluding factor prices and forecasted generation from renewable sources, the spot price equation excluding temperature, daylight hours and industrial production - the estimations is by GMM. The equation system is estimated for the most part using hourly observations over the complete calendar years 2009 to 2012 spanning the event we wish to evaluate.

5 Data and Empirical Model

The empirical model is composed of two equations representing (5) and (6). In the demand equation, Load (L_t) is regressed on prices (P_t) and a set of other variables, that is

$$\begin{aligned} L_t &= \beta_{01} + \beta_{11} P_t + \beta_{21} D_t^{Fuk} + \beta_{31} IP_t + \beta_{41} DL_t + \\ &+ \sum_{i=1}^{K_{11}} \varphi_{i1} T_{i,t} + \sum_{j=1}^{K_{21}} \lambda_{j1} Cal_{j,t} + \beta_{61} Trend_t + \varepsilon_{t1} \qquad (7) \end{aligned}$$

whilst in the supply equation, prices are regressed on load and a set of other variables, that is

$$\begin{aligned} P_t &= \beta_{02} + \beta_{12} L_t + \beta_{22} D_t^{Fuk} + \beta_{32} RSI_t + \sum_{i=1}^{K_{12}} \varphi_{i2} X_{i,t} + \\ &+ \sum_{j=1}^{K_{22}} \gamma_{j2} CI_{j,t} + \sum_{k=1}^{K_{32}} \alpha_{k2} Riv_{k,t} + \sum_{l=1}^{K_{42}} \lambda_{l2} Cal_{l,t} + \varepsilon_{t2} \qquad (8) \end{aligned}$$

where $X_{i,t}$ is a set of control variables consisting of fuel prices for gas and coal, prices for emission

[13] Technically, temperature does not affect the generation of solar power- it is the impact of the sun, not heat. Indeed, at very high temperatures production may be lower than at lesser temperatures.

rights and forecast generation from renewables, $CI_{j,t}$ are indices measuring the degree of interconnector congestion for imports and exports, $Riv_{k,t}$ is river temperature index and river level index, $Cal_{j,t}$ and $Cal_{l,t}$, respectively, are sets of calendar dummies (hour, office day and months); the remaining variable names are as above. The earthquake dummies have been fixed equal to 1 from March 18$^{\text{th}}$ 2011 when the "Atom Moratorium" was decided. Not shown above for simplicity, we engage in various interactions and introduce some non-linearities into the equations (7) and (8) in order to take account of known non-additive elements.

All variables are time series collected from January 1$^{\text{st}}$ 2009 to December 31$^{\text{st}}$ 2012. Prices are measured hourly in Euros/MWh. They have been obtained from the day-ahead auctions of the European Power Exchange (EPEX). The volumes of electricity consumption are the hourly Load data gathered from the ENTSO-E (European Network of Transmission System Operators for Electricity) website. They are the sum of German and Austrian load as Austria can be considered to be fully integrated in the German market due to sufficient interconnector capacity. The main independent variables that do not vary by the hour are industrial production, river variables and factor prices. A description of all variables affecting the demand side and the supply side, respectively, follows below.

5.1 Demand side

Monthly industrial production indices (IP_t) for Germany and Austria have been downloaded from the Eurostat website and refer to the total industry (excluding construction and electricity and gas supply). Data are adjusted by working days. Meteorological variables for Germany come from the Federal Ministry of Transport, Building and Urban Development of Germany (`http://www.dwd.de/`). Temperature is measured and published for every hour of the day for several measuring stations and is the air temperature at 2m high above ground. We collected hourly temperature data for the biggest cities by population of each German Bundesland (Federal States). If data for the biggest city was not available we chose a city nearby. Temperatures are then weighted in proportion to each Bundesland's percentage of Germany's population to compute an index.[14] Temperature data for three main Austrian cities are obtained from Mathematica 9.0 and included in the Temperature variable.[15]

We additionally compute an alternative temperature index which directly addresses the non-linear effect of temperature on demand and separates the two different demand effects "cooling" (*CDD*) and "heating" (*HDD*). This approach is relatively well-known in literature (c.f. Green, 2005 and, more recently, McDermott and Nilsen, 2014). These variables measure the extent to which temperature falls out of a given "comfort zone" between 18°C and 22°C within which temperature should not have an impact on demand. Beyond this range the *HDD* variable measures how far the temperatures drops below

[14] The original values are in degrees Celsius, but we transformed them in degrees Fahrenheit to avoid problems with mathematical transformations of negative values which could arise through the introduction of a quadratic term in the demand equation.

[15] The Austrian temperature index is built from the cities Vienna, Linz and Graz and is included in the overall temperature index in the ratio 1:10 which reflects the ratio of population.

Table 2: Yearly electricity production (in MW) from renewable sources and corresponding index numbers (2009=100)

			Index numbers (2009=100)	
Year	wind	solar	wind	solar
2009	36750790	5957694	100%	100%
2010	37891970	10272334	103%	172%
2011	45065264	19638341	123%	330%
2012	47775883	27941861	130%	469%

18°C and thus increases demand for the purpose of "heating" whereas *CDD* measures the extent to which temperature exceeds 22°C and thus requires "cooling".

The variable *DL* is a binary variable for daylight hours and controls for changes in the need of electric light in the morning and evening hours. Between 5am and 8am (earliest and latest sunrise within one year) it is equal to one if sun already has risen and between 5pm and 9pm (earliest and latest sunset) it is equal to one before sunset. For the hours from 9am to 4pm as well as for the hours from 10pm to 4am it is always zero. Furthermore, the variable *DLH* is an additional *daylight hours* variable and represents the total hours of day with daylight and is the difference between the time of sunset and the time of sunrise. We relax the assumption of a fixed input-output ratio by including a trend variable $Trend$. The trend should capture gradual negative impacts on demand through improved energy efficiency and a net price increase to end-consumers from the yearly rise of the EEG-surcharge.

5.2 Supply side

RE_t is our renewable energies variable and is the sum of the day-ahead forecast of wind and solar generation by hour. As described earlier the EEG provides renewables with an unlimited priority feed-in into the grid regardless of actual demand and owners of renewable energy plants receive fixed feed-in tariffs instead of market based spot prices. The TSO (Transmission System Operators) are obliged to place the forecasted amount on the EPEX day-ahead market at the lowest possible price. In other words, predicted generation from renewable energies shifts the merit order curve to the right which reduces the price that is paid to conventional power plants. Therefore, inherent to the current system, generation from renewables can be considered as exogenous.

Data of day-ahead wind forecasts are published on the websites of the four German TSOs for 2009 and on the Transparency Platform of the European Energy Exchange (EEX) for the remaining years. Solar data are obtained from the commercial provider Eurowind from 2009 until June 2010 and afterwards downloaded from the EEX Transparency Platform. Due to the almost riskless investments with fixed feed-in tariffs, Germany experienced a dramatic expansion of wind and in particular solar plants and thus generation from these sources in recent years as illustrated in Figure 5 and Table 2. Hence, renewables play a major role in explaining prices.

To control for price developments in the European Emissions System Trading Scheme (EU ETS) we

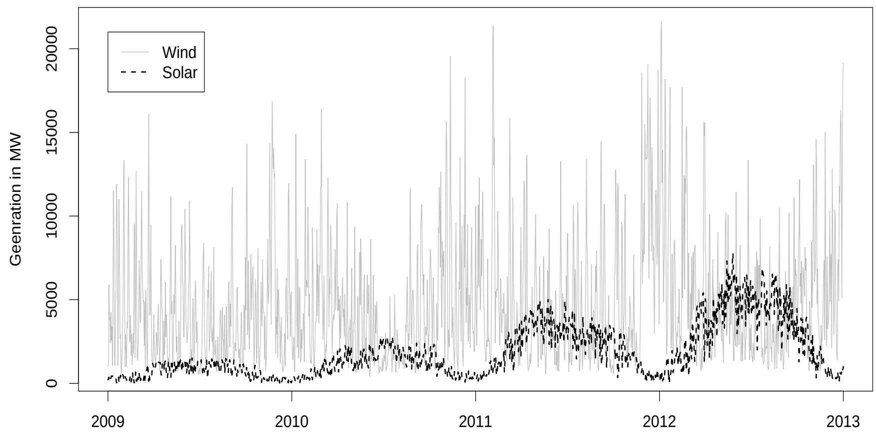

Figure 5: (Forecasted) Generation from Wind and Solar between 2009 and 2012. Average daily values.

use the Carbon Price Index (Carbix) which the EEX computes daily. Import price indices for natural gas and hard coal, respectively, at the German border serve as input price approximation. They are produced monthly by the Federal Statistical Office of Germany. The base year is 2005. In case of daily and monthly time series, each hour of the day and month, respectively, in our hourly initial matrix is given the same value. Prices for coal, gas and carbon are assumed to be exogenous, given that the prices for these inputs are determined on a supra-national basis rather than being set domestically within Germany. Coal and gas are traded on the world market and carbon within the EU ETS which covers all 28 EU states plus Norway, Lichtenstein and Iceland.

Furthermore, we use data on river levels and river temperatures to control for the impact of cooling water scarcity on thermal power plants' supply. The unavailability of thermal power plants due to cooling water scarcity is likely to have a positive impact on prices as shown by McDermott and Nilsen (2014). Generation from run of river power plants is affected by falling river levels in the same direction. These data have been obtained from the German Federal Waterways and Shipping Administration (WSV). They are daily measurements on all German rivers for shipping transport.[16] We use a 23°C threshold as for most of the rivers 23°C is the legally envisaged value that, if exceeded, forces power plants to decrease electricity generation on grounds relating to the protection of the environment. The river temperature variable *RivT* is the extent to which the mean temperature of all rivers temperatures exceeds 23°C. Our river level variable *RivLev* is constructed as the mean of the aggregated river's "low level dummies". Following McDermott and Nilsen, 2014, a river's "low level dummy" is equal to one if its river level falls below the 15% percentile and otherwise zero.

[16]These are Donau, Rhein, Main, Elbe, Mosel, Neckar, Weser, Spree and Ems.

5.3 Import and export congestion

The German electricity market is well connected with the neighbouring countries' markets. However, with the exception of the Austrian border, available interconnector capacity is limited and varies daily and even hourly. It is likely that the impact of the decrease of the nuclear power plant fleet can partly be compensated by electricity imports from neighbouring countries as far as available interconnector capacity allows. However, the incentive for cross-border trade arises through the existence of price differences between countries connected by interconnectors, which may cause endogeneity through two-way causalities. Due to aggregation of interconnector capacities and congestion and the relatively high number of connected countries, in particular given that each has only relatively low interconnector capacity compared to total German load, we do not think that endogeneity from simultaneity is a major concern in this case. By contrast, the interconnector capacity between Germany and a smaller neighbour can be big enough to directly affect prices in the *neighbouring* country when the ratio between its domestic load and the interconnector capacity is relatively high[17]. This issue will be investigated in section 7. In order to identify congestion we use spot price differences between Germany and each neighbouring country. In our analysis we include all countries or price zones, respectively, which share interconnectors with Germany, bar Sweden[18]. These are the Netherlands, France, Poland, Czech Republic, Switzerland, Denmark West and Denmark East. Hourly spot prices are gathered from each country's power exchange and, if required, transformed into Euro using daily exchange rates from Thomson Reuter Data Stream. To capture exchange rate errors and to reflect the fact, that on some borders allocation of interconnector capacity takes place via explicit auctions, we allow for small price differences up to 1 Euro. By doing this we hope to adjust for most of the explicit auctions' expectation errors.[19]

We then build hourly indices for import and for export congestion ($CI_t^{Imp(Exp)}$). Therefore, we first compute hourly dummies for import and export congestion ($D_{t,i}^{Imp(Exp)}$) at each border i in hour t which are equal to one if the interconnector is fully utilized and otherwise zero. These are multiplied by the border and direction specific day-ahead ATC (Available Transfer Capacity) to weight interconnectors by their maximum possible trade volume in a congested hour. Subsequently, we divide the sum of all border specific indices by the aggregated ATCs. That is

[17] Germany shares interconnectors with the Netherlands, France, Switzerland, the Czech Republic, Sweden, two Danish price zones and Poland. Furthermore, Germany is indirectly connected with Belgium and Slovakia through market coupling and coordinated auctions agreements. A table on the ratio between interconnector capacity and load for each country can be found in Table A.1

[18] Sweden is connected with Germany via a sea cable, the so called Baltic Cable, which has a maximum capacity of 600 MW. Unfortunately, there is no data on the Available Transfer Capacity (ATC) of the Baltic Cable published for our observation period so that we had to exclude Sweden from the import and export variables. ATC is the hourly interconnector capacity that is actually released for cross-border trade by the TSOs.

[19] In explicit auctions arbitrageurs submit bids for interconnector capacity in the direction from the low price to the high price country which reflect the expected price. Due to uncertainties with respect to the expectation of price differences, small price differences can occur even if there is no congestion between two countries in explicit auctions (see Gebhardt and Höffler, 2013). By contrast in the implicit auction, which gained popularity in recent years, there are no bids for interconnector capacities but an auction office collects the national spot exchanges' aggregated order books and optimizes cross-border capacity allocation. Thus, price differences cannot occur when interconnector capacities are fully utilized in the implicit auction. The one Euro price difference is arbitrary but we compared results from different specifications (no price difference, price differences of 1% and 10%, respectively); results are robust and only marginally sensitive to these changes.

$$CI_t^{Imp(Exp)} = \frac{\sum_{i=1}^{N} \left(D_{t,i}^{Imp(Exp)} \times ATC_{t,i}^{Imp(Exp)} \right)}{\sum_{i=1}^{N} ATC_{t,i}^{Imp(Exp)}} \tag{9}$$

with

$$D_{t,i}^{Imp} = \begin{cases} 1 & if \quad P_{t,G} - P_{t,i} > 1 \\ 0 & if \quad P_{t,G} - P_{t,i} \leq 1 \end{cases}$$

and

$$D_{t,i}^{Exp} = \begin{cases} 1 & if \quad P_{t,i} - P_{t,G} > 1 \\ 0 & if \quad P_{t,i} - P_{t,G} \leq 1 \end{cases}$$

P denotes the prices in N neighbouring countries i and Germany (G) in a certain hour t. Hourly day-ahead ATC data are obtained from the four German TSOs 50Hertz, TransnetBW, Amprion and TenneT TSO (EON sold its high voltage grid to the Dutch TSO TennetT Holding in 2010), the neighbouring countries' TSOs RTE (France), the TenneT Holding (the Netherlands), Energienet.dk (Denmark), CEPS (Czech Republic), PSE (Poland) as well as the auction offices CASC and CAO.

5.4 Market Power

To control for changes in market power over the time we compute hourly RSIs. The RSI indicates the degree of market power and (contrary to concentration ratios and Herfindahl-Hirschman Index) considers the dynamics of the demand side and thus has to be treated as endogeneous. If a supplier's RSI falls below 1 it is said to be a pivotal supplier, which means that its capacity is necessary to meet demand. To construct the RSI, we use plant and ownership specific master data from the EEX and adjust them for decommissioned and new power plants to build yearly ownership ratios for Germany's biggest electricity suppliers; the nuclear power plants affected by the Fukushima decision are eliminated on March 18th 2011.[20] With approximately 25% of the total conventional capacity in the German-Austrian market before Fukushima and 24% after Fukushima, RWE is the biggest supplier, followed by EON (20% before and 19% after Fukushima). Vattenfall is the number three with 15% market share before Fukushima and 14% afterwards. The Southern-German electricity supplier EnBW was hit hardest by the Ausstieg decision: its market share decreased from 10.6% to 8.5%. Following Twomey et al. (2005) we define the market's RSI as "lowest company RSI among all the companies in the market" which in our case is always RWE.

After we have computed the installed capacity of all firms except RWE -we deduct from it the capacity contracted in the reserve power market since reserve power auctions take place prior to the spot

[20]Even though they were not officially decommissioned at this date, they were not allowed to be on grid from then on as a result of the "Atom-Moratorium" decision.

market auctions which makes this capacity unavailable for spot trade.[21] Since reserve power auctions are anonymous we multiply reserve capacity by the aggregated market shares of all suppliers except RWE and subtract it from the system's total capacity. Data on reserve power auctions are downloaded from regelleistung.net.[22] We proceed analogously with the system's capacity that is not available e.g. due to outages and overhauls[23].

Cross-border trade is treated as follows: assuming that all suppliers have the same incentives to engage in cross-border trade (e.g. they do not want to raise suspicion of market power abuse if they do not participate in cross-border trade when prices in neighbouring countries are lower) or automatically participate in cross-border trade in the case of implicit auctions, exports reduce the available capacity, but ownership ratios remain unchanged. By contrast, against the background that the German giants RWE and EON only play a minor role in neighbouring countries' electricity generation, imports reduce the ownership ratios of the available capacity. Hence, available export capacity and available import capacity have to be treated in different ways. Exports are treated like reserve capacity: the available interconnector capacities for exports from countries with higher prices are multiplied by the aggregated market shares of all suppliers except RWE and afterwards subtracted from total installed capacity. By contrast, available import capacity is added as a whole if prices in the corresponding neighbouring countries are lower.

We then build the residual demand in the denominator by subtracting wind and solar generation from load as they have to be regarded as must-take capacities according to the EEG priority feed-in. RWE's RSI in t is then constructed as follows:

$$RSI_{t,RWE} = \frac{\sum_{k=1}^{K}(IC_{t,k} - UC_{t,k}) + \sum_{i=1}^{N} Imp_{t,i} - \left(\sum_{i=1}^{N} Exp_{t,i} + RP_t\right) \times (1 - S_{t,RWE})}{L_t - RE_t} \tag{10}$$

with

$$Imp(Exp)_{t,i} = \sum_{i=1}^{N} \left(D_{t,i}^{Imp(Exp)} \times ATC_{t,i}^{Imp(Exp)}\right) \tag{11}$$

$IC_{t,k}$ is firm k's installed capacity with $k = 1, \cdots, K$ and $k \neq RWE$. UC_t is unavailable capacity. Exp_i and Imp_i is the maximum export and import capacity from/to country $i = 1, \cdots, N$. RP denotes the contracted reserve power capacity in t. Again, L_t is the equilibrium quantity and RE_t is generation from renewable sources wind and solar. $S_{t,RWE}$ is RWE's market share, that is

[21] Reserve power, also called balancing power or control power, is an ancillary service required to stabilize the system if deviations between electricity fed into and withdrawn from the grid occur.

[22] We adjust for the reserve power qualities positive secondary and minute reserve power, but not for primary reserve, since primary reserve is not distinguished in positive and negative reserve and, furthermore, there are no capacity auctions for primary reserve. However, primary reserve only plays a minor role and accounts for less than 10 percentage of the reserve power market.

[23] Aggregated data on unavailable capacity is published on the EEX Transparency platform. As 2009 is not published we assume a similar structure to that in 2010 since overhauls take place at the same times in general and make up the biggest part of unavailable capacity. We do not have information on forward contracts, but in any case the effect on market power will depend significantly on precise details of how they range across firms (de Frutos and Fabra, 2012).

$$S_{t,RWE} = \frac{IC_{t,RWE}}{\sum_{k=1}^{K} IC_{t,k} + IC_{t,RWE}}.$$

Then, the RSI variable in our model is constructed as $(1.1 - RSI) \times I^{RSI<1.1}$. Here, $I^{RSI<1.1}$ is an indicator which is equal to one if the RSI is less than 1.1. The threshold of 1.1 is chosen to account for possible collusive patterns, explicit or implicit (e.g. from joint hockey stick bidding, see Rothkopf (2002) or Hurlbut et al. (2004)) in addition to pivotal market power. Thus, a high value of our RSI variable can be interpreted as an increase in market power.

5.5 Summary statistics

In Table 3 we report mean values and standard deviations (in parentheses) of our key variables. If we consider the whole observation period the EPEX spot price is around 44.26 Euro/MWh on average, however, it is approximately 9% higher after March 18$^{\text{th}}$ 2011, than it was before. By contrast, load remains quite stable. Generation from renewable energies (wind and solar) provides about 12% of total demand in the full sample with an increase from 10% to 15% if we consider the pre- and post-Fukushima periods separately. This is mainly a result of increased solar generation which tripled in the post-Fukushima sample and increased its share of total generation from 1.7% to 5.3% compared to the pre-Fukushima period. Concerning market power, the RSI variable increased by almost 50% from 0.035 to 0.049, which indicates that market power plays a bigger role after the nuclear plants have been shut-down. Interpreting import and export congestion is less straightforward as there have been several changes in the operation of interconnectors on several borders in recent years aiming to allocate cross-border capacity more efficiently (for instance, coordination of explicit auctions between a couple of countries, replacements of explicit auctions in favour of implicit auctions and market coupling arrangements). River levels have been around 13% higher in the pre-Fukushima sample which is of importance as we will show later.

6 Results

In Table 4-6, we report the results of our estimated model versions of (7) and (8).[24] Generation from renewables is transformed into logarithms to reflect the fact that marginal costs of the supply schedule of conventional power plants are convex to the origin. The transformation should capture the decreasing impact of renewable energy generation on prices. Furthermore, we allow for some interactions between variables where we consider this may be relevant. In particular we interact the generation from renewables with seasonal dummies as well as dummies for periods with low demand and periods with high demand.[25] It is straightforward that the impact of renewable energies on prices varies considerably between high

[24] Phillips-Perron and Augmented Dickey-Fuller tests for unit-root both reject the non-stationarity null for both, hourly and daily series. Test statistics are reported in Table C.1, in Appendix.

[25] We define peak hours (hours between 8am and 8pm) on working days as high demand and the remaining hours as low demand. Thus, just to clarify, peak hours on weekends are treated as low demand.

Table 3: **Summary statistics.**

	(1) Full Sample		(2) pre-Fukushima		(3) post-Fukushima	
Price (Euro/MWh)	44.26	(17.21)	42.58	(17.12)	46.33	(17.09)
Load (MW)	61458.5	(11451.8)	61355.06	(11143.6)	61585.8	(11819.1)
Renewables (MW)	6596.3	(4967.1)	5360.6	(3873)	8116.9	(5690.6)
Wind (MW)	4776.5	(3984.1)	4417.8	(3676.4)	5217.9	(4292)
Solar (MW)	1819.8	(3243.6)	942.8	(1559.6)	2899	(4285.3)
Gas Price Index	156.41	(27.82)	136.15	(20.31)	181.35	(9.59)
Coal Price Index	179.09	(16.04)	181.68	(19.93)	175.9	(8.15)
Carbon Index (Euro/EUA)	11.96	(3.229)	13.85	(1.39)	9.639	(3.333)
Imp. Cong. Index (0-1)	0.254	(0.278)	0.272	(0.316)	0.233	(0.219)
Exp. Cong. Index (0-1)	0.339	(0.313)	0.405	(0.338)	0.257	(0.258)
Avail. Imp. Cap. (MW)	12271	(1102.8)	12723.4	(1045.8)	11714.3	(897.3)
Avail. Exp. Cap. (MW)	6752.8	(1071.1)	6689.7	(1238.9)	6830.4	(812)
Aggreg. River Levels (cm)	1889.4	(435)	1994.22	(461.07)	1760.48	(360.93)
Aver. River Temp. (°C)	11.88	(6.99)	10.85	(7.22)	13.14	(6.47)
River Level Index (0-1)	0.15	(0.237)	0.0863	(0.191)	0.228	(0.263)
River Temp. Index	0.019	(0.177)	0.034	(0.238)	0	(0)
RSI	1.308	(0.309)	1.321	(0.292)	1.293	(0.328)
RSI Variable (0-1.1)	0.042	(0.069)	0.035	(0.061)	0.049	(0.076)
Temp. (in F)	49.78	(14.35)	47.88	(14.94)	52.12	(13.28)
Ind. Prod. Index	101.1	(9.89)	95.22	(8.67)	108.26	(5.63)
#Observations	35064		19344		15720	

Note: This table reports the mean values of the variables. Standard deviations are in parentheses to the right. The first sample includes the whole period from January 1st, 2009 to December 31st, 2012. The second sample includes the period from January 1st, 2009 to the closure of the nuclear power plants on March 18th, 2011. The third sample includes the period afterwards.

and low demand periods as they affect different parts of the merit order. Furthermore, the impact differs across seasons as general overhauls of conventional power plants mostly take place in warmer periods with lower demand, more generation from solar and thus lower prices (see the example in Figure 6). In addition, fuel and carbon prices as well as import and export congestion indices are interacted with low and high demand.

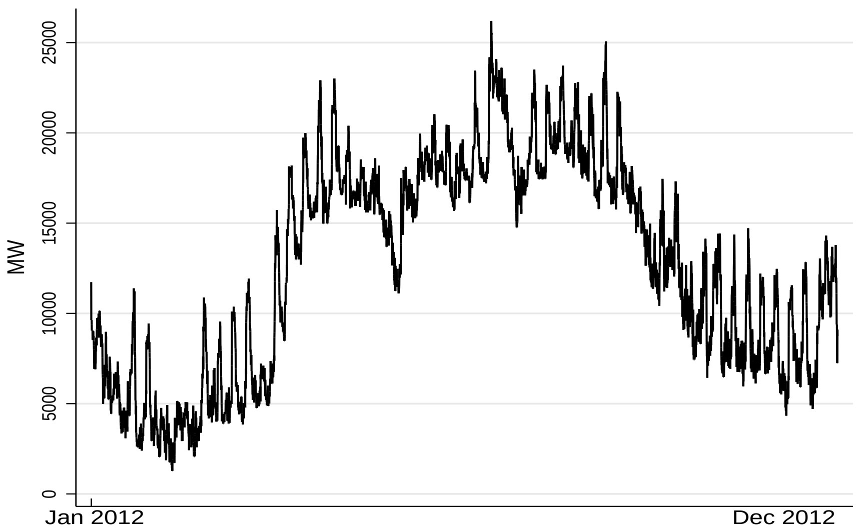

Figure 6: Offline capacity from conventional power plants in 2012

Due to potential simultaneity of electricity demand and supply we use an instrumental variable (IV) approach to ensure consistency of the estimators.[26] Estimation takes account of the heteroskedasticity and serial correlation in the underlying data series as do the reported standard errors and is performed using two-step feasible efficient GMM (EGMM).[27] As already described in section 5, our equations are overidentified. In the spot price estimates we present, instruments for the consumption of electricity (load) are Temperature, Temperature^2, Industrial Production Index and Daylight Hours. In the demand equation logarithms of renewable generation, the price indices of natural gas and carbon emission rights are deployed to instrument for the spot price. The F-Statistics of the excluded instruments in the first stage regression have sufficiently high values in the sense of Staiger and Stock (1997) in all estimations so our instruments appear to work properly. The correlation of our instruments with the error term is tested by the Hansen J-Statistic for overidentifying restrictions which confirms the validity of our instruments.

The general tenor of the results is as expected across all models, both in terms of coefficient signs and magnitudes. Supply price is related to most of the key variables, but the effect differs between hours of low demand and high demand. We had anticipated this, since the supply schedule is likely nonlinear. Signs on renewable power are negative- high renewables lower the market price. Input prices on gas, carbon, and coal take their expected positive value. Coal prices have the more important quantitative impact compared to gas prices in terms of standardized coefficients[28].

Most important for our purposes is the effect of the nuclear Ausstieg. We estimate several models in Table 4 in order to quantify the impact of the Ausstieg decision on prices. In the first model (Table 4, first column) we control neither for river level variables nor the existence of congestions and market power. In this model the coefficient of the Fukushima dummy is highest. River level and temperature variables are included in model (2). Low river levels lead to higher prices, because plant is then constrained in production whereas the river temperature variable remains insignificant. It might be that plants have already been ramped down in situations when the 23° C threshold is exceeded. Controlling for river characteristics significantly decreases the impact of the Fukushima dummy on prices by around one quarter. This result is not unexpected when bearing in mind that river levels have been significantly lower on average in the post-Fukushima period as reported in the summary statistics. Hence, output from run of river water plants and thermal power plants is lower.

We additionally control for cross-border trade congestions in model (3) and therefore include import and export index variables which take the expected signs; we would naturally expect that exports take

[26] It is often assumed that demand for electricity is completely inelastic in the short-term. The Wu-Hausman F-test for endogeneity, however, rejects the null hypothesis that demand is an exogeneous regressor as reported in the following tables. Hence, in our case, the IV estimates seem more sensible than OLS estimates. Nevertheless, results from OLS estimates are similar and are reported in Table B.1 and B.2.

[27] The Pagan-Hall test rejects the null of homoscedastic disturbance and the Cumby-Huizinga test rejects the null of no serial correlation in the error term. Thus, we deploy Newey-West variance-covariance estimators in all estimations. Band-width selection is via the Newey-West procedure. Estimations are by EGMM as in the case of overidentification and HAC (hetero-and autocorrelation consistent)-standard errors IV-GMM estimates are more efficient than the standard 2SLS (2-Stage-Least_Squares) estimator. We employ the Stata package *ivreg2* for our estimations (Baum et al., 2007)

[28] Standardized coefficients of coal and gas prices, computed as *coefficient of regressor* x × (*standard deviation of* x / *standard deviation of regressand* y) are 0.40 for coal price index in high demand hours, 0.59 for coal price index in low demand hours, for gas price index 0.27 in high demand times and 0.16 in low demand hours.

place when the price in Germany is low relative to its neighbouring countries and imports when it is relatively high. If interconnectors for import activities are congested then prices cannot be moderated anymore through cross-border trade and thus rise undamped, and vice versa for the case of congestions in the opposite direction. The estimation of model (3) reveals that the price increase was partially offset by cross-border trade as far as the interconnector capacities allowed. We consider model (3) as the most appropriate model to quantify the total price increase before we separate out the different effects: our estimates suggest that the sudden shutdown of a significant share of the nuclear power plant fleet after Fukushima has created, on average, approximately 7% (3.26 Euro/MWh) uplift on supply prices, *ceteris paribus*.

In model (4) we introduce the RSI variable to split the Fukushima dummy effect into two components. The first is the price increase from a general shift in the merit order. The second is the part of the price increase from changes in the frequency and intensity of situations with market power and capacity shortage, respectively. We add the RSI variable and the squares to model (3) since we assume the impact of the RSI variable is non-linear: trying to exercise market power encapsulates the risk of not being able to sell some share of ones capacity if the supplier erroneously expects to be pivotal. A higher value of the RSI variable and thus a bigger gap between residual demand and supply increases the dominant supplier's belief to be pivotal and thus his willingness to exercise market power.

As the RSI has to be considered as endogenous since it contains demand as part of the denominator we instrument for it and include available capacity, squared available capacity and squares of the load instruments as additional instruments in the estimation. As can be anticipated from Figure 6 there is sufficient variation in terms of available capacity resulting from planned outages to carry out legally required power plant overhauls and unplanned outages plus variation of the aggregated available interconnector capacity. Again, validity and relevance of the instruments are attested by the Hansen J-statistic and first stage F-tests. We additionally report the robust Kleibergen Paap rk Wald F-statistic which points towards a still acceptable relative IV bias around 20% according to the Stock and Yogo (2005) critical values. Our estimates suggest that market power has a significantly positive impact on prices and the inclusion of the RSI reduces the magnitude of the Fukushima dummy to 2.76. This indicates that the higher frequency and the higher intensity of situations with market power in the post-Fukushima period partly drive the price increase and thus the price increase is not just a result of a general shift in the merit order.

In model (5) we investigate a particular case: the German electricity market slid into a critical situation during a cold spell in February 2012. As most of the closed nuclear plants were located in the south (4.95GW out of 6.3GW) the German grid could not manage to conduct sufficient electricity from north to south to satisfy demand. Furthermore, some gas plants were forced to close during this period due to a lack of gas availability. As a result the German Federal Network agency additionally had to call expensive power from contracted "cold reserve" power plants in southern Germany and Austria. In model

(5) we test to what extent the post-Fukushima price increase was caused by this particular situation and include dummy variables for February 2012 and the months before and afterwards to model (3). The estimation indicates that approximately 20% of the price increase due to the Fukushima decision took place during the February crisis, however, the impact of the Fukushima dummy remains positive even after controlling for this special grid situation. Moreover, it is clear that this crisis was intensified by the earlier Ausstieg decision. In the last column of Table 4 we report results from estimates of model (3) with dynamics. In model (6) we include lags of 24 hours for the same hour one day before and 168 hours for a lag of one week. The results confirm the robustness of our estimations and the coefficient of the Fukushima dummy only changes slightly[29].

[29]Some further robustness experiments with daily values are reported in Appendix B. These include results from different functional specification as well as an estimation where residual load is used instead of load.

Table 4: Estimating the supply side (Price).

	(1)		(2)		(3)		(4)		(5)		(6)	
	Basic		River		Cong. Index		RSI		Feb.12		Dynamic	
Demand	0.214***	(0.021)	0.210***	(0.021)	0.229***	(0.022)	0.200***	(0.023)	0.220***	(0.020)	0.201***	(0.024)
Earthquake	4.891***	(0.845)	3.707***	(0.930)	3.263***	(0.944)	2.760**	(1.275)	2.556***	(0.890)	3.181***	(0.898)
RSI							245.9***	(87.39)				
RSI^2							-1001.4***	(370.6)				
Imp. Cong.×Low D.					5.784***	(0.596)	7.404***	(0.758)	5.369***	(0.549)	5.970***	(0.501)
Imp. Cong.×High D.					10.44***	(1.076)	16.12***	(2.437)	10.19***	(1.021)	10.48***	(1.021)
Exp. Cong.×Low D.					-8.085***	(0.785)	-9.816***	(1.139)	-8.610***	(0.769)	-8.257***	(0.717)
Exp. Cong.×High D.					-1.457	(0.898)	-3.317**	(1.491)	-1.844**	(0.817)	-2.332***	(0.863)
Low River Level			4.568***	(1.092)	3.745***	(1.064)	3.383***	(1.095)	4.176***	(1.039)	2.977***	(0.960)
High River Temp.			0.112	(0.556)	0.690	(0.539)	0.910	(0.570)	0.590	(0.525)	0.842*	(0.504)
January 2012									-1.713	(1.836)		
February 2012									6.702***	(2.069)		
March 2012									1.951	(1.469)		
24 Hours Lag											0.103**	(0.043)
168 Hours Lag											0.020	(0.027)
RE×Spr.×High D.	-8.034***	(0.556)	-8.082***	(0.555)	-7.128***	(0.614)	-5.179***	(1.188)	-7.011***	(0.567)	-6.494***	(0.647)
RE×Sum.×High D.	-7.904***	(0.553)	-7.904***	(0.550)	-7.005***	(0.598)	-5.386***	(1.082)	-6.804***	(0.544)	-6.381***	(0.625)
RE×Aut.×High D.	-8.388***	(0.531)	-8.216***	(0.537)	-7.359***	(0.557)	-6.015***	(1.003)	-7.241***	(0.530)	-6.784***	(0.607)
RE×Win.×High D.	-9.195***	(0.664)	-8.918***	(0.652)	-7.802***	(0.671)	-6.217***	(1.150)	-7.731***	(0.656)	-7.075***	(0.607)
RE×Spr.×Low D.	-5.938***	(0.462)	-5.930***	(0.459)	-4.694***	(0.458)	-3.132***	(0.682)	-4.592***	(0.439)	-4.302***	(0.451)
RE×Sum.×Low D.	-5.922***	(0.455)	-5.875***	(0.453)	-4.692***	(0.430)	-3.454***	(0.569)	-4.507***	(0.415)	-4.299***	(0.422)
RE×Aut.×Low D.	-6.460***	(0.526)	-6.245***	(0.542)	-5.055***	(0.509)	-3.800***	(0.629)	-4.969***	(0.507)	-4.696***	(0.522)
RE×Win.×Low D.	-7.678***	(0.727)	-7.327***	(0.720)	-5.916***	(0.684)	-4.521***	(0.808)	-5.880***	(0.688)	-5.331***	(0.602)
Gas Price×High D.	0.082***	(0.028)	0.097***	(0.028)	0.084***	(0.028)	0.088***	(0.029)	0.093***	(0.026)	0.067***	(0.023)
Gas Price×Low D.	0.107***	(0.023)	0.121***	(0.024)	0.094***	(0.024)	0.091***	(0.026)	0.100***	(0.020)	0.070***	(0.020)
Coal Price×High D.	0.124***	(0.023)	0.107***	(0.023)	0.078***	(0.025)	0.062**	(0.027)	0.076***	(0.024)	0.061**	(0.024)
Coal Price×Low D.	0.073***	(0.023)	0.053**	(0.024)	0.054**	(0.025)	0.079***	(0.026)	0.051**	(0.023)	0.039*	(0.021)
Carb.×High D.	1.058***	(0.150)	1.093***	(0.150)	1.054***	(0.152)	1.163***	(0.231)	1.072***	(0.140)	0.881***	(0.124)
Carb.×Low D.	0.934***	(0.141)	0.947***	(0.138)	0.817***	(0.135)	0.815***	(0.121)	0.839***	(0.121)	0.656***	(0.105)
First-stage F-test (Demand)	31.41		32.64		33.84		20.84		37.08		31.27	
First-stage F-test (RSI)							16.14					
First-stage F-test (RSI^2)							11.80					
Kleibergen-Paap Wald F-stat.	31.41		32.64		33.84		5.410		37.08		31.27	
Hansen J statistic	3.454		1.603		3.483		6.096		2.312		5.27	
χ^2 Prob J statistic	0.327		0.659		0.323		0.529		0.510		0.153	
Wu-Hausman F-test	0.000		0.000		0.000		0.000		0.000		0.000	
R^2	0.658		0.664		0.679		0.606		0.691		0.715	
#Observations	35064		35064		35064		35064		35064		34896	

Standard errors are in parentheses. Estimation is by 2-step EGMM. Endogenous variables are *Demand*, *RSI* and RSI^2. Instruments for the *Demand* variable are *Temperature*, $Temperature^2$, *IndustrialProductionIndex* and *DaylightHours*. In Model 4 *AvailableCapacity* and its square as well as squares of the *Demand* instruments are additionally employed to instrument for the *RSI* variables. Statistics are robust to heteroscedasticity and autocorrelation. Calendar dummies and a constant term are not reported. Coefficients and standard errors for Demand are multiplied by 100 for clarity. Significant for * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: **Time and date varying impact of the earthquake.**

	(1) Basic (Est. (3) in Tab. 4)	(2) Low & High D.	(3) Seasons	(4) Low/High D. & Seas.
Demand	0.229***	0.229***	0.228***	0.229***
	(0.022)	(0.023)	(0.022)	(0.022)
Earthquake	3.263***			
	(0.944)			
Earthqu. × Low		5.116***		
		(0.998)		
Earthqu. × High		-0.251		
		(1.306)		
Earthqu. × Spring			2.208**	
			(1.081)	
Earthqu. × Summer			2.418**	
			(1.181)	
Earthqu. × Autumn			2.646**	
			(1.035)	
Earthqu. × Winter			5.073***	
			(1.614)	
Earthqu. × Spring × Low				3.840***
				(1.213)
Earthqu. × Summer × Low				4.890***
				(1.293)
Earthqu. × Autumn × Low				4.802***
				(1.197)
Earthqu. × Winter × Low				6.530***
				(1.54)
Earthqu. × Spring × High				-0.803
				(1.437)
Earthqu. × Summer × High				-2.358
				(1.603)
Earthqu. × Autumn × High				-1.471
				(1.347)
Earthqu. × Winter × High				2.379
				(2.771)
First stage F-Test	33.84	33.75	34.54	34.41
Hansen J-Statistic	3.483	4.089	3.467	3.858
χ^2 Prob J-Stat.	0.323	0.252	0.325	0.277
R^2	0.679	0.68	0.68	0.681
# Observations	35064	35064	35064	35064

The standard errors are in parentheses. Estimation is by 2-step EGMM. Statistics are robust to heteroscedasticity and autocorrelation. The estimation includes all variables from estimation (3) in Table 4. *Demand* is endogenous again. Instruments for the *Demand* variable are $Temperature$, $Temperature^2$, $IndustrialProductionIndex$ and $DaylightHours$. Coefficients and standard errors for Demand are multiplied by 100 for clarity. Significant for $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$

Even though the effect of the nuclear Ausstieg is quite stable across the estimations in Table 4, it varies across periods and seasons as can be seen in Table 5. These estimations are on the basis of model (3) in Table 4. Thus, the RSI is not included in order to capture the full effect of the closure of 6GW nuclear during the different periods. While there was no significant price increase during times of high demand, prices rose significantly in the low demand times (5.1 Euro/MWh, column 2). This result may at first sight seem counterintuitive. However, we should recall the peculiarities of the German situation. Germany has a demand peak in the middle of the day, which is well served in many months by solar output (Figure 3). Of course, this has no impact on the off-peak as there is no PV generation at night.

The impact of the After-Fukushima decision between seasons is similar: the Earthquake Dummy is

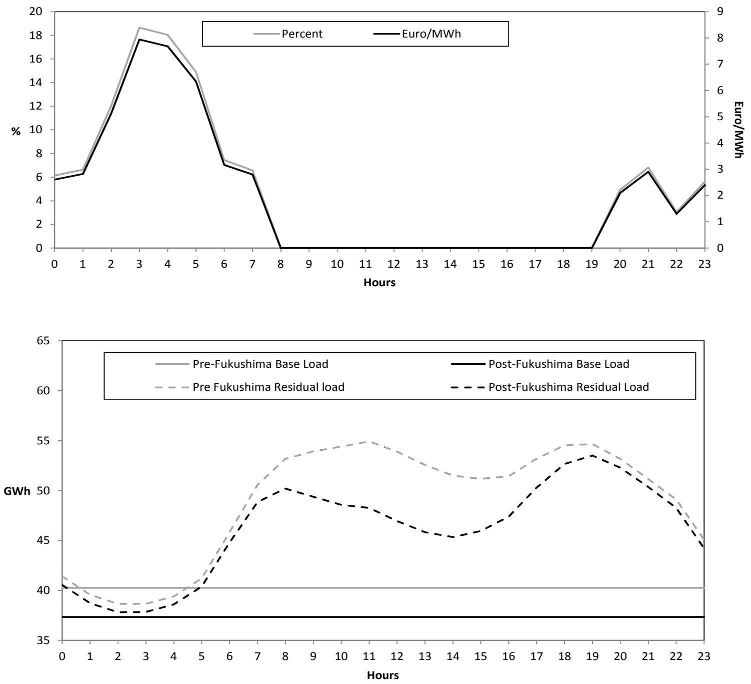

Figure 7: (1) Absolute and relative price increase on hourly basis; (2) comparison of residual load and average available capacity from baseload technologies in 2010 and 2012

significant in winter where the price increased by around 5.1 Euro/MWh (12%) but much less in spring, summer and autumn when days are longer and sunnier and demand is lower. The highest price increase, as a result from the nuclear Ausstieg, can be observed in low demand hours in winter when prices are 6.5 Euro/MWh higher, while there is no significant price increase during high demand hours across all seasons. In both cases, when we calculate the overall impact suggested by our estimates, the summary impact of increased prices is approximately the same whether we use the aggregate impact from Table 4 or the disaggregated impacts coming from Table 5, as we discuss in section 8.

To add to the intuition on these results, we can think of the supply function as being made up of a series of separate sections relating to particular technologies and different efficiencies of the same technology. The results then suggest that in high demand periods on the whole the marginal technology is unchanged by the shrinkage in nuclear provision, due to increased generation from solar. However, in the low demand periods, where nuclear anyway contributes a higher proportion of supply, the marginal plant has on average been changed to a higher cost technology or less efficient plants of the same technology more to the left of the merit order. To examine this we have estimated model (3) separately for every hour of the day. The average development of the earthquake dummy's coefficient across the hours of a day is illustrated in Figure 7 (1). It can be seen that the earthquake dummy's coefficient is highest in the early morning hours while all peak hours remain insignificant. This can be explained by a technology jump in the merit order in the early morning following the closure of the nuclear plants.

We illustrate this in the lower panel of Figure 7. (Residual) load is significantly higher in the evening hours when people cook, watch TV and enjoy their evening while it is much lower in the early morning when everybody sleeps. Thus, the price increase seems to be closely negatively correlated with the residual load level in off-peak hours. We approximate average available baseload capacity using yearly data from nuclear, biomass, water and lignite generation (BMWi, 2014) for the years 2010 and 2012 and compare it with residual load. As Figure 7 reveals, capacity from baseload technologies was sufficient to cover residual load in the early morning hours before the Ausstieg but this was not the case afterwards. As a result the higher coefficients of the earthquake dummy in the early morning hours are caused by a technology jump from lignite to hard coal while they are driven by the use of less efficient plants of the same technology in the evening.

What is perhaps more surprising is that the coefficient on average price increase in the winter high demand period does not achieve statistical significance, given that there the standard deviation of residual load does increase markedly across the day[30]. More generally, where the impact of a cut in conventional generation falls most significantly will depend on the particular features of the market, and in this case these push towards most of the effect taking place in the low demand periods, where baseload plant has been removed.

We now investigate the demand side. Demand is very inelastic with respect to price, at mean values the elasticity is less than 0.1 in absolute terms. The demand estimations in Table 6 only differ slightly if we use Temperature and its square in Fahrenheit or HDD and CDD variables. Demand is minimised at a temperature of 73.6°F (23°C, 1$^{\text{st}}$ column), other things equal, which is almost exactly what would be expected. Industrial production and lack of daylight are very important in affecting demand positively, as expected. It is important to note that the equilibrium outcome was *not* materially influenced by the reduction in generation capacity caused by the Ausstieg, i.e. there was no appreciable rationing as a result. The estimations presented in Table 6 present no evidence for an impact of the "Atomausstieg" event on average demand. This might be because the German Federal Network Agency (Bundesnetzagentur) has contractually ensured 2.5GW so called "cold reserves" power plants (e.g. old and already decommissioned oil plants in Austria) in order to be prepared for the increased risk of outages. These German and Austrian reserve power plants were called upon on more than one occasion in winter (Bundesnetzagentur [Federal Network Agency], 2012).

Column 4 additionally reports the case where the forecast of renewable energy generation is not considered as an instrument which actually is the case in many studies of the German market. The increasing importance of renewables for prices is highlighted here. Spot prices then have a positive sign. Surprisingly, however, the first stage F-Test still is high enough to accept the null of sufficiently strong instruments and misleadingly indicates the spot prices to be insignificant.

[30] Note that we have classified periods into high and low demand and not into peak and off-peak. Thus, solar contributes to low demand in peak hours on weekends and holidays. We have also done estimations with classification into peak and off-peak periods. Then, peak becomes significant for winter but remains insignificant for the remaining seasons.

Table 6: Estimation of the demand side (load).

	(1) Temp, Temp^2	(2) HDD, CDD	(3) HDD, CDD & squar.	(4) RE not as an Instr.
Price	-62.96***	-57.28***	-63.37***	30.16
	(18.39)	(18.16)	(18.33)	(64.92)
Earthquake	-361.7	-205.4	-305.7	-841.2*
	(427.8)	(428.3)	(431.7)	(507.8)
Temperature	-565.0***			-436.6***
	(60.04)			(99.95)
Temperature^2	4.380***			3.452***
	(0.48)			(0.752)
HDD		370.4***	92.14*	
		(39.48)	(47.41)	
CDD		421.8***	612.5***	
		(62.23)	(138.1)	
HDD^2			11.33***	
			(2.176)	
CDD^2			-40.87**	
			(16.68)	
Ind. Prod. Index × High D.	532.4***	530.8***	534.3***	392.9***
	(39.01)	(39.32)	(39)	(99)
Ind. Prod. Index × Low D.	457.6***	456.6***	459.7***	323.3***
	(38.47)	(38.81)	(38.47)	(95.43)
Daylight × Week	-1241.0***	-1165.8***	-1214.7***	-932.6***
	(140.9)	(138.6)	(139.5)	(243.9)
Daylight × Weekend	-4513.0***	-4409.5***	-4486.6***	-3891.2***
	(206.9)	(203.9)	(204.8)	(467.1)
Daylight hours	-437.7**	-248.2	-370.9*	-472.0**
	(212.4)	(221.4)	(213)	(197.6)
Trend	-1836.4***	-1910.9***	-1870.6***	-993.5
	(306.1)	(312.1)	(307.5)	(609)
First-stage F-test	162.5	162.9	163.6	17.9
Hansen J statistic	3.93	6.11	4.32	2.67
χ^2 Prob J stat.	0.14	0.05	0.12	0.10
R^2	0.87	0.87	0.87	0.89
#Observations	35064	35064	35064	35064

The standard errors are in parentheses. Estimation is by 2-step EGMM. *Price* is endogenous. Instruments are logarithms of *Renewables*, Indices for *GasPrice* and *CarbonEmissionPrices*. Statistics are robust to heteroscedasticity and autocorrelation. Calendar dummies and a constant term are not reported. Significant for * p < 0.1, ** p < 0.05, *** p < 0.01.

7 Broader European impacts, a VAR approach

We now turn to studying the impact that the decision taken unilaterally by the German government had on the electricity markets of neighbouring countries which are directly connected to the German market that is: Netherlands, France, Poland, Czech Republic, Switzerland, Denmark West and Denmark East.[31] We do not intend a complete investigation of each country's supply-demand framework, which would require detailed knowledge of the peculiarities of each country and would also bring in to consideration interconnection between these countries and their own neighbours that are not German neighbours. Rather, we simply wish to establish whether effects of the German decision are found outside Germany and Austria and contribute to the discussion on the development of a single European electricity market.

[31] As in the univariate analysis, German and Austrian markets have been studied as a single market. Even though Germany and Belgium are neighbours, there is no direct connection between the two countries. The TSOs of the two countries are currently considering a HVDC line of 1000 MW, but it could be realized not before 2016-2017 (Jauréguy-Naudin, 2012).

As the study focuses on the links between markets and only marginally on the determinants of prices and demands, the multivariate analysis is carried out on daily time series. We will focus on the supply side, that is on electricity prices. As it is well known, prices observed on contiguous and connected electricity markets are usually correlated and tend to affect each other (see, among others, Lindström and Regland, 2012; Zachmann, 2008). One natural way to carry out this analysis of market interconnection is to estimate a Vector AutoRegressive (VAR) model where the time series of prices are considered as endogenous variables.

Vector AutoRegressive (VAR) analysis has evolved as a standard instrument in econometrics (Sims, 1980) because it can be considered a natural extension of the univariate autoregressive model to dynamic multivariate time series. VAR models could be applied both to the analysis of covariance stationary multivariate time series and to the analysis of nonstationary multivariate time series incorporating cointegration relationships. To select which kind of approach should be followed in our study we need to test for the presence of a unit root in the analysed series. The Dickey- Fuller and the Phillips-Perron test for the presence of a unit root have been carried out on the whole sample and are reported in Table C.1. The null hypothesis of the presence of a unit root is always rejected. These results justify the estimation of a covariance stationary VAR model.

In its basic form, the estimated VAR model for the supply side consists of a set of eight endogenous variables given by the time series of electricity prices $P_t = (P_{Dt}, P_{CHt}, P_{NLt}, P_{DKWt}, P_{DKEt}, P_{Ft}, P_{PLt}, P_{CZt})'$ in the analysed countries and a set of M deterministic and exogenous regressors contained in the $(M \times 1)$ column vector R_t. The VAR(p)-process is then defined as

$$P_t = A_1 P_{t-1} + \cdots + A_p P_{t-p} + CR_t + \varepsilon_t \tag{12}$$

where A_i are (8×8) coefficient matrices for $i = 1, \cdots, p$ and ε_t is a 8-dimensional white noise process with time-invariant positive definite covariance matrix $E(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon$. The matrix C is the coefficient matrix of external regressors with dimension $(8 \times M)$. Among deterministic regressors we have included a constant, one dummy for week days (week day dummy is 0 for week-end, 1 otherwise), seasonal dummies (spring, summer, autumn) and the earthquake dummy defined as in section 5. Among a set of potential exogenous variables we have selected the regressors which could be thought of as affecting the correlations among Germany and its neighbours: European carbon prices, import prices of gas on the German market, production of electricity from wind and solar.

The identification of the proper order p of the VAR model is usually performed through the computation of information criteria. According to the Schwarz Bayesian Information Criteria we have identified a VAR(1) model as the best compromise between goodness of fit and complexity of the model.[32]

[32] According to Akaike Information Criteria a VAR(8) model is identified. However, most of the coefficients for lags larger than 1, even for lag 7, has been found insignificant. Moreover, the autocorrelation functions of residuals of the VAR(1) model do not present significant values, apart from weakly significant values at lag 7 for a few countries. For these reasons the final choice was to estimate a VAR(1) model.

In equation system (12) each equation has the same regressors. Hence, the VAR model is just a seemingly unrelated regression (SUR) model with lagged variables and deterministic terms as common regressors. As a SUR model, coefficients are consistently estimated by OLS. It is very well known that the OLS estimator is strongly affected by the presence of extreme observations (see, for example, Atkinson and Riani, 2000) which is a well-established stylized fact of electricity prices that can clearly be detected visually in our data. In this case, robust estimators must be used to avoid a few observations dramatically affecting the estimates of final parameters. According to the most recent literature on robust statistics, one of the best efficient robust estimators for multivariate regression models is the MM estimator (Maronna et al., 2006, pp. 124-126)[33] which is obtained through an iterative procedure called IRWLS (Iteratively ReWeighted Least Squares) and extreme observations are down-weighted according to a particular choice of a weighting function.[34] The coefficients of model (12) have been obtained using a MM estimator with a weighting Huber function (Maronna et al., 2006, p. 194) which gives a good combination of robustness and efficiency. Estimated coefficients are reported in Table 7.

[33]This estimator has proven to achieve a very good compromise between robustness and efficiency (Yohai, 1987), because it has a high Breakdown Point (fraction of outliers which can be present in the dataset without changing the estimates) mantaining a level of efficiency very close to that of OLS estimator.

[34]Muler and Yohai (2013) suggest to use a bounded MM-estimator for VAR(p) models. The bound is introduced to avoid the propagation of the effect of extreme observations to subsequent observations. We prefer to use the usual and more efficient MM estimator because when the order p of the model is low, as in our case, the propagation effect is quite limited.

Table 7: VAR estimates across-market effect. VAR(1) model estimated on the electricity prices observed in the seven countries with deterministic and exogenous regressors.

	P_{Dt}		P_{CHt}		P_{NLt}		P_{DKWt}		P_{DKEt}		P_{Ft}		P_{PLt}		P_{CZt}	
P_{Dt-1}	0.0422		0.0229		-0.1221	***	-0.3298	***	-0.2914	***	-0.1719	***	-0.0141		0.062	*
P_{CHt-1}	0.0832	***	0.7871	***	-0.0083		0.0171		0.0274		0.0307		-0.0064		0.0336	**
P_{NLt-1}	0.1388	***	-0.0986	***	0.5061	***	0.0474		-0.0013		-0.0573		0.0054		0.061	*
P_{DKWt-1}	0.0181		-0.0531	**	0.047	**	0.6397	***	-0.2046	***	0.0215		0.0176		0.0466	**
P_{DKEt-1}	0.0085		0.03	***	0.0019		0.0139	**	0.9138	***	0.0067		0.0061		0.0011	
P_{Ft-1}	0.0509	***	0.0053		0.1051	***	0.0707	***	0.0666	***	0.791	***	0.0027		0.0605	***
P_{PLt-1}	0.0085		-0.0864	***	0.0003		0.0655	***	0.0414	*	-0.013		0.8394	***	-0.0166	
P_{CZt-1}	0.0774	**	-0.1574	***	-0.0562	**	0.0037		-0.049		-0.1265	***	-0.033	*	0.2483	***
Constant	-13.9127	***	-10.7388	***	-9.8805	***	-10.75	***	-9.7938	***	-8.5051	***	1.6238	*	-11.016	***
Earthquake	3.0848	***	1.2025	**	2.4072	***	1.9166	***	1.9924	***	2.0122	***	1.1651	***	3.6719	***
Carbon Price	1.2423	***	0.9996	***	0.8878	***	1.2138	***	1.2185	***	0.9336	***	0.2567	***	1.0759	***
Week-day	9.9538	***	9.6613	***	8.1056	***	5.9808	***	6.3226	***	10.076	***	2.9228	***	10.0357	***
Spring	-3.3564	***	-4.8513	***	-3.5265	***	-3.0825	***	-3.5067	***	-4.1491	***	-0.7813	***	-2.9535	***
Summer	-3.1911	***	-5.0986	***	-3.5166	***	-3.1807	***	-3.248	***	-4.4072	***	-0.9986	***	-2.2946	***
Autumn	-0.1963		-1.0248	**	-0.36		-1.2836	***	-0.8478	*	-0.4678		-0.0315		0.6162	
Gas Price	0.1408	***	0.139	***	0.133	***	0.1091	***	0.1064	***	0.1085	***	0.0073		0.0992	***
Wind	-0.0009	***	-0.0004	***	-0.0005	***	-0.0007	***	-0.0007	***	-0.0005	***	0		-0.0006	***
Solar	-0.0004	***	-0.0002		-0.0001		-0.0004	***	-0.0002		0		0.0002	**	-0.0002	

Robust MM estimates. Key: Prices are expressed in the following form: P_{CCt} means the price for country CC at time t. Countries are expressed using their international driving designations, with DKE and DKW being Denmark East and West. Coefficients significant for * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

One important characteristic of a VAR(p)-process is its stability. This means that it generates stationary time series with time-invariant means, variances, and covariance structure, given sufficient starting values. We have analysed the stability of the estimated VAR(1)-process by considering the companion matrix associated to the model and calculating the eigenvalues of the coefficient matrix (Lütkepohl, 2007). The eigenvalues of the companion form are less than one for the model and are provided in Table C.2.

The most interesting finding in Table 7 is that the Fukushima dummy is positive and highly significant for all countries, meaning that the energy policy taken by Germany after the nuclear accident had a clear impact, not only on the domestic market, but also on electricity prices of connected countries. The value of the earthquake dummy for Germany is very close to that estimated in the univariate case and may be considered as a robust check of validity of the estimated models. Moreover, the coefficients of the exogenous variables are coherent with the theoretical expectations.

The seven countries considered in the study appear quite connected as many of the coefficients of the (8×8) A_1 matrix are significant. The country with most influence is Germany, confirming its crucial role in central Europe. On the other hand, some countries' impacts on the others look weaker and their causal role could be questioned. One reason might be the different capacity of connectors between pairs of countries, but given our focus on price correlations, Granger causal analysis (Granger, 1969) is appropriate to reveal particular "structures" of the data. Recall that variable X Granger-causes variable Y if variable X helps to predict variable Y. We have applied Granger's causality test for each country versus the set of remaining countries and the output is shown in Table C.3. Starting from these results, a new robust MM restricted VAR(1) model has been estimated. The rationale underlying the restricted models is to exclude from the set of endogenous variables countries which do not Granger-cause the others. Taking 0.01 as the significance threshold for the Granger causality test, we have excluded DKE and F which do not statistically cause the other countries. Then, in the restricted model they are excluded as regressors in the equations for the other countries. The new restricted model is provided in Table C.4. Estimates are quite close to those obtained by the unrestricted VAR reinforcing the validity of previous remarks on the impact of the earthquake on Germany's neighbours.

To control for variables which can be thought of as influencing demand, we estimate a new restricted VAR model including temperatures and Industrial Production (IP) indexes for each country. The estimation output is shown in Table C.5. As can be seen, results are not very different from those presented in Table 7. The biggest difference is that the earthquake coefficient becomes insignificant for Poland.

Summarising the main findings of this section, the VAR models estimated on the supply side have produced coefficients largely in accordance to the economic theory. For example, we have found positive signs for the coefficients of carbon and gas prices and a negative impact of renewable sources production on electricity prices. A similar result was found by Traber and Kemfert (2009) who investigate the impact of generation from renewables in Germany on prices in neighbouring countries and found them to have a negative impact on prices. When control variables for any country have been introduced (Table C.5) the negative sign of the temperature coefficient and the positive effect of the industrial production index are in accordance with our expectations. These results are important evidence on the quality of the dataset and on the validity of the theoretical model used to study the impact of the exogenous event represented by the earthquake.

Most significantly, our VAR modelling confirms that the strongly significant and positive coefficients on the earthquake dummy obtained on the supply side mean the nuclear phase-out has spread out at least to encompass the markets directly connected to Germany, in addition to the clear impact on Austria.

8 Concluding remarks

In deciding, almost on the spur of the moment, to close a substantial proportion of its nuclear power plant fleet as the result of a chance event in Japan, far away, Germany made a bold decision; almost certainly this was the most extreme reaction to Fukushima outside Japan. Germany's unexpected political U-turn did not lead to a disaster. This outcome is assisted by Germany being relatively well connected with other European countries in terms of exports/imports. Taking the impact on Germany alone, an implication of the average 7% uplift on wholesale prices is that German consumers face an annual cost, assuming unchanged conditions otherwise, of around 1.5Bn €, according to our estimates in Table 4.[35] The disaggregated estimates in Table 5 suggest a similar overall impact, albeit of course broken down differentially across seasons and times. The various robustness checks we have engaged in also suggest a similar magnitude.

However of equal significance in our view is that this chance German decision gave Europe a glimpse into the future, where non-biddable renewables will play a much larger part in the power markets than hitherto, and energy prices are expected to rise as a result (as have the EEG payments). We are able to draw a number of further lessons from this. First, Germany is in the fortunate position that solar power matches well with peak demand. Other European countries may not be so fortunate. The other side of this coin is that doubt is cast, for countries reliant primarily on solar renewable power, on the common assumption that electric vehicles charged overnight will provide useful storage. At least given current wind production, relative to solar, our estimates suggest this would be precisely the opposite of an appropriate strategy! Here we note that the main impact has been felt on increased low demand period prices as jumps in the merit order to more expensive technologies are better absorbed in peak hours than in off-peak hours as soon as baseload plants are at least partly replaced by solar plants.

[35] The calculation is as follows: Mean load is 53.8GW, which on average is uplifted in price by 3.2€/MWh, so on an annual basis is $53800 \times 365 \times 24 \times 3.2$€. Estimates from Table 5 are calculated similarly, but of course applied only to the relevant time periods. An additional impact of the price increase is on the EEG surcharge which is computed from the yearly difference between aggregated fixed feed-in payments for renewables and the revenues from selling them on the spot market (broadly speaking). Hence, the spot price increase actually decreases the EEG surcharge which is charged at the retail level. In this context it is worth noting that the spot price increase hits energy intensive industries much more than household as industry is virtually exempted from the EEG surcharge whereas the EEG surcharge accounts for more than 20% of the electricity retail price for households. Therefore, the EEG surcharge can be considered as a subsidy to industry which decreased through the phase-out decision. (Actually, the issue remains open since the Commission opened an in-depth inquiry into support for industry benefitting from a reduced renewables surcharge in December 2013, http://europa.eu/rapid/press-release_IP-13-1283_en.htm.)

The reduction in the gap between high and low demand prices equally brings into question the profitability of bulk storage reliant on arbitrage gains to fund the store. This is quite likely true also for countries in southern Europe, such as Spain and Italy, where solar is of growing importance yet air conditioning is not widespread. For countries such as Ireland, storage in electric vehicles or through new bulk stores may make more sense to make use of excess wind. But a naive assumption that such storage can rely upon intensified periods of low demand coupled with high production from renewables is clearly unwarranted. In fact, one issue that our study reveals is the desirability of a strategic combination of renewable technology investments in order to minimise the potential increased variance in requirements from conventional generation. More does not necessarily mean better.

There is a more general political dimension to our analysis. There is no doubt that significantly electrically interconnected countries benefit in many ways from this interconnection in terms of power smoothing and the resultant smoothing in prices; evaluating this benefit is beyond the scope of our paper. But there is also a downside to this interconnection, as observed here most clearly in the case of Austria. The German political decision to phase out nuclear plants cost Austrian consumers approximately $0.2Bn$€[36] per annum, around 24 € each. Interconnection does imply that political decisions in one country can have significant ramifications on energy prices in another, even between friends. This issue is additionally highlighted in section 7 where the VAR estimates show that both spot price decreases in Germany from the subsidy of renewables and spot price increases from the post-Fukushima closure of 6GW nuclear plants significantly impact electricity prices (and thus industrial competitiveness) in neighbouring countries. The evidence provided of the externalities of unilateral decisions in one country on others demonstrates the importance of coordination of European energy policy in an already well integrated European electricity market. This should be kept in mind for example in the context of the current discussion in Europe on the necessity of capacity markets (e.g. Cramton and Ockenfels, 2012, E-Bridge Consulting et al., 2013, Frontier Economics, 2011).

[36] With an average load of 7.75GW for Austria, the corresponding calculation is $7750 \times 24 \times 365 \times 3.2$€

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Original report (in german) available at http://www.bundesnetzagentur.de/shareddocs/downloads/de/sachgebiete/energie/unternehmen_institutionen/versorgungssicherheit/berichte_fallanalysen/bericht_1.pdf?___blob=publicationfile&v=1.

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Appendixes

A An argument for the use of RSI

Consider figure A.1, in a Bertrand framework, where generators bid prices and the “pivotal generator” is considering how to bid. If all other generator capacities together exceed demand at marginal cost (assumed constant across firms for simplicity), then the only feasible bid will be at marginal cost. However, if adding all other generator capacities together, there is unsatisfied demand above the pivotal generator’s marginal cost, then this firm is in effect a monopolist over the remaining demand. Therefore, it can set marginal revenue, as pictured, equal to marginal cost, and set price accordingly. The RSI captures circumstances where this situation obtains. This is an alternative argument for the use of the RSI different from the argument due to Newbery (2008), for example.

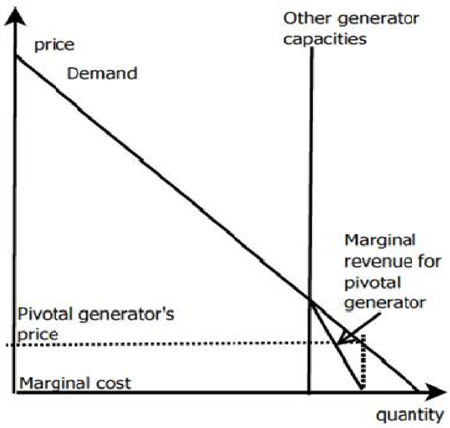

Figure A.1: RSI in a Bertrand framework

Table A.1: Ratio between average theoretically available interconnector capacity and countries load. The terms imports and exports represent the German perspective. CZ=Czech Republic, CH= Switzerland, PL=Poland, NL=Netherlands, F=France, DNW=Denmark West, DNE=Denmark East, D & A=Germany and Austria

	CZ	CH	PL	NL	F	DNW	DNE	D & A
Load (GW)	7.1	5.6	16.3	12.4	56	2.3	1.6	61.5
Import Capacity (GW)	1.1	4.3	0.5	2.6	2.3	1	0.5	
Imp. Cap. /Load for Ger.-Aus. Market (%)	2%	7%	1%	4%	4%	2%	1%	
Imp. ATC/Load for neighb. country (%)	15%	77%	3%	21%	4%	42%	33%	
Export Capacity (GW)	2	0.7	0.2	2.1	2.7	0.8	0.5	
Exp. ATC/Load for Ger.-Aus. Market (%)	3%	1%	0%	3%	4%	1%	1%	
Exp. ATC/Load for neighb. country (%)	28%	12%	1%	17%	5%	36%	32%	

B More Robustness Checks

In table B.1 we show results from OLS estimations of the supply side. Here the impact of the earthquake is little lower but remains significant. In table B.2 we report results from three more robustness checks. In models (1) and (2) we estimate our supply side model with daily average values in level-level and log-log specifications of our variables. The parameter of the earthquake dummy remains significant and positive and even its magnitude changes only slightly (model 1). The estimation after logarithmic transformation in model (2) supports the results and indicates a price increase of around 8%. In model (3) we drop the renewable variable and use residual load instead of total load to estimate the price on this basis. Again, the results are very similar. All three models attest the basic supply side models' robustness.

Table B.1: OLS estimation of the supply side

	(1) Basic		(2) River		(3) Cong. Index		(4) RSI	
Demand	0.128***	(0.007)	0.126***	-0.007	0.125***	(0.006)	0.126***	(0.008)
Earthquake	4.136***	(0.764)	2.749***	(0.815)	1.861*	(0.798)	1.864*	(0.794)
RSI							-10.16	(6.993)
RSI^2							43.16	(22.23)
Imp. Cong × Low D.					3.623***	(0.488)	3.556***	(0.521)
Imp. Cong × High D.					9.449***	(0.992)	9.234***	(1.024)
Exp. Cong × Low D.					-9.890***	(0.820)	-9.830***	(0.753)
Imp. Cong × Low D.					-2.793***	(0.713)	-2.742***	(0.773)
Low River Level			5.487***	(0.989)	4.892***	(0.943)	4.901***	(0.958)
High River Temp			0.594	(0.493)	1.316**	(0.441)	1.312**	(0.453)
RE × Spring × High D.	-7.134***	(0.470)	-7.173***	(0.464)	-6.077***	(0.453)	-6.140***	(0.481)
RE × Summer × High D.	-6.804***	(0.483)	-6.755***	(0.473)	-5.656***	(0.459)	-5.706***	(0.479)
RE × Autumn × High D.	-7.780***	(0.479)	-7.509***	(0.474)	-6.499***	(0.451)	-6.533***	(0.480)
RE × Winter × High D.	-9.022***	(0.646)	-8.877***	(0.631)	-7.808***	(0.613)	-7.858***	(0.732)
RE × Spring × Low D.	-5.561***	(0.410)	-5.616***	(0.402)	-4.270***	(0.354)	-4.330***	(0.367)
RE × Summer × Low D.	-5.437***	(0.437)	-5.405***	(0.430)	-4.060***	(0.385)	-4.107***	(0.394)
RE × Autumn × Low D.	-6.540***	(0.493)	-6.278***	(0.512)	-5.000***	(0.467)	-5.043***	(0.477)
RE × Winter × Low D.	-8.041***	(0.815)	-7.913***	(0.811)	-6.604***	(0.738)	-6.659***	(0.786)
Gas Price × High D.	0.165***	(0.021)	0.182***	(0.0195)	0.187***	(0.020)	0.186***	(0.020)
Gas Price × Low D.	0.170***	(0.017)	0.186***	(0.017)	0.167***	(0.017)	0.167***	(0.018)
Coal Price × High D.	0.054**	(0.018)	0.034*	(0.016)	-0.009	(0.016)	-0.008	(0.016)
Coal Price × Low D.	0.007	(0.018)	-0.011	(0.018)	-0.022	(0.018)	-0.023	(0.018)
Carbon Price × High D.	1.478***	(0.105)	1.514***	(0.098)	1.527***	(0.10)	1.517***	(0.104)
Carbon Price × Low D.	1.381***	(0.086)	1.409***	(0.084)	1.338***	(0.078)	1.338***	(0.078)
R^2	0.700		0.704		0.740		0.740	
#Observations	35064		35064		35064		35064	

The standard errors are in parentheses. Statistics are robust to heteroscedasticity and autocorrelation. Calendar dummies and a constant term are not reported. Coefficients and standard errors for Demand are multiplied by 100 for clarity. Significant for *p< 0.1, **p< 0.05, ***p< 0.01

Table B.2: **Robustness checks with daily values.**

	Level-Level (1)			Log-Log (2)			Residual Load (3)		
Earthquake	3.7080	***	(1.3400)	0.0853	**	(0.0347)	3.2190	**	(1.4530)
Demand	0.0022	***	(0.0002)	3.7700	***	(0.4870)			
RE	-0.0011	***	(0.0001)	-0.1820	***	(0.0188)			
Residual Demand							0.0015	***	(0.0001)
Gas Price	0.1180	***	(0.0281)	0.2930	**	(0.1300)	0.1850	***	(0.0282)
Coal Price	0.0442		(0.0303)	0.3780	**	(0.1820)	-0.0035		(0.0291)
Carbon Price	0.9770	***	(0.1490)	0.1640	***	(0.0510)	1.1910	***	(0.1340)
Imp. Cong. Index	14.0000	***	(3.0180)	0.0628	***	(0.0156)	10.3800	***	(2.4420)
Exp. Cong. Index	-1.0650		(2.5210)	-0.0245	*	(0.0138)	0.0215		(2.3400)
Low River Level	4.7620	***	(1.0950)	0.0015		(0.0065)	5.0370	***	(1.1440)
High River Temperature	0.4330		(0.7900)	0.0018		(0.0054)	0.2900		(0.7400)
First stage F-Test		17.38			13.06			27.50	
Hansen J-Statistic		4.966			5.874			7.693	
χ^2 Prob J-Stat.		0.174			0.118			0.0528	
R^2		0.765			0.597			0.787	
# Obs.		1461			1461			1461	

Standard errors are in parentheses. Estimation is by two-step EGMM. Endogenous: *Demand*. Instruments: *Renewables*, Indices for *GasPrices* and *CarbonEmissionPrices*. Statistics are robust to heteroskedasticity and autocorrelation. Calendar dummies and a constant term are not reported. Significant for * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Tables on VAR model

Table C.1: Unit root tests applied to the original series of prices.

	D	CH	NL	DK1	DK2	F	PL	CZ
Augmented Dickey-Fuller test	-5.38 ***	-4.78 ***	-6.13 ***	-4.7 ***	-5.25 ***	-7.38 ***	-4.44 ***	-5.9 ***
Philips-Perron test	-486 ***	-215 ***	-418 ***	-335 ***	-475 ***	-675 ***	-174 ***	-442 ***

*** p-value<0.01, ** pvalue<0.05.

Table C.2: Eigenvalues of the companion form for supply-side model estimated in Table 7

	1	2	3	4	5	6	7	8
Eigenvalues	0.859	0.708	0.549	0.507	0.387	0.368	0.107	0.073

Table C.3: Granger causality test on the supply side model.

	D	CH	NL	DKW	DKE	F	PL	CZ
Granger test	23.89 ***	13.18 ***	2.72 ***	2.94 ***	1.16	1.13	4.71 ***	3.55 ***

The null hypothesis is: country X does not Granger cause remaining countries. Test significant for * p < 0.1, ** p < 0.05, *** p < 0.01.

Table C.4: VAR estimates across-market effect. RESTRICTED VAR(1) model estimated on the electricity prices observed in the seven countries with deterministic and exogenous regressors.

	P_{Dt}		P_{CHt}		P_{NLt}		P_{DKWt}		P_{DKEt}		P_{Ft}		P_{PLt}		P_{CZt}	
P_{Dt-1}	0.0375		0.0127		-0.1076	***	-0.3208	***	-0.2676	***	-0.1742	***	-0.0151		0.0536	*
P_{CHt-1}	0.1121	***	0.7928	***	0.0292	**	0.0395	*	0.0449	***	0.0315	*	-0.0037		0.0658	***
P_{NLt-1}	0.1636	***	-0.0846	*	0.5726	***	0.0943	***	0.0258		-0.0555		0.0089		0.0953	***
P_{DKWt-1}	0.0310		-0.0257		0.0489	*	0.6512	***	-0.2042	***	0.0277		0.0232	*	0.0469	*
P_{DKEt-1}	-	-	-	-	-	-	-	-	0.9134	***	-	-	-	-	-	-
P_{Ft-1}	-	-	-	-	-	-	-	-	-	-	0.7924	***	-	-	-	-
P_{PLt-1}	0.0130		-0.0864	***	0.0081		0.0729	***	0.0500	**	-0.0119		0.8401	***	-0.0148	
P_{CZt-1}	0.0872	**	-0.1467	***	-0.0499	*	0.0114		-0.0457		-0.1264	***	-0.0323	*	0.2647	***
Constant	-12.7306	***	-9.6992	***	-8.2102	***	-8.8150	***	-8.6997	***	-8.2898	***	1.9168	**	-10.1570	***
Earthquake	3.0680	***	1.2083	**	2.2182	***	1.8172	***	1.8205	***	2.0324	***	1.1704	***	3.5497	***
Carbon Price	1.1933	***	0.9797	***	0.8114	***	1.1511	***	1.1638	***	0.9301	***	0.2507	***	1.0391	***
Week-day	9.9738	***	9.6797	***	8.1116	***	5.9778	***	6.3550	***	10.0847	***	2.9326	***	10.0376	***
Spring	-3.4494	***	-5.0848	***	-3.5481	***	-3.2353	***	-3.5120	***	-4.1985	***	-0.8351	***	-3.0260	***
Summer	-3.2967	***	-5.3420	***	-3.6535	***	-3.4504	***	-3.3606	***	-4.4575	***	-1.0539	***	-2.3928	***
Autumn	-0.2666		-1.2412	***	-0.3709		-1.4161	***	-0.8260	*	-0.5192		-0.0753		0.5753	
Gas price	0.1312	***	0.1312	***	0.1187	***	0.0953	***	0.0989	***	0.1069	***	0.0049		0.0910	***
Wind	-0.0009	***	-0.0004	***	-0.0005	***	-0.0007	***	-0.0007	***	-0.0005	***	0.0000		-0.0006	***
Solar	-0.0004	***	-0.0002		0.0000		-0.0003	**	-0.0002		0.0000		0.0002	**	-0.0002	

Robust MM estimates. Key: Prices are expressed in the following form: P_{CCt} means the price for country CC at time t. Countries are expressed using their international driving designations, with DKE and DKW being Denmark East and West. Coefficients significant for * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: VAR estimates across-market effect. RESTRICTED VAR(1) model estimated on the electricity prices observed in the seven countries with deterministic and exogenous regressors. Temperatures and Industrial Production (IP) indexes have been included.

	P_{Dt}		P_{CHt}		P_{NLt}		P_{DKWt}	
P_{Dt-1}	0.0753	**	0.0717	**	-0.0457	*	-0.2539	***
P_{CHt-1}	0.0783	***	0.7223	***	-0.0115		0.0144	
P_{NLt-1}	0.1456	***	-0.1359	***	0.5483	***	0.0701	**
P_{DKWt-1}	-0.0276		-0.062	**	-0.0224		0.5614	***
P_{DKEt-1}	-	-	-	-	-	-	-	-
P_{Ft-1}	-	-	-	-	-	-	-	-
P_{PLt-1}	-0.0577	**	-0.0971	***	-0.0429	**	0.0661	***
P_{CZt-1}	0.0991	***	-0.1375	***	-0.0437	*	0.0143	
Constant	-6.926	***	12.6459	***	1.4066		1.6559	
Earthquake	2.7779	***	1.7689	***	2.4226	***	2.2976	***
Carbon Price	1.3175	***	1.1995	***	1.0095	***	1.3298	***
Week-Day Dummy	9.9016	***	9.8924	***	8.167	***	6.1426	***
Spring Dummy	-2.396	***	-0.907		-1.9753	***	-1.5532	***
Summer Dummy	-2.1146	***	-0.0354		-0.9523		-0.7452	
Autumn Dummy	-0.4618		2.377	***	0.4369		0.1267	
Gas price	0.1192	***	0.1306	***	0.1181	***	0.0909	***
Wind	-0.0008	***	-0.0003	***	-0.0004	***	-0.0007	***
Solar	-0.0004	***	0.0002		0.0002		-0.0001	
Day Length	-0.1237		-0.3587	***	-0.2472	**	-0.0025	
$Temp_{Dt}$	-0.5213	***	-	-	-	-	-	-
$Temp^2_{Dt}$	0.0046	***	-	-	-	-	-	-
$Temp_{CHt}$	-	-	-0.7974	***	-	-	-	-
$Temp^2_{CHt}$	-	-	0.0063	***	-	-	-	-
$Temp_{NLt}$	-	-	-	-	-0.7062	***	-	-
$Temp^2_{NLt}$	-	-	-	-	0.0061	***	-	-
$Temp_{DKWt}$	-	-	-	-	-	-	-0.6605	***
$Temp^2_{DKWt}$	-	-	-	-	-	-	0.0055	***
IP_D	0.1503	***	-	-	-	-	-	-
IP_{CH}	-	-	0.0299		-	-	-	-
IP_{NL}	-	-	-	-	0.1394	***	-	-
IP_{DK}	-	-	-	-	-	-	0.0679	***

[Continued]

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	P_{DKEt}		P_{Ft}		P_{PLt}		P_{CZt}	
P_{Dt-1}	-0.1532	***	-0.0463		0.0052		0.0916	***
P_{CHt-1}	0.0177		-0.0046		-0.0038		0.0408	**
P_{NLt-1}	-0.0377		-0.0496		0.0011		0.088	***
P_{DKWt-1}	-0.1289	***	-0.0292		-0.0098		0.0012	
P_{DKEt-1}	0.7608	***	-	-	-	-	-	-
P_{Ft-1}	-	-	0.5828	***	-	-	-	-
P_{PLt-1}	0.0311		-0.0553	**	0.7889	***	-0.0434	*
P_{CZt-1}	-0.0494		-0.0414		-0.0267		0.2543	***
Constant	12.3298	***	39.9602	***	-1.9858		-5.2183	**
Earthquake	3.0126	***	3.0005	***	0.4701		3.5395	***
Carbon Price	1.324	***	1.0855	***	0.3445	***	1.1097	***
Week-Day Dummy	6.5501	***	10.2091	***	2.9282	***	10.146	***
Spring Dummy	-0.9233		-0.5282		-0.9671	***	-1.7541	***
Summer Dummy	0.8654		-0.0053		-0.5383		-0.7059	
Autumn Dummy	1.7904	***	3.2776	***	-1.2161	***	0.8221	
Gas price	0.0734	***	0.0922	***	-0.0045		0.0798	***
Wind	-0.0006	***	-0.0003	***	0.0000		-0.0006	***
Solar	0.0002		0.0004	**	0.0002	***	-0.0001	
Day Length	-0.2398	.	-0.1585		-0.1494	**	-0.1496	
$Temp_{DKEt}$	-0.7269	***	-	-	-	-	-	-
$Temp^2_{DKEt}$	0.0058	***	-	-	-	-	-	-
$Temp_{Ft}$	-	-	-1.6573	***	-	-	-	-
$Temp^2_{Ft}$	-	-	0.0131	***	-	-	-	-
$Temp_{PLt}$	-	-	-	-	-0.0333		-	-
$Temp^2_{PLt}$	-	-	-	-	0.0002		-	-
$Temp_{CZt}$	-	-	-	-	-	-	-0.3763	***
$Temp^2_{CZt}$	-	-	-	-	-	-	0.0033	***
IP_{DK}	0.0395		-	-	-	-	-	-
IP_{F}	-	-	0.0513	***	-	-	-	-
IP_{PL}	-	-	-	-	0.1023	***	-	-
IP_{CZ}	-	-	-	-	-	-	0.099	***

Robust MM estimates. Key: Prices are expressed in the following form: P_{CCt} means the price for country CC at time t. Countries are expressed using their international driving designations, with DKE and DKW being Denmark East and West. Coefficients significant for * p < 0.1, ** p < 0.05, *** p < 0.01.