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When are consumers responding to electricity prices? An hourly pattern of demand elasticity

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Abstract

System security in electricity markets relies crucially on the interaction between demand and supply over time. However, research on electricity markets has been mainly focusing on the supply side arguing that demand is rather inelastic. Assuming perfectly inelastic demand might lead to delusive statements regarding the price formation in electricity markets. In this article we quantify the short-run price elasticity of electricity demand in the German day-ahead market and show that demand is adjusting to price movements in the short-run. We are able to solve the simultaneity problem of demand and supply for the German market by incorporating variable renewable electricity generation for the estimation of electricity prices in our econometric approach. We find a daily pattern for demand elasticity on the German day-ahead market where price-induced demand response occurs in early morning and late afternoon hours. Consequently, price elasticity is lowest at night times and during the day. Our measured price elasticity peaks at a value of approximately -0.13 implying that a one percent increase in price reduces demand by 0.13 percent.
Keywords: Electricity markets, Hourly price elasticity of demand, Empirical demand analysis

JEL classification: C26, L94, Q21, Q41

1. Introduction

Understanding the price elasticity of demand is important since demand adjustments based on price movements contribute to the functioning of electricity markets. In electricity markets it is worth stressing

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that balancing demand and supply occurs on a high temporal frequency which, not only in Germany, results in debates on whether or not it is possible to match demand and supply at all times. An inelastic price elasticity of demand assumption, as often argued for the short-run, would imply that the burden of balancing electricity consumption and generation at all times rests with the supply side.

The empirical literature estimating long-run and short-run price elastictiy of demand in electricity markets is extensive. For the short-run, peer-reviewed studies have estimated the elasticity for different sectors and time intervals. Table 1 shows that estimates of price elasticity vary from -0.02 to -0.3 depending on the chosen approach, the country-specific data and the sector. Taylor et al. (2005), for instance, find that short-run elasticity ranges from -0.05 to -0.26 for the industrial sector in North Carolina by using annual data. He et al. (2011) confirm this finding whereas Bardazzi et al. (2014) measure a slightly higher elasticity in terms of magnitude for the Italian industry sector. For the residential sector, numerous studies have been performed as well (i.e. Ziramba (2008), Dergiades and Tsoulfidis (2008) and Hosoe and Akiyama (2009)). However, little attention has been devoted to the price response of the whole market with respect to wholesale prices. So far, this market has only been investigated by Genc (2014) and Lijesen (2007). Whereas Genc (2014) applies a bottom-up Cournot modeling framework, Lijesen (2007) uses a regression approach in order to quantify the price elasticity during peak hours. Genc and Lijesen conclude from their chosen approaches that the hourly price elasticity is rather small. They furthermore argue that in peak hours demand switching behavior of consumers barely occurs in practice.

In this article we extend the existing literature on short-run elasticity with respect to the wholesale price in two ways. First, we use wind generation as an instrument variable to solve the simultaneity problem of demand and supply.[1] Second, we account for the variation in utility from electricity consumption during the day. Using data on load, temperature, prices and wind generation for the German day-ahead market in 2015, we quantify the level of price elasticity and its variation throughout the day.

Our results show that the short-run price elasticity of demand in the German electricity market is not perfectly inelastic. Even though our obtained short-run price elasticity of demand is generally low, consumers still react to price movements. We stress that a price elasticity of demand with respect to the day-ahead price is not explicitly showing the contribution of each consumer group. However, measuring the price elasticity of demand can give a more meaningful understanding of the contribution of demand reactions to system security. The daily pattern of our estimate of price elasticity reveals some prominent peaks in the morning and evening, where the price elasticity of demand is highest. As expected, these hours show overall

[1] The approach is similar to Bönte et al. (2015).

Source	Type of model	Type of data	Elasticity	Sector	Region
Garcia-Cerrutti (2000)	Dynamic random variables model	Annual	-0.79 to 0.01, mean -0.17	Residential	California
Al-Faris (2002)	Dynamic cointegration and Error Correction Model	Annual, 1970-1997	-0.04 / -0.18		Oman
Bjørner and Jensen (2002)	Log-linear fixed effects	Panel, 1983-1996	-0.44		
Boisvert et al. (2004)	Generalized Leontief		Peak: -0.05	TOU	
Holtedahl and Joutz (2004)	Cointegration and Error Correction Model	Annual, 1955-1996	-0.15	Residential	Taiwan
Reiss and White (2005)	Reduced form approach	Annual , 1993 and 1997	0 to -0.4	Residential	California
Taylor et al. (2005)	Generalized McFadden with nonlinear OLS and Seemingly Unrelated Regression	1994-2001	-0.26 to -0.05	Industry	Duke Energy, North Carolina
Bushnell and Mansur (2005)	lagged residential prices		-0.1	Residential	San Diego
	Error Correction Model	Annual, 1969-2000	-0.263	Residential	Australia
Bernstein et al. (2006)	dynamic demand model with lagged variables and fixed effects	Panel, 1977-2004 1977-1999	-0.24 to -0.21	Residential, Commercial	US
Rapanos and Polemis (2006)		1965-1999	-0.31		Greece
Halicioglu (2007)	Bounds testing approach to cointegration within ARDL model	1968-2005	-0.33		Turkey
Lijesen (2007)	reduced form regression linear, loglinear		-0.0014 -0.0043	Wholesale	Netherlands
Dergiades and Tsoulfidis (2008)	Bounds testing approach to cointegration within ARDL model	1965-2006	-1.06	Residential	US
Ziramba (2008)	Bounds testing approach to cointegration within ARDL model	1978-2005	-0.02	Residential	South Africa
Hosoe and Akiyama (2009)	OLS/Translog cost function	1976-2006	0.09 to 0.3	Residential	Japan
He et al. (2011)	General equilibrium analysis	2007	-0.017 to -0.019, -0.293 to -0.311, -0.0624 to -0.0634	Industry, residential, agriculture	China
Bardazzi et al. (2014)	Two-stage translog model	Panel, 2000-2005	−0.561 to -0.299	Industry	Italy
Genc (2014)	Cournot competition model	Hourly 2007, 2008	-0.144 to -0.013 -0.019 to -0.083	Wholesale	Ontario

Table 1: Literature review of estimated short-run elasticity

high price levels providing incentives to consumers for a reduction of their consumption. In the morning and evening hours, price elasticity varies between -0.08 and -0.13. Thus, we infer that demand adjustments in these hours are to some extent beneficial for consumers. On the contrary, we measure a lower price elasticity of demand at night times and during the day. A lower elasticity indicates less willingness of consumers to adjust the consumption due to high or low electricity prices. This can be due to the fact that economic activity in general is higher during daytime.

The remainder of the paper is organized as follows. Section 2 deepens the understanding of supply and demand in electricity markets. Section 3 describes the data and presents the applied econometric approach. Section 4 discusses the estimation results. Section 5 concludes.

2. Measuring market demand reactions based on wholesale prices

In order to specify our econometric model capturing demand reactions due to electricity wholesale price movements, knowledge about the supply and demand functions in electricity markets is pivotal. In this section, we therefore describe the functioning of the retail and wholesale electricity market before arguing that demand elasticity can be estimated based on market demand being defined as aggregated demand of all end consumer groups and wholesale electricity prices. We further specify the drivers of demand and supply by setting up the respective functions.

2.1. The retail market for electricity

Consumers commonly sign contracts with retailers to take charge of their electricity demand. These contracts are subject to different possible tariff schemes ranging from time-invariant pricing to real-time pricing. Tariff structures vary depending on the consumer group and metering facilities.[2] Small end consumers (e.g. households, businesses, or small industries) in Germany are mostly on time-invariant tariffs. This means that the price of electricity for these consumer groups is at the same level for every hour over the entire year. These consumers therefore have little incentive to adjust their demand in the short-run. For larger consumers, such as big industrial companies, contracts are differently designed allowing them to benefit from adjusting consumption in the short run.[3]

In Germany, the retail price that consumers pay for electricity consists of several components. The most important component is the price for electricity generation, which is the price that generators charge

[2]The electricity consumption of many end consumers is not observable over time because the metering facilities only display the amount of electricity consumed but not during which period measurement is performed.

[3]According to Bundesnetzagentur (2016), consumers can be grouped by their metering profile into customers with and without interval metering. Only consumers with interval metering have the technical capability to be billed depending on the time of usage. For Germany in 2014, 268 TWh were supplied to interval metered customers and 160 TWh to customers without interval metering.

for the generation of electricity. Besides paying for the generation of electricity, end consumers also pay for the transmission and distribution of electricity, as well as for additional taxes and levies. In Germany, for instance the retail price consists of network charges, the renewable support levy, and taxes which are added to the wholesale price. Some of these additional price components vary substantially depending on the consumer group.[4] The differing retail prices for each consumer group lead to a total electricity demand of all consumers that varies over the year. This aggregated demand of all end consumers is equal to the observed load in the total electricity system.

2.2. The wholesale market for electricity

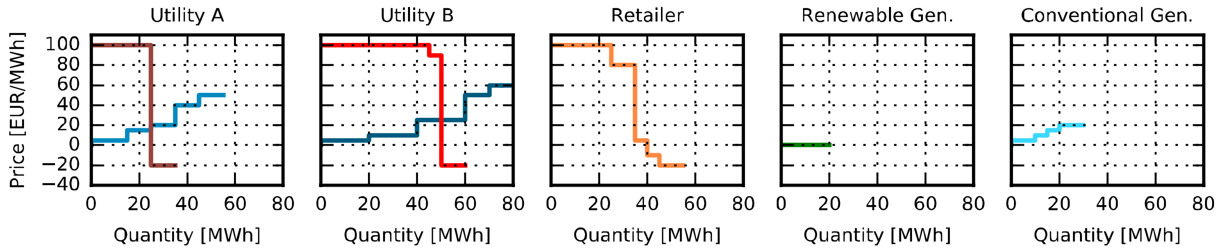
The price for electricity generation is determined in the wholesale market. In principal, the wholesale market allows different players to place bids that eventually either result in produced quantities or demanded quantities for a specific point in time. Participants in these markets are for example utilities, retailers, power plant operators and large industrial consumers.

Figure 1a gives an exemplary overview of the five different players and their corresponding electricity demand and supply on the wholesale market. The first two players are two different utilities, A and B. As such, utility A and B illustrate cases for players with different generation assets while at the same time each of them possesses different customer bases. However, for both utilities, we would expect that generation for their own customer base depends on the marginal cost of generation. In other words, if the wholesale price is above the marginal cost of the utility's marginal cost of generation, the utility chooses to supply their customer base instead of demanding quantities from the wholesale market. The next player in the market we refer to is the retailer. As a retailer, supplying electricity is by default not an option and therefore we expect them to demand electricity quantities only. The opposite is true for renewable and conventional generation players. With marginal costs of zero, renewable generation players offer their production at very low cost compared to conventional generation players where marginal costs are greater than zero and vary depending on the generation technology.

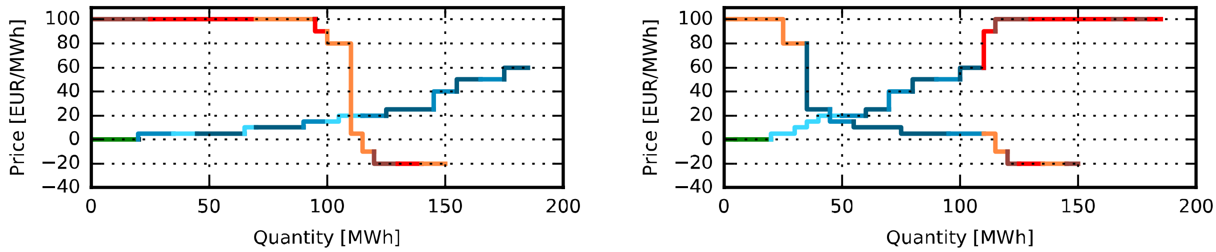
Figure 1b horizontally aggregates all demand and supply curves from each player we identified. It thus shows the aggregated demand and supply, as well as the realized equilibrium electricity price of 20 EUR/MWh.

Figure 1c shows the resulting supply and demand bids by the individual players in the wholesale market. First, players that can only supply electricity, such as renewable or conventional generators, appear in ascending order on the supply side only. Second, retailers demand quantities and generally more, if prices

[4] In Germany, for example, electricity intensive industries are exempted from paying the renewable support levy.



(a) Wholesale market players



(b) Supply and demand aggregation

(c) Supply and demand in the wholesale market

Figure 1: Electricity price formation on the wholesale market

are low. Third, players that own generation assets and also have customers, net their supply and demand positions internally before submitting bids. This is the case for utility A and B. In a second step, the bids for the demand and supply side depend on the internal netting of supply and demand. In total this results in four possible outcomes for placing bids which can be describes as follows

- sell bid on the supply side for generation units that have not been internally matched and could satisfy the demand of other participants
- purchase bid on the demand side for demand that has not been internally matched
- sell bid on the supply side, resulting from demand that has been matched internally but would be able to reduce consumption if the price rises above a given threshold (see e.g. demand of utility B with 90 EUR/MWh)
- purchase bid on the demand side for generation units that have internally be matched but that would substitute their production if the price falls below their marginal costs of generation.

Whereas the first two outcomes are intuitively straightforward due to netting procedures, outcomes three and four may seem counter intuitive at first. Due to the internal matching of supply and demand, parts of the demand and supply curve that have been internally matched result in bids on the opposite side.

By placing these bids, utilities can optimize their position and choose to substitute formally demanded quantities to supplied quantities or vice versa, above or below a certain wholesale price.

The supply and demand curves in Figure 1b and 1c look very different from a first glance, but both result in the same price for electricity and lead to the same allocation of resources. Nevertheless, both provide a very different impression of the price responsiveness of the demand side. Based on Figure 1b the demand side can be characterized as rather price inelastic. In the example, the level of demand would not change if prices stay within a range of 5 to 80 EUR/MWh. Figure 1c may however lead to the misleading conclusion that the demand side in electricity markets is rather price elastic. Within the submitted supply and demand bids at the wholesale market it is not possible to identify separate bids that actually stem from generators or actual consumers of electricity. It is therefore not possible to estimate the demand elasticity of actual electricity consumers based on the curves observed in the wholesale market. In order to estimate the demand elasticity of the actual electricity consumers it is, however, possible to combine the wholesale equilibrium price with the total load observed.

2.3. The interaction of wholesale and retail markets

Within this article we are interested in the reaction of electricity demand to electricity prices. Because disaggregated load data for each consumer group with the respective retail prices are not available, we focus our attention on the interaction of total hourly demand and hourly wholesale electricity prices. Figure 2 shows the relation we are interested in for an exemplary hour. The blue line depicts the supply curve for electricity generation. The red line is the aggregated demand curve of all consumers for electricity consumption. Consumers pay an average retail price of p^r, which is made up of the wholesale price for electricity (p^w) and additional price components (c).[5] When we account for the effect of the additional price components, we obtain the demand function that is observable in the wholesale market (*wholesale demand*, red dashed line). The intersection of wholesale demand and wholesale supply leads to point A and determines the wholesale price p^w, as well as the quantity consumed and produced q^{el}. By inferring the relationship illustrated in Figure 2 and using the wholesale price and total electricity demand, we are able to estimate the point elasticity of the red dashed demand curve.

The relations of the demand and supply curve in electricity markets are only vaguely sketched in Figure 2. In reality, demand is fluctuating over time due to varying utility levels throughout the day. The demand for electricity can be regarded as a function of various inputs and the relation can be written as

[5]In Germany, most additional price components are added to the wholesale price independent on the price level or quantity consumed.

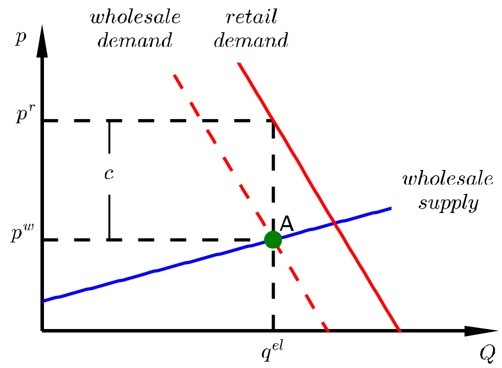


Figure 2: Supply and demand curves for one exemplary hour

$$q^{el} = f(p^w, HDD, \textit{time-of-the-day}) \tag{1}$$

, where q_{el} is the quantity consumed, p^w is the wholesale price for electricity, HDD are heating degree days capturing the seasonality within the data. HDD measure the temperature difference to a reference temperature. The variable therefore captures the seasonal variation of electricity demand. For example, if outside temperature is low, heating processes consume more electricity compared to warmer weather conditions.[6] Furthermore, temperature has an effect on consumer habits, such that higher temperature levels affect outside activities in a positive manner (Bessec and Fouquau, 2008). In addition, electricity consumption depends on the time of usage. This is mainly driven by the variation of the consumer's utility function over the day. Additional variables determining the level of demand, such as economic activity, may also alter demand but are assumed to be time-invariant on an hourly basis and within the considered time span. Therefore, we abstract from including additional variables for the demand side in the short run.

Like the demand function, the supply of electricity can also be regarded as a function of multiple inputs with the wholesale price p^w being one of them. We define the supply function as:

$$q^{el} = f(p^w, p^{fuel}, r) \tag{2}$$

, where q^{el} is the quantity produced, p^{fuel} is a vector of fuel prices and r is the production of variable renewable energy.

In electricity markets, the structure of the supply side is commonly represented by the merit order curve. It represents the marginal generation costs of all conventional (fossil) power plants. The shape of the curve

[6] The data in Section 4 reveals that this relation is true for Germany, however it may not be applicable to other countries. In warmer climates also cooling degree days (CDD) determine the demand for electricity.

mainly depends on the technologies being used for power generation and their respective fuel prices p^{fuel}.[7] However, variable renewable electricity generation is becoming increasingly important within the generation portfolio. This is particularly true for the German market region. Since renewable technologies do not rely on fossil fuel inputs to generate electricity, their fuel costs are close to zero. Additionally, its stochastic nature that is driven by wind speeds and solar radiation makes generation vary throughout time. We will later make use of the stochastic nature and by using wind generation as an instrument variable within our econometric model.

3. Empirical Framework

3.1. Data

Our data set consists of hourly data for 2015. We include hourly data for load, day-ahead-prices and the forecast of production from variable renewables for Germany. In addition, HDD are calculated based on hourly temperatures that we obtain from the NASA Goddard Institute for Space Studies (GISS). Summary statistics for all variables are provided in Table 2.

Variable	Mean	Std. Dev.	Min.	Max.	Source
Load [GWh]	61.688	9.428	38.926	77.496	ENTSO-E
Wind Generation [GWh]	8.574	6.864	0.153	32.529	EEX Transparency
Day-ahead price [EUR/MWh]	35.6	11.5	-41.74	99.77	EPEX Spot
Temperature [°C]	10.4	7.9	-6.3	34.6	NASA MERRA
Heating degree days [K]	10.1	6.9	0	26.3	NASA MERRA

Table 2: Descriptive statistics (for weekdays, without public holidays and Christmas time)

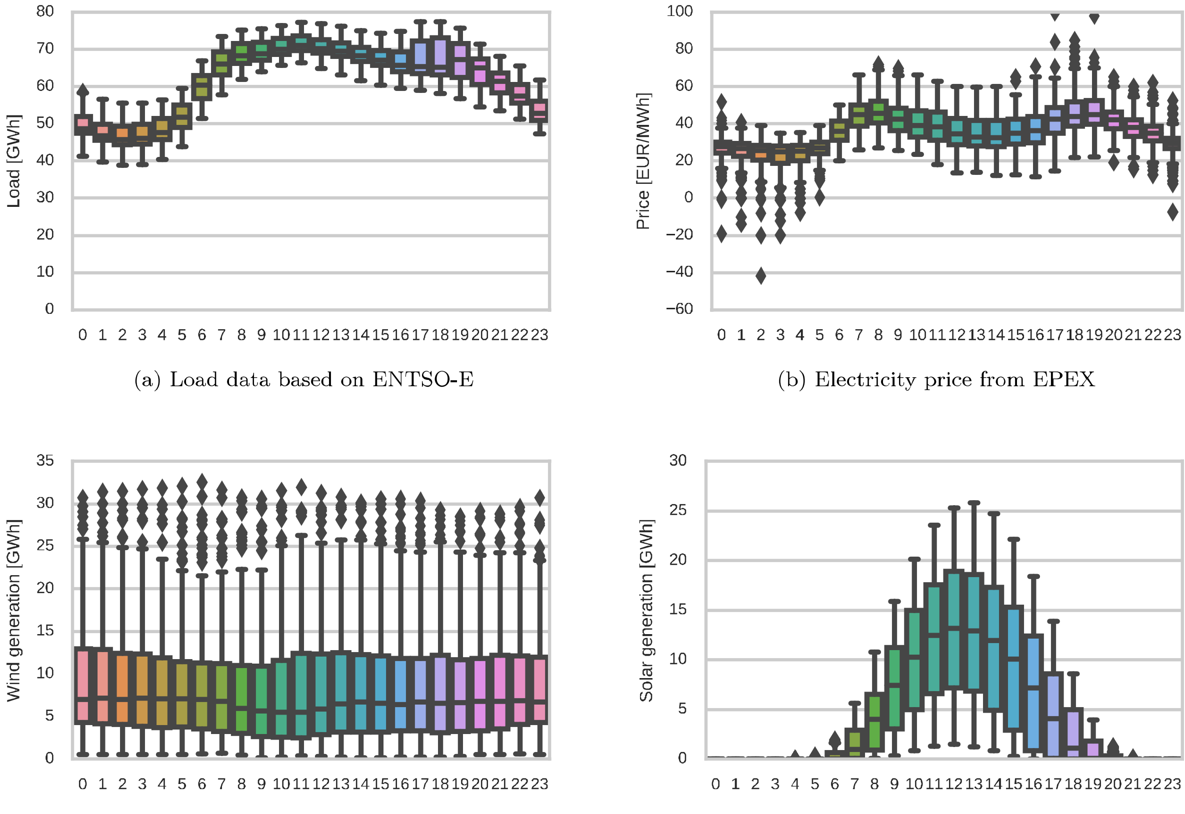
The hourly load profile for Germany was taken from ENTSO-E. According to ENTSO-E, load is the power consumed by the network including network losses but excluding consumption of pumped storage and generating auxiliaries.[8] The load data includes all energy that is sold by German power plants to consumers.[9] Load therefore is the best indicator on the level of demand in the German market area since almost all energy sold has to be transferred through the grid to consumers. Figure 3a shows average hourly values for weekdays in the German market area in a box plot. The plot shows significant differences in the level for night hours (00:00-6:00, 19:00-00:00) compared to daytime. Also load peaks in the morning (9:00-12:00) and evening hours (16:00-18:00). Especially in the evening, variation in load levels is higher

[7] Common power plant types and fuels are hydro power, nuclear, lignite, coal, gas and oil.

[8] ENTSO-E collects the information from the four German transmission system operators (TSO) and claims that the data covers at least 91% of the total supply. These quantities may also be reflected in the day-ahead price which we can not account for.

[9] To a small amount load may also include energy that is sold from neighboring countries to the German market. These trade flows impact the domestic electricity price and load. However, we expect this impact to be rather small.

than at other times. The average load level is 62 GW and the maximum peak load is 77 GW in the early evening hours.



(a) Load data based on ENTSO-E

(b) Electricity price from EPEX

(c) Wind generation from EEX Transparency

(d) Solar generation from EEX Transparency

Figure 3: Hourly data for load, electricity price, wind and solar generation for 2015

We obtain the hourly day-ahead price for electricity from the European Power Exchange (EPEX) which is the major trading platform for Germany. Historically the day-ahead price has evolved as the most important reference price on an hourly level in the wholesale electricity market. The day-ahead market run by EPEX Spot is by far the most liquid trading possibility close the point of physical delivery.[10] The price is determined in a uniform price auction at noon one day before electricity is physically delivered. We follow this perspective and use the day-ahead price as our reference price for electricity generation. Although not all electricity is sold through the day-ahead-auction, the price reflects the value of electricity in the respective hours and contains all available information on demand and supply at that specific point in time. Figure 3b shows a box plot for the hourly day-ahead electricity price for each hour of the day. The average hourly

[10]In 2015 264 TWh have been traded in the day-ahead market, compared to 37 TWh traded in the continuous intraday market (EPEX Spot, 2016).

day-ahead electricity price is at 36 EUR/MWh over the 24 hours time interval and for weekdays (without public holidays and Christmas time). The electricity price pattern is similar to the load pattern emphasizing the fact that higher demand levels tend to increase prices in the day-ahead market. Especially during peak times in the morning and evening one can observe higher standard deviations and peaking prices. Standard deviation over all hours is around 12 EUR/MWh.

Electricity generation from wind and solar power is taken from forecasts published on the transparency platform by the European Energy Exchange (EEX). These forecasts result from multiple TSO data submissions to the EEX. Since they are submitted one day before physical delivery, they contain all information that is relevant for participants in the day-ahead market.[11] Figure 3c and 3d show box plots for electricity generation from wind and solar power. Due to weather dependent generation volatility, we observe a larger amount of volatility in the hourly data. Wind generation varies steadily throughout the day with a small increase during the day. Solar generation shows its typical daily pattern with no generation at night and peak generation values for midday.

The level of demand does not only depend on the electricity price which in return is partially influenced by generation from wind. We add weather as an additional parameter to our investigation of electricity demand since the level of temperature is a main driver for the seasonal variation of demand. We compute a Germany wide average temperature based on the reanalysis MERRA data set provided by NASA (NASA, 2016). The hourly values are based on different grid points within Germany that are spatially averaged in order to obtain a consistent hourly value for Germany. Based on the hourly temperature we derive HDD that are relevant for the seasonal variation of demand in electricity markets.[12]

3.2. Econometric Approach

Due to the fact that the electricity price is endogenously determined by the interaction of demand and supply, we choose a two-stage approach to solve the simultaneity problem.[13] As we are interested in estimating the demand function (1), possible instruments affecting the price but not the level of demand have to be determined. Possible instruments can be found on the supply side in (2), where fuel prices (p^{fuel}) and the production of variable renewable energy (r) are considered. Although fuel prices are one of the major drivers for generation decisions, a closer look reveals that they show little variation over the

[11] We also considered taking the actual generation from renewables but reckon that the ex-ante forecasts are reflecting the causal relationship in a better way since decisions made on the day-ahead market are based on forecast values.

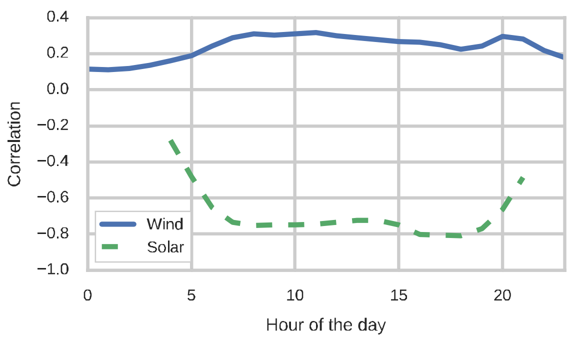
[12] We calculate HDDs based on a reference temperature of 20 °C.

[13] Durbin and Wu–Hausman test statistics show highly significant p-values. The null hypothesis tests for all variables in scope being exogenous. With p-values for both test of both equal to 0,000 we reject the null of exogeneity implying that prices and demand are endogenous.

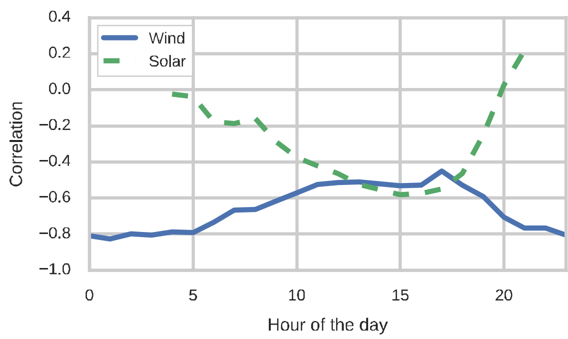
year 2015 (cf. Figure .5 in the Appendix). Therefore, we exclude them from a further analysis within our framework.

The production of variable renewable energy (r) can further be split into wind (w) and solar (s) generation. Figure 4 depicts the respective correlations of renewable generation with prices and load for each hour interval of the day. In Figure 4a, we observe that the correlation between solar generation and load is higher in absolute values than the correlation between wind generation and load. However, wind and solar generation are correlated opposite in sign with load being positively correlated with wind generation and solar generation negatively correlated with load.

Figure 4b shows the correlation between renewable generation and electricity price. Both, wind and solar generation are negatively correlated with the electricity price, however their patterns are different throughout the day. The correlation between wind generation and electricity price weakens over the day until 17:00 where the correlation is lowest with an absolute value of -0.45. From 17:00 on the correlation between wind generation and price increases again. The pattern for the correlation between solar generation and electricity price is reversed whereas the increasing correlation until 17:00 is mainly driven by an increasing solar radiation. Based on the generally high correlation of wind and prices and at the same time low correlation of wind and load, we choose wind generation as an instrument for the price.[14]



(a) Correlations with load



(b) Correlations with price

Figure 4: Correlations with load and prices in 2015

More formally, wind generation as a variable fulfills the two conditions (1) $cov[w, p^w] \neq 0$ and (2) $cov[w, \mu] = 0$, where w is wind generation, p^w the wholesale electricity price and μ the error term. The first condition is needed in order to provide unbiased electricity price estimates. In our context the chosen

[14]Statistically speaking, weak instruments may cause estimation bias if the correlation with the endogenous explanatory variable (in our case $p^w_{h,t}$) is very low.

instrument w correlates with the electricity price (c.f. Figure 4b). From the second condition it follows that w and μ are not correlated.[15] Because wind can be regarded as a stochastic variable especially throughout the day and load inhibits strong daily patterns, both can be regarded as independent (c.f. Figure 4a). With these two conditions fulfilled we are now able to postulate the first and second stage equations. The first stage can be written as

$$p_{h,t}^{w} = \gamma_{0,h} + \gamma_{1,h} \cdot w_{h,t} + \epsilon_{h,t} \tag{3}$$

and the second stage as

$$q_{h,t}^{el} = \beta_{0,h} + \beta_{1,h} \cdot p_{h,t}^{w} + \beta_2 \cdot HDD_t + \beta_3 \cdot MON_t + \beta_4 \cdot FRI_t + \mu_{h,t}. \tag{4}$$

We estimate price coefficients $\beta_{1,h}$ and dummy coefficients $\beta_{0,h}$ on an hourly basis h. We do this, because we expect the utility of electricity consumption to be different in each hour of the day. Here, $\beta_{0,h}$ captures the price independent change of utility from electricity consumption throughout the day. Since we observe a different demand pattern for working days and week-ends, we eliminate week-ends and holidays from the data. Furthermore, we add dummies for Monday (MON) and Friday (FRI)[16] to capture differing demand levels at the beginning and end of the working week. Based on our estimates, we can calculate the average hourly price elasticity of electricity demand according to

$$\epsilon_h = \frac{\overline{p}_h^w}{\overline{q}_h} \frac{\partial q_h}{\partial p_h} = \frac{\overline{p}_h^w}{\overline{q}_h} \beta_{1,h}, \tag{5}$$

where ϵ_h is the hourly elasticity using the average price $\overline{p}_h^w$ and average demand $\overline{q}_h$ in the respective hour of the day (h).

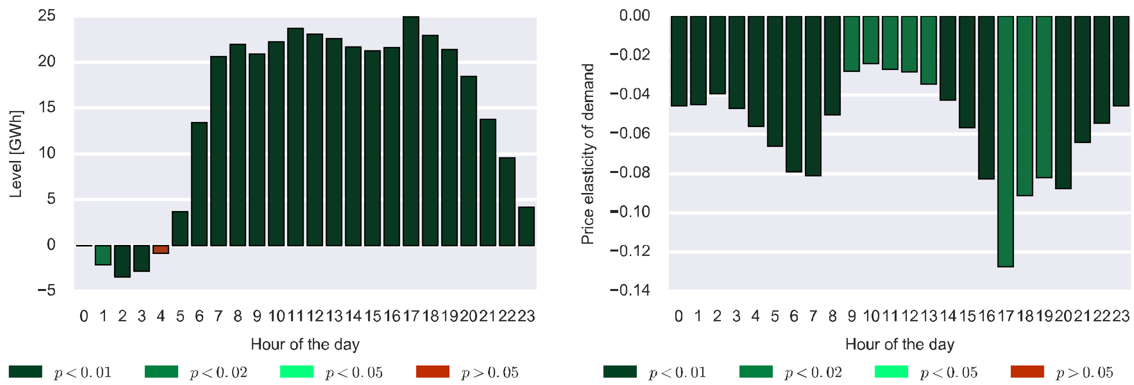
4. Empirical Application

By applying the econometric framework, we are able to estimate the level of price elasticity of demand for the German day-ahead market on an hourly basis. The regression is based on levels and elasticity is calculated with respect to the average prices and quantities in each hour.[17]

The results of the estimation can be found in Table 3. When taking a look at the price coefficients in Table 3a, we can see that all price coefficients are negative in sign and are significant at least at the 1% level.

[15] Testing for validity expressed by $cov[w, \mu] = 0$ within our framework is not feasible since our model is exactly identified.
[16] For Mondays the dummy is positive for the time between 0:00 and 9:00. For Fridays the time frame is from 17:00 to 23:00.
[17] In a previous version of the paper, we normalized our data to the median, which is why previous estimates differ from this version. Furthermore, elasticity was calculated with respect to the average price and quantity level including values of zero. As we are running a pooled regression many observations of zero were included which resulted in low estimates of the elasticity.

We note that coefficients during morning hours (9:00-12:00) are lower in absolute values. The highest value can be found at 17:00. In this particular hour, a wholesale price increase of 1 EUR/MWh leads to a demand reduction of 201.8 MWh. The hourly dummy coefficients in Table 3a capture the varying level of utility throughout the day. During the day, hourly coefficients are higher than at other times. In the evening, we can observe a peak in the level of utility, especially between 16:00 - 20:00 (c.f. Figure 5a). Beside the hourly coefficients, we also account for the influence of temperature and weekdays on electricity demand. All coefficients are significant at the 0.1% level and can be explained in their sign. HDD have a positive sign and thus increase electricity demand. Mondays and Fridays are negative in sign, indicating that demand is generally lower at the start of the week and at the end compared to other working days.



(a) Hourly dummies for the electricity demand

(b) Hourly price elasticity of electricity demand

Since the focus of our work is on the hourly price elasticity of demand, we estimate the elasticity based on the results from the basic regression. The results are displayed in Figure 5b and the numerical values can be found in Table 3c.[18]

As observed before, all coefficients are negative in sign and significant at a strict 1% level. With the elasticity estimates at hand, we are able to plot a distinctive pattern for the hourly price elasticity of demand for the German day-ahead market. The unique shape of the hourly price elasticity of demand pattern is depicted above in Figure 5b. Our results show that demand reactions are rather small. However, a perfect inelastic demand assumption can also be neglected. More precisely, the elasticity is the lowest during night times (22:00 - 6:00). During these hours electricity demand and utility from electricity consumption is

[18] It is important to note that elasticity is calculated with respect to the wholesale price level and not the retail price level, as represented by the dashed red demand curve in Figure 2. The elasticity with respect to retail prices would be higher. For example if we consider the sum of additional price components (c) to be 150 EUR/MWh, which is an average value based on Eurostat (2016) for Germany, the highest elasticity measured would be -0.58 at hour 17:00-18:00. Without the sum of additional price components, we obtain an elasticity of -0.13 as indicated in Table 3c.

Hour	Price	Dummy
0	-0.0847*** (-3.98)	.
1	-0.0853*** (-4.18)	-2.135** (-2.91)
2	-0.0781*** (-4.23)	-3.429*** (-4.94)
3	-0.0960*** (-4.89)	-2.816*** (-4.01)
4	-0.1150*** (-5.60)	-0.8526 (-1.18)
5	-0.1298*** (-6.01)	3.714*** (4.70)
6	-0.1322*** (-4.96)	13.410*** (11.95)
7	-0.1192*** (-4.37)	20.620*** (15.14)
8	-0.0743*** (-3.55)	21.960*** (19.48)
9	-0.0452** (-2.95)	20.940*** (24.20)
10	-0.0421** (-2.69)	22.230*** (26.42)
11	-0.0496** (-2.92)	23.720*** (27.34)
12	-0.0557** (-3.01)	23.080*** (26.61)
13	-0.0688*** (-3.30)	22.590*** (24.57)
14	-0.0844*** (-3.58)	21.660*** (22.02)
15	-0.1069*** (-4.02)	21.240*** (19.26)
16	-0.1486*** (-3.66)	21.630*** (13.19)
17	-0.2018** (-2.90)	24.990*** (8.15)
18	-0.1349** (-2.65)	22.970*** (9.41)
19	-0.1175** (-3.19)	21.410*** (11.81)
20	-0.1327*** (-5.14)	18.490*** (15.26)
21	-0.1034*** (-5.68)	13.760*** (15.81)
22	-0.0890*** (-4.66)	9.565 (11.29)
23	-0.0836*** (-4.05)	4.164 (5.25)

(a) Dummy and price coefficients

	Coefficient
Heating degree days	0.4679*** (81.99)
Monday dummy	-3.340*** (-28.08)
Friday dummy	-1.997*** (-12.07)
Constant	46.57*** (84.62)
Observations	5760
R^2	0.940
Adjusted R^2	0.939

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(b) Regression coefficients

Hour	Elasticity
0	-0.0456*** (-3.96)
1	-0.0451*** (-4.15)
2	-0.0394*** (-4.20)
3	-0.0467*** (-4.85)
4	-0.0561*** (-5.57)
5	-0.0661*** (-5.99)
6	-0.0792*** (-4.95)
7	-0.0810*** (-4.36)
8	-0.0501*** (-3.54)
9	-0.0279** (-2.95)
10	-0.0240** (-2.68)
11	-0.0271** (-2.91)
12	-0.0283** (-3.00)
13	-0.0345*** (-3.29)
14	-0.0425*** (-3.57)
15	-0.0566*** (-4.01)
16	-0.0828*** (-3.64)
17	-0.1275** (-2.88)
18	-0.0912** (-2.64)
19	-0.0821** (-3.18)
20	-0.0875*** (-5.12)
21	-0.0640*** (-5.65)
22	-0.0543*** (-4.63)
23	-0.0456*** (-4.03)

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(c) Elasticity

Table 3: Regression results

generally lower (as we can also observe from Table 3a). The graph shows two prominent peaks of price elasticity of demand in the morning and in the evening. At these times working hours start and end. Possible reasons for a high elasticity of demand at those times is the shifting or delaying of consumption. When prices are low in the morning, some processes may be able to start the operation earlier and thereby circumventing a time with a higher electricity price level. The same might be true for the evening, when the workday ends. Here working hours may be extended to lower price levels at other times. Throughout the day, the price elasticity of demand remains relatively low and is less significant. At those hours, economic activity is high and the option to shift or delay electricity consumption might not be feasible for consumers. In other words, consumers are bound to consume electricity which results in high electricity consumption regardless of the price level.

5. Conclusion

We estimate the hourly pattern of price elasticity of demand for the German day-ahead market, using hourly data on load, price, generation of wind and temperature. By doing this, we are able to determine the degree of short-run demand response within this market. To the best of our knowledge, a market-wide hourly analysis of the price elasticity of demand has not been conducted so far.

Based on our two-stage regression approach which uses wind generation as an instrument to proxy the electricity price, we find that hourly price elasticity of demand is not completely price inelastic. Especially during the morning and evening demand is responding to price signals. Values for price elasticity range from approximately -0.02 to -0.13 depending on the investigated hour. The hourly price elasticity pattern reveals that elasticity is lowest in the night hours and around mid day. Low values for price elasticity during night time (22:00 - 06:00) indicate that consumers are less likely to react. Around middle day economic activity is high which may explain the low elasticity values. Price elasticity of demand is the highest in the early morning (04:00 - 07:00) and late afternoon (16:00 - 20:00) hours, with levels between -0.08 and -0.13.

The empirical results indicate a high level of variation in the price elasticity of demand throughout the day in the German day-ahead market. Although the hourly elasticity is low from a first glance, load shifting accumulates over the year. The found elasticity pattern helps to understand when demand shifting occurs and when demand may be able to contribute to system security in situations of low supply. We find that especially during critical situations, such as peak times in the morning and evening, price elasticity of demand is high and may contribute to a secure electricity system.

Our research sheds some light on how flexible the German electricity market has already been in 2015, given the underlying renewable generation of the German day-ahead market. It may also give policy makers a starting point for evaluating the interaction of supply and demand in electricity markets. In addition to the analysis of the day-ahead market, we reckon that further research on demand response could focus on short-term markets, such as the intraday market. These markets are essential to the integration of large amounts of renewable electricity because they are able to balance forecast errors of wind and solar electricity. Whereas this additional research would gain further insights onto the short-term demand response, we argue that currently the day-ahead market remains the most important market where demand and supply are balanced.

Appendix

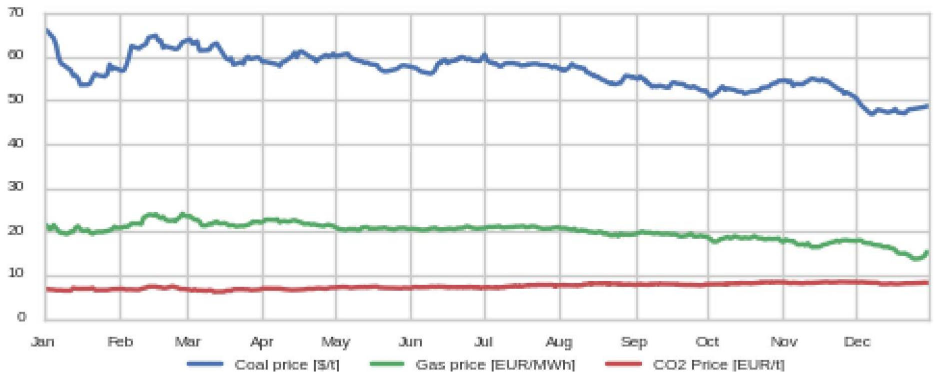


Figure .5: Prices for coal, gas and co2 certificates from January to December 2015

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