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How aggregate electricity demand responds to hourly wholesale price fluctuations

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Abstract. Electricity needs to be consumed at the very moment of production, leading wholesale prices to fluctuate widely at (sub-)hourly time scales. This article investigates the response of aggregate electricity demand to such price variations. Using wind energy as an instrument, we estimate a significant and robust short-term price elasticity of about -0.05 in Germany and attribute this to industrial consumers. While seemingly modest, our results imply that even with limited exposure to real time prices, short-term demand response facilitates decarbonization of the electricity grid by reducing the need for battery storage or backup fossil power by approximately 8%.

Keywords: Short-term price elasticity, electricity markets, demand response, instrumental variables, wind energy

1 Introduction

Topic. Electricity is a peculiar good in that it must be produced at the very moment of consumption. Reflecting this physical requirement, wholesale electricity markets clear at hourly or even sub-hourly intervals. The corresponding prices fluctuate widely within a day, regularly reaching multiples of their average and even turning negative occasionally. This study investigates the response of aggregate, nationwide electricity demand to these price fluctuations, given that only some consumers are exposed to time-varying wholesale prices. There are many studies on the demand response to more persistent price changes and of distinct consumer groups, but studies on the price elasticity of aggregate demand at short time scales have remained inconclusive to date.

Relevance. However, robust estimates of the aggregate high-frequency demand elasticity are critical for many analyses of electricity systems and markets. First, the aggregate demand response substitutes for generation capacity at a given level of security of supply (Bushnell, 2005; Hogan, 2005). Therefore, it is a key input parameter to regularly conducted resource adequacy studies (e.g., ENTSO-E, 2022; NERC, 2022). Second, the aggregate demand response limits the incentive to exercise market power (Borenstein et al., 1999; Albadi and El-Saadany, 2007). Third, the degree to which demand is responding to prices drives policy decisions, such as the current assessments of the spatial granularity of European electricity markets (ACER, 2020; Ofgem, 2022). Notably, government-mandated capacity mechanisms are often justified by a lack of demand response (Cramton et al., 2013). Finally, the aggregate demand response helps in integrating wind and solar energy to enable long-term decarbonization scenarios, avoid curtailment, and substitute other costly flexibility options such as fossil power plants or energy storage (Roscoe and Ault, 2010; Ruhnau, 2022).[1]

Literature on longer time scales/persistent price changes. The large body of literature on the price elasticity of electricity demand can be structured along time scales. Many studies examined how electricity demand responds to monthly and annual changes in consumer prices (for a review, see Labandeira et al., 2017). By design, these studies do not capture the demand response to high-frequency changes in wholesale prices. Rather, they identify the response to more persistent changes in wholesale prices to the extent that they are passed through to consumers. In fact, such a study design matches with the fact that many consumers are subscribed to tariffs that change only annually.[2] Interestingly, some studies evaluated how such more persistent consumer price changes affect the hourly pattern of electricity demand (Fan and Hyndman, 2011; Filippini, 2011). However, such a time-dependent response to persistent consumer price changes is fundamentally different from responding to high-frequency changes in wholesale prices, which is the focus of the present study.

Individual consumers on shorter time scales. In fact, based on theoretical arguments, authors have argued since the onset of liberalization of electricity markets that real-time retail tariffs, which pass through high-frequency changes in wholesale prices to consumers, would improve efficiency (e.g., Borenstein and Holland, 2005). Several studies have investigated the effect of such real-time pricing on individual consumers. Faruqui and Sergici (2013) as well as Harding and Sexton (2017) summarize international evidence from numerous experimental studies on the demand response of domestic consumers. Fabra et al. (2021) investigate the response of Spanish households to the nationwide implementation of real-time pricing as a default tariff option. Others focus on industrial consumers or sectors (Patrick and Wolak, 2001; Taylor et al., 2005; Hopper et al., 2006; Zarnikau and Hallett, 2008; Choi et al., 2011; Møller and Andersen, 2015). While these studies provide evidence on and detailed

[1] Note that precise information about demand response can also improve short-term electricity price forecasting, dispatch planning, load flow modeling, and other operational decisions.
[2] This includes time-of-use, where different prices apply for peak and off-peak times, but the levels of the different prices change only annually.

insights into the price response of distinct consumer groups, they cannot be extrapolated to the aggregate wholesale electricity demand—which is what ultimately matters for power systems and markets.

Aggregate demand on shorter time scales. There is no consensus on the price elasticity of aggregate electricity demand to short-term fluctuations in wholesale prices among the few studies that have previously investigated this topic. Such an aggregate demand response is the result of both the extent to which consumers are exposed to real-time pricing and the price elasticity of these exposed consumers. As an example of the inconclusiveness of existing evidence, Lijesen (2007) found an aggregate demand elasticity of –0.0043 in the Netherlands in 2003, while Bönte et al. (2015) estimated an aggregate elasticity of –0.43 in the German wholesale demand in 2010–2014. There could be multiple reasons for this stark discrepancy of two orders of magnitude. The lagged price used as an instrument by Lijesen (2007) may not fulfill the exogeneity assumption because of intertemporal relationships in power systems.[3] On the other hand, Bönte et al. (2015) examined the bids on a single wholesale trading platform, where only a fraction of aggregate consumption is traded.[4] More recently, Kulakov and Ziel (2019) tried to decompose German bid data into underlying aggregate demand curves and Damien et al. (2019) used a hierarchical Bayesian model and data from Texas to regress demand on prices, but it is unclear to us how these studies address endogeneity concerns. Finally, Knaut and Paulus (2016) used wind energy as an instrument and found an aggregate demand elasticity of –0.02 to –0.13 in Germany in 2015.

Contribution. This study adds to this previous literature in five major aspects. First, we develop a theoretical framework for the causal identification of demand response, using wind energy as an instrument. To do so, we discuss in-depth discussion of how prices impact load, given the institutional context of the German and European electricity market. Second, we conduct a broad range of sensitivity analyses and robustness checks to show the soundness of using wind energy as an instrument and define the bounds of the estimates of price elasticity. Importantly, we perform a long list of tests and analyses concerning challenges to the exogeneity of the instrument, including alternative and additional instruments. Third, we use multiple model specifications, including a purely linear specification (as in Knaut and Paulus, 2016), a log-linear specification, and specifications with nonparametric elements. This matters because there are many reasons to expect nonlinear relationships in power markets. The models are estimated using a 2-stage least squares (2SLS) and a 2-stage generalized additive models (2SGAM). This allows us to study the shape of the demand curve. Fourth, we study the heterogeneity of demand response across time, including the time of the day, day of the week, and season of the year, as well as across different regions, and compared the spatial heterogeneity to the uneven distribution of industrial load across Germany. Finally, we update and extend the scope of previous analyses to five years from 2015 to 2019.[5] This is important for ascertaining the robustness of the analysis and accounting for time trends.

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[3] For example, in the main wholesale market, the day-ahead auction, all hourly prices of the next day are determined at the same time, considering the thermal inertia of power plants and energy storage. As a result, hourly prices in one hour can not only affect prices in the next hour but also in the previous hour, which violates the exogeneity assumption.

[4] Bönte et al. (2015) used data from Germany's largest electricity exchange, EPEX SPOT. In our sample period, trading volumes at EPEX SPOT were about half the German electricity demand. This is due to integrated utilities and over-the-counter trades outside of the exchange.

[5] Note that our estimates of demand elasticity correspond to the "normal period" of 2015-19. The period since 2020 has been excluded from the analysis because the COVID induced lockdowns and the energy crisis in Europe since late 2021 caused disruption in the energy markets and could have temporarily altered consumer behavior in response to the unusually high fluctuations in prices (Fezzi and Fanghella, 2021; Ruhnau et al., 2023).

Findings. We estimate that a 1 €/MWh increase in the price in the wholesale markets causes the aggregate electricity demand in Germany to decline by 67–80 MW (linear estimates) or 0.12–0.14% (log-linear estimates). At the average price and demand, these estimates correspond to a price elasticity of demand of about −0.05. Comparing situations with high and low wind energy (5–95th percentile), we estimate that prices vary by 26 €/MWh, and the corresponding demand response is about 2 GW, or 4% of average demand. Our estimates are robust across years or seasons. We find a strongly nonlinear demand curve during nighttime and a quite linear curve during daytime hours. Our estimates of the regional distribution of demand response match with the regional distribution of energy-intensive industry in Germany, consistent with the fact that it is mostly industrial consumers who are exposed to wholesale electricity price variations. The results are statistically significant and remarkably robust across a broad range of model specifications, estimators, time periods, alternative instruments, and other sensitivity analyses.

Implications for renewable integration. Our estimates show that, even if only a fraction of (industrial) consumers are exposed to wholesale price variations at very short intervals, their demand response is substantial enough to help in the decarbonization of the electricity sector. The ongoing energy transition heavily relies on variable wind and solar energy, but their further expansion is impeded by the fact that they are not always available when electricity is needed. On the other hand, there may be times when renewables are abundant and curtailed. However, our estimate for price elasticity implies that in Germany the integration of about 8% of wind energy production is facilitated by an increase (decrease) in aggregate demand during periods of high (low) wind generation and correspondingly low (high) electricity prices. This reduces the need for expensive battery storage and fossil-fueled back-up power plants.

Outline. We continue with providing background and explaining our identification strategy for demand response in wholesale electricity markets in Section 2. On that basis, Section 3 introduces our models and data. Sections 4 and 5 present the main results and robustness checks, respectively. Section 6 discusses the results and draws conclusions.

2 Estimating demand response in wholesale electricity markets

Price elasticity of demand. We are interested in estimating the price elasticity of electricity, i.e., the causal effect of the wholesale electricity price from the day-ahead market (treatment) on the aggregate electricity demand (outcome) at very short time scales, such as hours. The causal graph in Figure 1 provides an overview of the main causal relationships of interest to this study, which are discussed in more detail in the following.

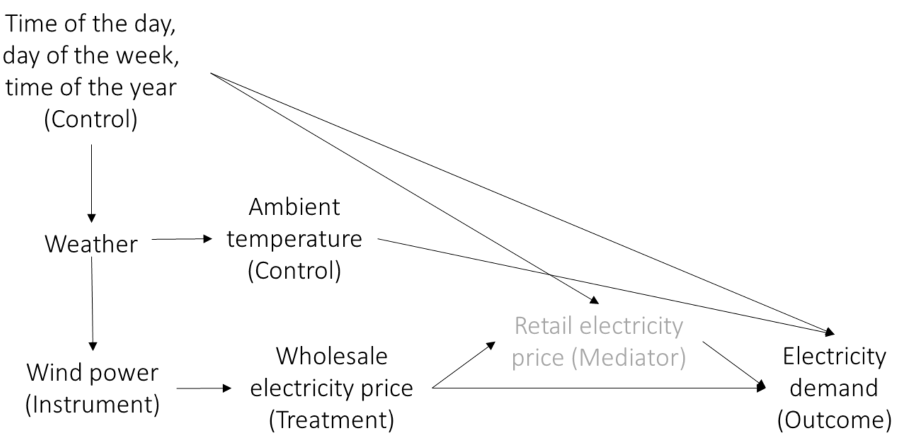

Figure 1: Main causal relationships

2.1 Price exposure

Price exposure. When investigating demand response in wholesale electricity markets, it is critical to understand to what extent consumers are exposed to variations in wholesale prices. In fact, most electricity consumers in Germany are not directly exposed to variations in day-ahead market prices. Instead, retail suppliers of electricity purchase electricity in the wholesale markets for them (Duso and Szücs, 2017). These consumers can freely choose between retail suppliers and tariffs that reflect wholesale prices in day-head markets to varying degrees: from not at all (constant price during a year) to real-time pricing (prices change hourly). During our observation period, real-time pricing tariffs were not available to households, but commercial consumers were exposed to wholesale prices to different degrees. The very largest energy-intensive firms procure electricity directly from the wholesale market and are fully exposed to variations in the day-ahead wholesale price of electricity (the direct causal path between wholesale prices and demand in Figure 1). Additionally, some commercial consumers have real-time tariffs that reflect the wholesale price variation (the indirect causal path between prices and demand in Figure 1). Using hourly day-ahead prices in the wholesale markets enables us to estimate the aggregated response of consumers with direct procurement and with real-time pricing. However, we cannot identify the role of individual consumers or types of consumers.

Time-of-use pricing. Some retail tariffs feature deterministic time-of-use pricing in the sense that the price of electricity changes in predetermined ways to reflect recurring diurnal trends in the wholesale electricity markets.[6] For example, consumers may pay higher prices for the electricity consumed during the day than at night. Such tariffs do not reflect the stochastic part of the variation in wholesale prices caused by, for example, the stochasticity of wind speed. Although electricity demand may respond to such time-of-use prices, our instrumental regression using wind energy as an instrument while controlling for diurnal seasonality does not capture such a response.

Additional price components. For all electricity consumers, the wholesale price of energy is only one part of what they pay as the retail electricity price. What comes on top are additional price components such as grid fees, taxes, levies (e.g., renewable energy financing costs), metering costs, and retail margins. In Germany, these price components are independent of fluctuations in the wholesale price of electricity. This has two implications for our research. First, while fluctuations in wholesale electricity prices may be fully passed through to the consumer in absolute terms, the relative variation in retail prices will be smaller. As our model is based on prices in absolute terms, this should not affect our estimates. Second, the structure of these additional price components may incentivize certain behaviors. For example, industrial network fees often include large capacity payments that are calculated based on consumption during the hour with the highest demand during the year. Therefore, the marginal cost of consumption during such hours, on top of the wholesale price and other taxes and levies, is very high. To minimize such payments, industrial consumers may try to avoid consumption peaks, even if the wholesale market prices are low. Hence, the current German regulation of additional price components will be reflected in our estimates, and our results cannot directly be extrapolated to differently regulated electricity markets and countries. However, future research may apply our method to different datasets to investigate the temporal evolution and international heterogeneity of demand response in wholesale electricity markets.

2.2 Causal identification

Instrument variable. There is a long tradition in economics of applying instrument variables for estimating supply and demand curves and the price elasticity of demand for all kind of goods. Because

[6] In Germany, time-of-use pricing is rare and mostly applies to night storage heating. We can think of time-of-use pricings as a causal path between the time variables and retail electricity prices (Figure 1).

the supply and demand curves shift over time, the observed data on quantities and prices reflect a set of equilibrium points on both curves. Due to this simultaneity problem, ordinary least squares cannot be used to determine either the supply or the demand curve (Angrist and Krueger, 2001; Wooldridge, 2013). To isolate the demand curve and estimate the price elasticity of demand from time series data, we use the quantum of hourly wind energy generation as an instrument for electricity prices. To be a valid instrument, wind energy must fulfill three conditions: it must be exogenous, relevant, and fulfill the exclusion restriction. We discuss these conditions in turn.

Exogeneity. The first condition, the exogeneity condition, means that wind generation must be unaffected by electricity prices and demand. The potential wind power supply is driven by weather conditions—more precisely, wind speed, which is certainly unaffected by electricity markets. Indeed, because of its natural stochasticity, weather variables have long been used as instruments to estimate the demand elasticity of other goods, such as oil and fish (e.g., Wright, 1928; Graddy, 2006). We can also assume that wind generation is strictly exogenous in the sense that current wind generation is unaffected by past electricity market outcomes, which is important for causal inference with time series.

Wind generation vs. speed. Instead of using wind speed directly, we include wind generation in the main model specification. This is because the relationship between wind speed and wind generation is nonlinear due to the underlying S-shaped power curves of wind turbines. Furthermore, wind turbines shut down at very high wind speeds, which may compromise the condition that the relationship between the instrument and the endogenous variable must be monotonous. However, we use wind speed as an instrument for sensitivity analyses, and we exploit the nonlinear relationship between wind speed and wind energy to perform a zero-first-stage test, finding supporting evidence for the validity of our instrument (see Sections 5.1 and 5.2 below).

Curtailment. In contrast to the *potential* wind power supply, which is determined by physics, the *actual* supply may be affected by the decision not to produce, even though the wind is blowing. This may be due to two reasons: negative wholesale electricity prices or congested networks. We argue that negative prices play only a minor role[7] and that congested networks may only cause an underestimation of demand elasticity, i.e., we would find a conservative estimate[8]. In addition, we conduct two sensitivity analyses to address endogeneity concerns: one in which we exclude hours with negative prices from the dataset and one using wind *speed* instead of wind *generation* as an instrument. As our estimates are robust in both cases (see Sections 5.1 and 5.3 below), we conclude that the endogeneity of wind energy is not an issue.

Relevance. The second requirement for wind generation to be a good instrument is that it must meet the relevance condition, i.e., wind generation must be sufficiently correlated with electricity prices. In economic terms, increased wind generation is a supply shock that affects the electricity price by shifting the electricity supply curve outward. An increase in wind energy generation, *ceteris paribus*, leads to a decrease in electricity prices, while a decrease in wind energy generation causes electricity prices to increase. Indeed, wind energy has a high explanatory power for price variations that cannot

[7] The marginal cost of generating wind energy is virtually zero, and many wind generators receive, on top of wholesale revenues, additional income for each MWh produced (e.g., in the form of contracts-for-difference or tradable green certificates). Because of the opportunity costs related to this additional income, they will stop producing only if the wholesale price turns steeply negative. This is the case during only a few hours of the year.
[8] Transmission network congestion mostly occurs when both wind speed and electricity demand are high. Hence, conditional on high wind speed, high demand may cause somewhat lower wind supply through curtailment, which would be a negative relationship between wind and demand. Because the demand elasticity causes a positive relationship between wind supply and demand through lower prices, a positive relationship due to curtailment would imply an *underestimation* of demand elasticity.

be explained by other covariates: the partial R^2 of wind energy in the first stage of our two-stage regression is high, indicating that wind energy is a relevant instrument for wholesale electricity prices (see Section 4.1 below).

Exclusion restriction. The third and essential condition for using wind generation as a valid instrument is the exclusion restriction, i.e., wind generation must not affect the electricity demand other than through the wholesale electricity price. The wind energy supply is naturally stochastic because of the underlying weather patterns. Nevertheless, there are four potential threats to the exclusion restriction: concomitant seasonality in wind speeds and electricity consumption, correlation between wind generation and temperature, wind-sensitivity of electricity demand for heating and cooling, and wind-induced service interruptions. These are discussed in the following paragraphs.

Seasonality. First, both wind speeds and electricity demand feature diurnal and annual seasonality. The root causes for these are different: winds are driven by atmospheric physics, while demand seasonality reflects patterns of human life and business activity. Nevertheless, this correlation could bias our estimate of the price elasticity of demand. To correct for this, we control for time of day and time of year in our regressions, using hourly and monthly dummy variables, as well as nonlinear time trends in electricity demand and prices.

Temperature. Second, beyond seasonality, electricity demand is impacted by weather, particularly ambient temperature, because electricity is used for heating and cooling. Hence, the degree to which wind speeds and temperature are physically correlated may bias our estimate of the price elasticity of demand. To address this issue, we control for the ambient air temperature using heating and cooling degrees or nonparametric specifications.

Wind sensitivity of heating and cooling. Third, wind speeds affect the apparent temperatures and heat loss in buildings, implying that heating and cooling demand may be a function of not only temperature but also wind speed directly (Huang et al., 1990; Sholahudin and Han, 2016). Thus, wind speed could directly affect electricity demand through heating and cooling. If this was the case, we would expect the sign of the effect to depend on the season: wind would increase heating and electricity demand during winter and decrease cooling and electricity demand during summer. This would lead to an overestimation of the price elasticity of demand during winter because demand increases in times of high wind speeds are related not only to low prices but also to the direct positive link between wind and demand. The potential bias would be reversed during summer (and probably smaller because there is less electric cooling than heating in Germany). We investigate this hypothesis in a sensitivity analysis, in which we run separate regressions using observations from only one season (see Section 4.2 below). Because our estimates remain unchanged, we conclude that our findings on price elasticity are not substantially biased by direct wind-heating or wind-cooling effects.

Wind-related demand disruption. Finally, storms may lead to interruptions of electric services, such as the railways, leading to lower electricity consumption. This lower demand in times of high wind supply (and low electricity prices) would lead us to *underestimate* the price elasticity of demand. To explore this possible effect, we conduct a sensitivity analysis excluding hours with very high wind speeds from our dataset (see Section 5.3). As our estimates remain virtually unchanged, we conclude that wind-related demand disruptions are not a serious threat to the exclusion restriction.

3 Models and data

Overview. This section presents our five main model specifications as well as the data that we use to identify hourly demand response in wholesale electricity markets. All specifications comprise two equations: one for price as a function of supply and one for demand as a function of price. For all models, we use wind as a supply-side instrumental variable to address the simultaneity problem of price and demand. The models differ in their assumptions on the linearity of relationships (Table 1). The first two specifications assume a linear and a log-linear relationship between demand and price, with linear control variables (Section 3.1). The other specifications assume a linear, a log-linear, and a nonparametric demand–price relationship, while including nonparametric smooth functions for control variables (Section 3.2).

Table 1: Overview of our five main model specifications

Model	**1**	**2**	**3**	**4**	**5**
Model class	Parametric models		Nonparametric models		
Specification of controls	Linear		Linear/Nonparametric		
Estimator	Two-stage least squares (2SLS)		Two-stage generalized additive model (2SGAM)		
Demand–price relationship	Linear	Log-linear	Linear	Log-linear	Nonparametric

3.1 Parametric models

Linear specification. For the purely linear specification, we define the simultaneous equation model as

$$Price_t = \alpha_0 + \alpha_1 I_t + \boldsymbol{\alpha_2 C_t} + \boldsymbol{\alpha_3 D_t} + v_t \tag{1}$$

$$Demand_t = \beta_0 + \beta_1 Price_t + \boldsymbol{\beta_2 C_t} + \boldsymbol{\beta_3 D_t} + u_t \tag{2}$$

where

$Price_t$	Wholesale price of electricity at hour t
$Demand_t$	Electricity demand at hour t
β_1	Price elasticity of demand
I_t	Instrument (wind energy)
$\boldsymbol{C_t}$	Controls (solar power, heating and cooling degrees, prices of coal, gas, and carbon)
$\boldsymbol{D_t}$	Dummy controls (hour of the day, weekday, month of the year, and year)
α, β	Modeled linear coefficients
u, v	Error terms

and bold letters indicate vectors of multiple variables or coefficients.[9] The second model specification uses the logarithm of demand in the second stage. The coefficient of price (β_1) can then be interpreted as the *relative* change in demand per absolute change in price. Taking the logarithm of price to estimate the dimensionless elasticity parameter with the typical log-log specification is not possible because hourly electricity prices at times become zero or negative.

2SLS estimator. Because of the simultaneity of the equations, the key regressor (price) is correlated with the error term of Eq. (2), implying that ordinary least squares estimates are biased. Hence, we use the 2SLS model with Eq. (1) as the first and Eq. (2) as the second stage. In the first stage, the price is regressed on our exogenous instrument (wind energy). In the second stage, the price is replaced by the predicted price based on Eq. (1).

[9] Note that some of the control and dummy variables (e.g., hour of the day) are necessary to fulfill the exclusion restriction because both wind energy and electricity demand feature diurnal patterns (see Section 2.2). Other variables are included to improve the explanatory power of the model (e.g., weekdays); they explain demand patterns (as they approximate exogenous variations in economic output) but are uncorrelated to wind speeds.

2SLS standard errors. Our input data feature strong serial correlation, and so do the error terms v_t and u_t in Eqs. (1) and (2). To account for this, we calculate heteroscedasticity and autocorrelation (HAC) robust standard errors of the estimates. More precisely, we calculate kernel standard errors using the Bartlett kernel with automatic bandwidth selection as implemented in the *linearmodels* Python package. Related to this, Section 5.4**Error! Reference source not found.** presents a sensitivity regression based on first differences, which significantly reduces serial correlation in the residuals.

3.2 Nonparametric models

Nonparametric specifications. A priori, there is no reason to believe that the relationship between demand and price should be linear. For example, industrial consumers may respond only to very high prices when it becomes profitable for them to disrupt their industrial production processes. To allow for the determination of such possible nonlinear effects of predictors on the response variable in Eqs. (1) and (2), we use a generalized additive model (GAM) that can be specified as follows:

$$Price_t = \alpha_0 + \mathrm{s}_{\alpha,1}(I_t) + \mathbf{s}_{\boldsymbol{\alpha},\mathbf{2}}(\boldsymbol{C_t^s}) + \boldsymbol{\alpha_3 D_t} + v_t \tag{3}$$

$$Demand_t = \beta_0 + \beta_1 Price_t + \mathbf{s}_{\boldsymbol{\beta},\mathbf{2}}(\boldsymbol{C_t^s}) + \boldsymbol{\beta_3 D_t} + u_t \tag{4}$$

where

$Price_t$	Wholesale price of electricity at hour t
$Demand_t$	Electricity demand at hour t
β_1	Price elasticity of demand
I_t	Instrument (wind energy)
$\boldsymbol{C_t^s}$	Controls (solar power, temperature, time, prices of coal, gas and carbon)
$\boldsymbol{D_t}$	Dummies (hour of the day, weekday, month of the year, and year)
$\mathrm{s}(\cdot)$	Nonparametric smooth functions
α, β	Modeled linear coefficients
u, v	Error terms

The terms $s_1(x_1) \dots s_p(x_p)$ denote smooth, nonparametric functions, which, depending on the underlying patterns in the data, may be nonlinear. The GAM structure allows for the parametric and nonparametric terms to be combined additively, allowing for the usual interpretation of the parametric terms. The expected value of the dependent variable is $g(E(Y)) = \alpha + s_1(x_1) + \dots + s_p(x_p)$, where Y is the dependent variable, $E(Y)$ denotes the expected value of the dependent variable, and $g(Y)$ denotes a link function (for example, a linear or logarithmic function), which links the expected value to the predictor variables $x_1, \dots x_p$. In addition to the linear demand–price relationship defined in Eq. (4), we run two more specifications with a log-linear and a nonparametric demand response, obtained by replacing $\beta_1 Price_t$ in Eq. (4) with $s(Price_t)$.

2SGAM. As in the case of the linear specification, the presence of a simultaneous relationship between demand and price can lead to inconsistent estimates of Eq. (4). To address this issue, we use the 2SGAM approach laid out by Marra and Radice (2011). For the endogenous variable, the price, consistent estimates of α, and $s(\cdot)$ are obtained by fitting the GAM corresponding to Eq. (3). Then, we estimate the value of the residuals $\hat{v}_t = Price_t - (\hat{\alpha}_0 + \hat{\mathrm{s}}(I_t) + \hat{\mathbf{s}}(\boldsymbol{C_t^s}) + \boldsymbol{\hat{\alpha}_3 D_t})$, which captures the endogenous variation in the price variable. Next, a GAM defined by equation Eq. (4) that includes an additional term $s(\hat{v}_t)$ is calculated to flexibly account for the endogenous variation in the price variable. In doing so, the linear/nonlinear effects of price can be estimated consistently. Note that $s(\hat{v}_t)$ will contain a mixture of effects, which makes it not interpretable. However, this is not problematic, since all that is required is to account for the presence of endogeneity (see Marra and Radice, 2011). In practice, the 2SGAM estimator can be implemented using GAMs represented via any penalized regression spline approach. The 2SGAM approach described in this section is fitted using the *gam* function in the R package *mgcv.* The *mgcv* package fits the 2SGAM estimator using penalized likelihood, which can be maximized by penalized iteratively reweighted least squares (P-IRLS) (Marra and Radice, 2011; Zanin et al., 2015; Wood, 2017).

2SGAM confidence intervals. Confidence intervals for the components of a GAM can be constructed using Bayesian confidence intervals (Wood, 2006; Marra and Wood, 2012; Gu, 2013). Because the second stage of 2SGAM cannot account for the additional source of variability introduced via the residuals calculated in the first step, the intervals for the components in the second-step model will be too narrow, leading to poor coverage probabilities. This can be rectified via posterior simulation (Zanin et al., 2015). Intuitively, samples from the posterior distribution of each first-step model are used to obtain samples from the posterior of the quantities of interest v_t. Then, given that the N_b vector replicates for each v_t, N_d random draws from the N_b posterior distributions of the second-stage model are used to construct approximate intervals for the smooth functions. Marra and Radice (2011) suggested that N_b = 25 and N_d = 100 yield good coverage probabilities. These settings were used to construct 95% intervals for the function estimates obtained using the 2SGAM.

Alternative modeling approach. Because prices and demand in each hour are related to prices and demand in the adjacent hours, an alternative modeling approach could be Vector Autoregressive Models (VAR). Some previous articles have used this approach to estimate the impact of wind and solar generation on electricity prices (e.g., Paschen, 2016). However, there are challenges to using VAR for estimating a causal relationship. To the best of our knowledge, there is no previous literature on combining VAR with instrumental variables in the context of the energy markets. An approach for causal identification has been suggested for monetary policy analysis, but this is not easily generalizable to other economic variables, because amongst other things, it would require the observations of the instrument to be serially uncorrelated (Kilian and Lütkepohl, 2017). There is also no clear way of combining VAR with nonparametric estimation. We therefore prefer to use linear and nonparametric specifications and account for the inter-temporal relationship between demand and prices through HAC-robust standard errors and in a sensitivity based on first differences (see Section 5.4).

3.3 Data

Variables considered. We apply our model to a large set of data from Germany for the years 2015 to 2019. Hourly time series for German wholesale electricity prices, electricity demand, wind and solar generation, ambient temperature, and other weather variables were obtained from the Open Power System Data platform (Wiese et al., 2019). This platform aggregates data from different primary sources, which are mentioned in Appendix A. We complemented this dataset with monthly coal and gas prices as well as daily carbon prices from the relevant trading platforms. All data is presented and discussed in detail in Appendix A.

Excluded observations. We exclude holidays, bridge days (days between holidays and weekends), and the Christmas vacation period (between Christmas and New Year) from the analysis, as the demand and price patterns on these days are distinctive and not representative of the general relationship between prices and demand. This leaves us with a total number of 38,448 observations. Table 2 reports descriptive statistics of all considered variables.

Table 2: Descriptive statistics

	Mean	Std. Dev.	Min	Max
Electricity price (€/MWh)	36.30	15.75	-130.09	163.52
Electricity demand (GW)	56.52	9.91	31.31	77.55
Wind energy (GW)	10.85	8.52	0.14	45.08
Solar energy (GW)	4.38	6.64	0.00	29.97
Temperature (°C)	10.10	8.19	-11.15	35.48
Heating degrees (°C)	6.42	6.16	0.00	26.15
Cooling degrees (°C)	1.52	3.12	0.00	20.48
Carbon price (€/t)	11.77	7.77	3.93	29.81
Coal price (€/MWh)	9.19	2.19	5.92	13.16
Gas price (€/MWh)	18.00	5.01	9.59	29.31

4 Results

Outline. In this section, we first present the main results on demand elasticity for all five model specifications (Section 4.1). We then split the dataset into temporal subsets, such as seasons and day and night (Section 4.2) and investigate regional differences (Section 4.3).

4.1 Demand elasticity

First stage. The results of the first-stage regressions are reported in Table 3. The first stage is independent of whether the demand–price relationship is assumed to be linear, log-linear, or nonparametric, but it does differ between 2SLS and GAM estimation. As expected, we find that wind energy has a significant negative effect on prices in both model specifications (at the 0.001 level). Furthermore, in the linear model, the partial R^2 of wind energy and the F-statistic of the excluded instrument are very high (0.46 and 930, respectively). The F-statistic exceeds by far the critical values 13.91 and 16.38 for weak instrument tests based on max. 5% 2SLS bias and max. 10% 2SLS size, respectively (Stock and Yogo, 2005). In addition, the first-stage partial F-statistic calculated using bootstrapped standard errors is calculated as 14,669, much higher than even the most stringent criteria suggested by (Lal et al., 2021). We hence conclude that wind energy generation is a strong instrument. The results from the nonparametric models are similar to those of the linear specification. The relationship between price and wind generation is largely linear, with a slight nonlinearity at higher levels (Figure 2). The relationship between price and other coefficients turns out to be nonlinear, as detailed below.

Table 3: First-stage regression of the endogenous price variable on the instrument wind power and controls

	2SLS (Models 1, 2)	GAM (Models 3, 4, 5)
Adjusted R²	0.76	0.79
Partial R² of wind energy	0.46	-
Partial F-statistic	930	-
Wind energy (GW)	−0.94 *** [−1.01, −0.88]	Spline***
Solar energy (GW)	−1.12 *** [−1.19, −1.05]	Spline***
Temperature (°C)	-	Spline***
Heating degrees (°C)	0.36 *** [0.22, 0.49]	-
Cooling degrees (°C)	0.45 *** [0.33, 0.58]	-
Carbon price (€/t)	1.08 *** [0.84, 1.32]	Spline***
Coal price (€/MWh)	1.67 *** [1.33, 2.01]	Spline***
Gas price (€/MWh)	0.35 *** [0.12, 0.57]	Spline***
Hour	Dummies	Dummies
Weekday	Dummies	Dummies
Month	Dummies	Dummies
Year	Dummies	Dummies
Time	-	Spline***

95% confidence intervals are reported in brackets; significance levels: *** 0.001 ** 0.01 * 0.05.
The significance of the dummy variables can be found in Figure B2 in Appendix B1.
The partial F-statistic is the F-statistic of the excluded instrument (wind energy).

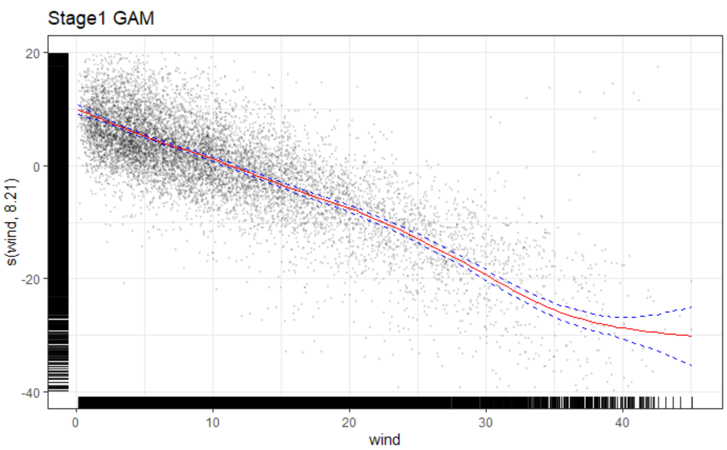

Figure 2: Estimated nonparametric wind–price relationship from the GAM. The Y-axis shows the change in price at different levels of wind generation while holding all the other variables constant.

Second stage. The results of the second stage are presented in Table 4. For all model specifications, we find the coefficient of price to be statistically significant at the 0.001 level. For a 1 €/MWh increase in the day-ahead electricity price, the electricity demand is estimated to decrease by about 67–80 MW (linear estimates) or 0.12–0.14% (log-linear estimates). The nonparametric specifications yield about 10% smaller estimates than the linear specifications. The confidence intervals reported for the 2SLS model in Table 4 were calculated using HAC standard errors to correct for serial correlation in errors (see Appendix C for treatment of serial correlation). As a robustness check, we also use bootstrap methods and calculate the Anderson-Rubin confidence intervals for the IV coefficient, but these do not diverge from our 2SLS estimates.[10] Table 4 also reports Bayesian confidence intervals for 2SGAM that are calculated using posterior simulation (see section 3.2).

Table 4: Second-stage regression of demand and log (demand) on price and other covariates

	Linear		**Log-linear** [a]	
	2SLS (Model 1)	**GAM (Model 3)**	**2SLS (Model 2)**	**GAM (Model 4)**
Adjusted R^2	0.89	0.94	0.90	0.94
Price (€/MWh)	−79.6 *** [−91.3, −67.8]	−67.3 *** [−72.2, −62.7]	−0.14 *** [−0.16, −0.12]	−0.12 *** [−0.13, −0.11]
Solar energy (GW)	−125.3 *** [−153.6, −97.1]	Spline	−0.14 *** [−0.19, −0.10]	Spline
Temperature (°C)	-	Spline ***	-	Spline ***
Heating degrees (°C)	310.9 *** [279.8, 342.0]	-	0.55 *** [0.49, 0.61]	-
Cooling degrees (°C)	149.9 *** [113.0, 186.8]	-	0.32 *** [0.25, 0.38]	-
Carbon price (€/t)	98.1 *** [37.5, 158.7]	Spline ***	0.19 *** [0.06, 0.31]	Spline ***
Coal price (€/MWh)	299.8 *** [221.0, 378,7]	Spline ***	0.53 *** [0.37, 0.68]	Spline ***
Gas price (€/MWh)	14.1 [−39.4, 67.7]	Spline ***	0.03 [−0.08, 0.14]	Spline ***
Hour	Dummies	Dummies	Dummies	Dummies
Weekday	Dummies	Dummies	Dummies	Dummies
Month	Dummies	Dummies	Dummies	Dummies
Year	Dummies	Dummies	Dummies	Dummies
Time	-	Spline ***	-	Spline ***

[a] All estimated parameters of the log-linear model are reported as percentages.
95% confidence intervals are reported in brackets; significance levels: *** 0.001 ** 0.01 * 0.05.
The significance of the dummy variables can be found in Figure B4 in Appendix B1.

Nonparametric demand curve. In the fifth model specification, we allow for a nonparametric relationship between price and demand. Here, we find a statistically significant and generally negative relationship between price and demand (Figure 3). Furthermore, the estimated relationship is also significantly nonlinear; the estimated degrees of freedom (EDF) for the price variable are equal to 8.758. At high and low prices, the relationship appears to be largely linear and negative, although demand seems largely insensitive to price changes between 20 and 50 €/MWh. However, Figure 3 also reveals a wide variation in the values of demand around the estimated relationship.

[10] The 95% confidence interval obtained using bootstrap methods [-83.98, -75.10] is smaller than the one obtained using HAC standard errors for the linear specification of 2SLS. Further, the Anderson-Rubin confidence [-84.02, -75.14], which is robust to arbitrarily weak instruments (Lal et al., 2021), is also smaller than the confidence interval that we report for the 2SLS model.

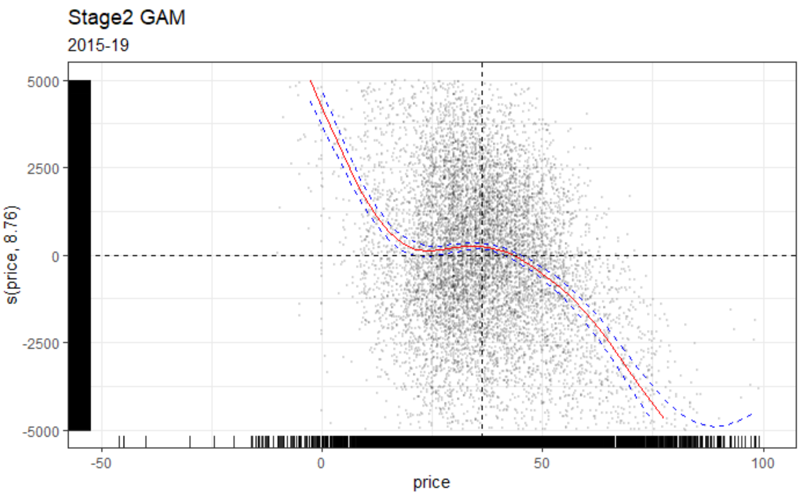

Figure 3: Estimated nonlinear demand curve in the GAM (Model 5)

4.2 Temporal heterogeneity

Approach. So far, we have presented results based on the entire 5-year dataset. In the following paragraphs, we run the same model specifications on temporal subsets of the data. These subsets separate the data along four dimensions: into different years, different seasons, weekdays and weekend, and day and night. There are two motivations for doing so. First, we want to explore the robustness of our estimates against changes in the data sample, in part because previous studies only used a single year of data. Second, we want to investigate whether the estimated elasticity varies over time and whether consumers respond differently to price changes at different times of the day or over the weekends.

Linear estimates. Figure 4 shows the linear price coefficients for the different subsets. Across years, the 2SLS estimates are very stable, with a decrease in demand of 61–82 MW per 1 €/MWh increase in price. The results from the GAM show somewhat higher variation but remain highly significant in all years. We cannot identify a consistent year-to-year trend in the price elasticity of demand. While the seasonal variation in the GAM estimates is difficult to explain, it is reassuring to see that the 2SLS estimates are fairly stable across seasons. This is an important finding because it suggests that heating and cooling are not challenges to our identification (see Section 2.2). Finally, we find that the linear estimates for demand response from both the 2SLS model and GAM are larger during weekdays and daytime hours (8 a.m. to 8 p.m.) than during weekends and nighttime hours. This seems plausible, as it correlates with (industrial) demand and economic activity in general.

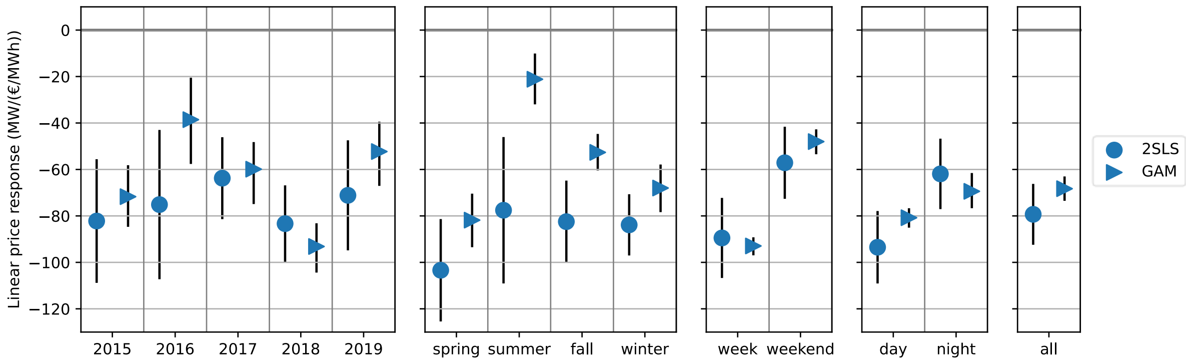

Figure 4: Estimates of linear demand elasticity based on the dataset being split into years, seasons, weekdays, weekends, and daytime and nighttime hours compared to the estimate based on the entire dataset ("all"). The whiskers indicate the 95% confidence interval.

Nonparametric estimates. The log-linear estimates are very similar to the linear specification and highly robust for both estimators (see Figure B5 in Appendix B2). The nonparametric estimates show distinct patterns for day and night: during daytime hours, the demand curve is almost linear, but during nighttime hours, it shows a distinct level around the mean price (Figure 5). Similarly, we observe an almost linear curve for weekdays but a nonlinear shape for weekends. The nonlinearity of the demand curve estimated for the total data (Figure 3) seems to be driven by the nonlinearities during nighttime and weekends. This is confirmed by model diagnostics (see Figures B6-8 in Appendix B3).

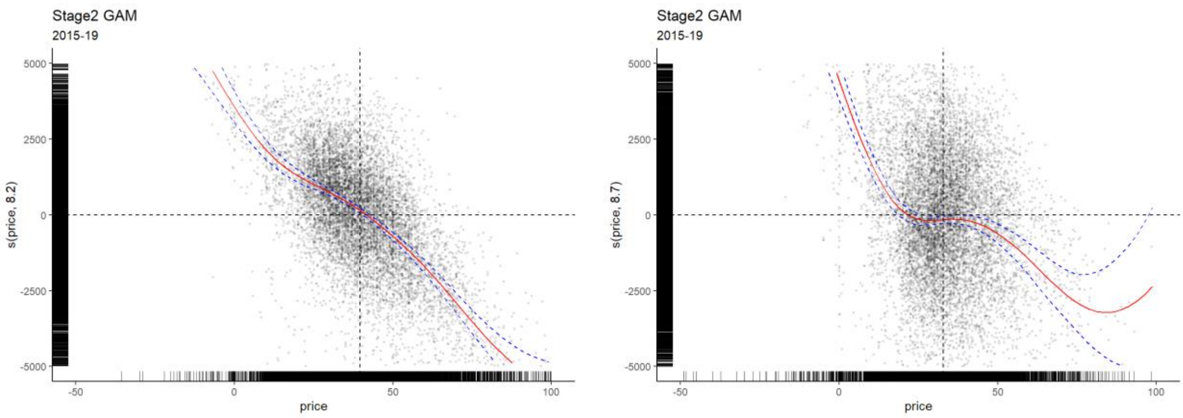

Figure 5: Estimates of the nonlinear demand curve based on the dataset being split into daytime (left) and nighttime hours (right)

4.3 Spatial heterogeneity

Approach. The previous results are based on the aggregated electricity demand for Germany as a whole. Germany is served by four transmission system operators (TSOs) that report load data for their respective service areas: 50Hertz, Amprion, TennetT, and TransnetBW. We ran the linear and log-linear specification with regional demand as the dependent variable in the second stage to test whether regional elasticities vary (since Germany has one national wholesale electricity price, the first stage is identical across regions).

Results. Figure 6 displays the results for the linear (left) and log-linear (right) 2SLS models. The linear specification reveals how the absolute per-€/MWh demand elasticity is distributed to different regions. While demand in the areas of 50Hertz and TransnetBW is virtually inelastic, roughly two thirds of the national elasticity occur in the Amprion and one third in the TenneT area. The log-linear model yields similar results: the estimate for relative change in demand is close to zero for 50Hertz and TransnetBW, similar to the national estimate for TenneT, and about twice as large for Amprion. This is revealing because the Amprion region is home to most of Germany's heavy industry. This finding matches well with our expectation that it is the industrial consumers who are able to respond to variations in electricity prices in the wholesale markets.

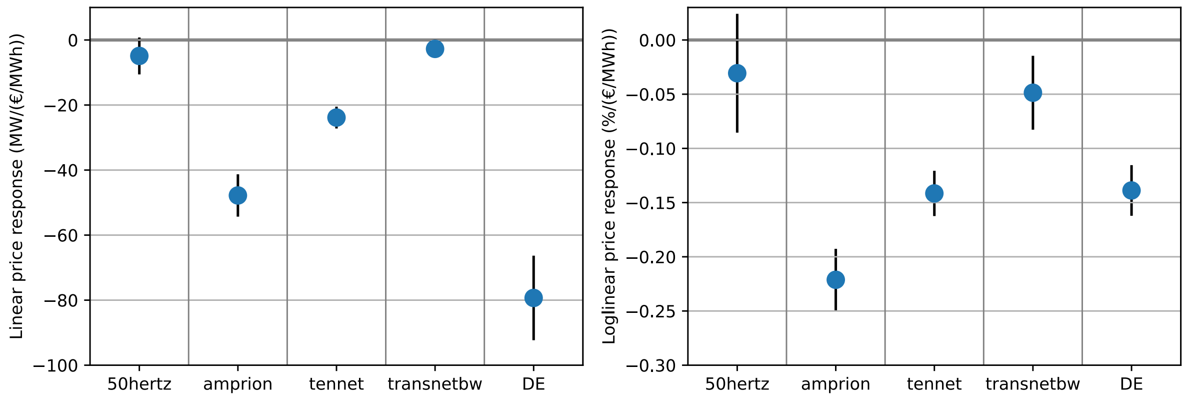

Figure 6: Estimates of linear (left) and log-linear (right) demand elasticity obtained using the 2SLS model based on demand data from single TSOs compared to the estimates based on the aggregated German demand ("DE"). The whiskers indicate the 95% confidence interval.

5 Robustness checks

This section checks the robustness of the results, testing alternative instruments (Section 5.1), conducting a zero-first-stage test (Section 5.2), excluding extreme events (Sections 5.3), and running the model based on first differences (Section 5.4).

5.1 Other instruments

Other instruments. To further assess the robustness of our estimates, we repeated our analysis with different instruments (using the non-differentiated time series): wind speed and solar generation.

Wind speed. First, we use wind *speed* as an instrument instead of wind *energy*. We do this to address endogeneity concerns: wind energy, in contrast to wind speed, may be affected by economic or grid curtailment (see Section 2.2). Wind speed, a purely meteorological variable, is clearly exogenous. We calculate wind speed as the population-weighted average wind speed across Germany. Substituting the instrument hardly changes our estimates (see Figure 7). We take this as an indication that the potential endogeneity of wind energy generation is not an issue.

Solar energy. As a second robustness check, we use solar energy as a second instrument (in addition to wind energy). We refrained from using solar energy as an instrument in our main specification because of concerns that solar energy might be inaccurately estimated, violating the exclusion restriction (see Appendix A1). Figure 7 suggests, however, that including solar energy as an additional instrument does not substantially change our estimate. If anything, including solar as a second instrument reduces the size of the estimate, in contrast to our concern that it might inflate it. This suggests that solar energy is also a valid instrument.

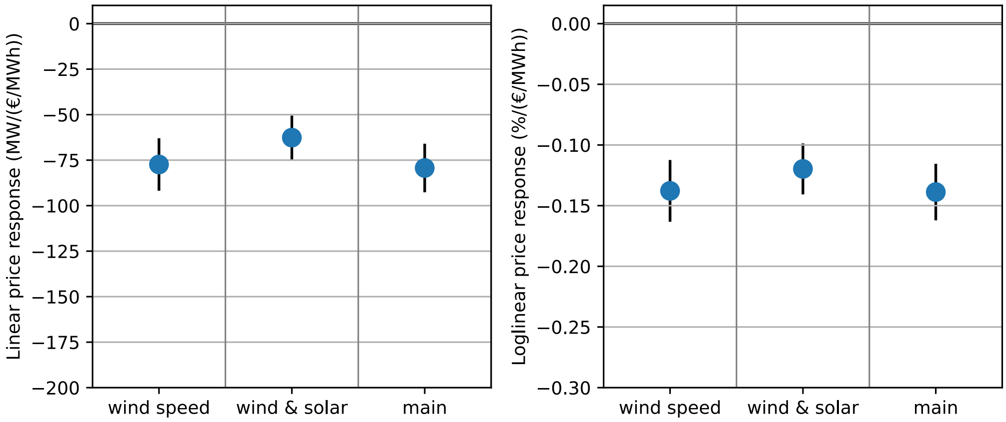

Figure 7: Estimates of linear (left) and log-linear (right) demand elasticity obtained via the 2SLS model using wind speed and wind and solar energy generation as instruments compared to the main estimates obtained using wind energy as an instrument. The whiskers indicate the 95% confidence interval.

5.2 Zero-first-stage test

National power curve. As explained in Section 2.2, we expect the relationship between wind speed and wind energy to be nonlinear because of the S-shaped power curve of wind turbines and the shutdown of turbines at very high wind speeds. This is also evident at the national level (Figure 8).

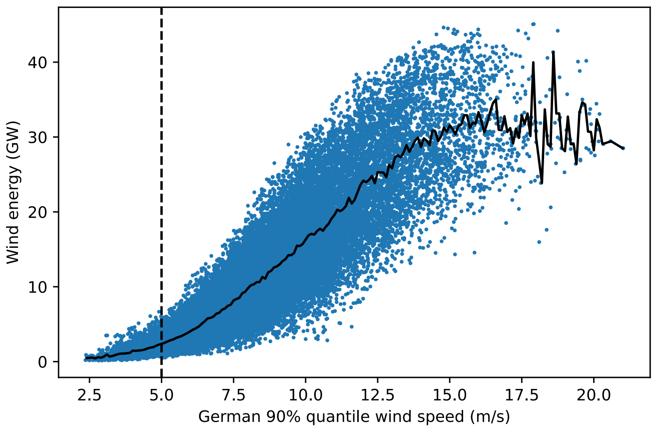

Figure 8: Wind energy in Germany compared to wind speed. For every observation (hour), the x-axis shows the 90% quantile wind speed across all locations. This is because wind turbines tend to be located at windy locations. The solid black line indicates the local average wind energy per 0.1 m/s wind speed. The dashed black line indicates the threshold below which observations are considered for the zero-first-stage test.

Test setting. We make use of this nonlinearity to check the validity of our instrument in a zero-first-stage test (van Kippersluis and Rietveld, 2018; Lal et al., 2021). In the first step, we limit our dataset to observations for which the wind speed is below 5 m/s (about 8% of the data). For this subset, we do not expect a change in wind to have a significant effect on wind energy because the power curve is very flat in this range (zero first stage), and we want to test if variation in wind speed still has a significant effect on electricity demand in the reduced-form equation. Because a direct relationship between wind speed and electricity demand can be suspected in populated areas, we use the population-weighted wind speed for these significant tests. This is the same wind speed variable we used as an instrument in Section 5.1 based on the entire dataset, yielding the same demand elasticity estimate as for wind energy as an instrument.

Test results. Compared to the full dataset, the first-stage effect of mean wind speed on electricity prices in the subsample decreases by a factor of four and becomes statistically insignificant. All other coefficients remain qualitatively unchanged. In the reduced-form equation, the effect of the mean wind on load also becomes statistically insignificant. This indicates the exclusion restriction holds: wind affects load only through prices.

5.3 Extreme events

Extreme events. Two types of situations may give some reason for concern regarding the exogeneity and exclusion restriction of our instrument: hours with negative prices and hours with extremely high wind speeds. We exclude those observations in turn.

Negative prices. We exclude negative prices because they could lead to the curtailment of wind energy, violating the exogeneity requirement for wind energy as an instrument. As our estimate does not change substantially (Figure 9), we conclude that wind energy does fulfil the exogeneity requirement.

Storms. The exclusion of extreme wind speeds is due to the concern that storms could interrupt electricity demand from services such as railways, thereby reducing demand through another channel than electricity prices. This would defy the exclusion restriction (see Section 2.2). We exclude observations corresponding to the highest 1% wind speeds based on different aggregations of the spatially resolved wind speed time series across Germany (population-weighted mean, median, 90% quantile, maximum). The estimates remain extremely robust to these changes in the dataset (see Figure 9 for the results based on the population-weighted mean wind speed).

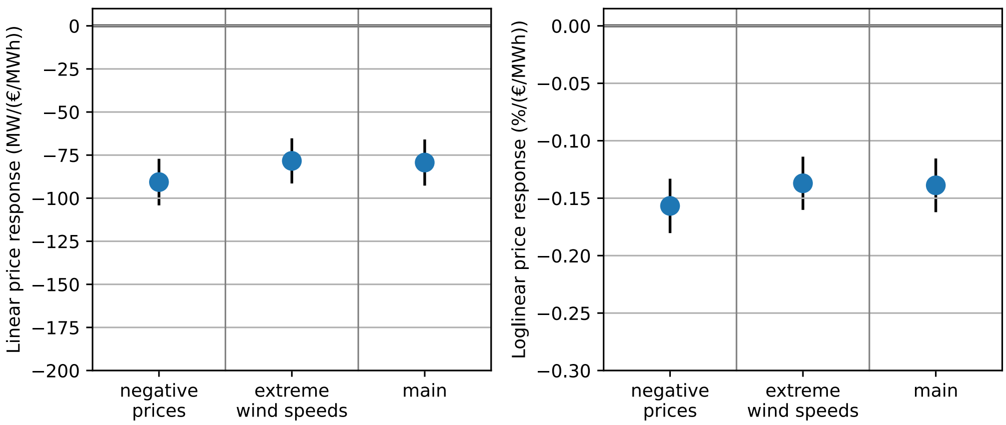

Figure 9: Estimates of linear (left) and log-linear (right) demand elasticity obtained using the 2SLS model excluding hours with negative prices and the 1% highest wind speeds from the dataset compared to the main estimates based on the entire dataset. The whiskers indicate the 95% confidence interval.

5.4 First differences

Approach. As an alternative to our main model specification, this section explores an estimation of the price elasticity of demand based on first differences. Such a specification can remove or at least reduce serial correlation from the data, as an alternative or additional measure to calculating HAC robust standard errors, which we did in our main model specification.

Results. The 2SLS results based on first differences are displayed in Figure 10. Both the linear and loglinear 2SLS-estimates of demand response remain significant, and their magnitude even increases.

As expected, the serial correlation in the residuals of the first differences model is lower than in the model with level variables (see Appendix C). Additionally, the model fit for the first stage also decreases, although the F-statistic is still above the acceptable threshold.

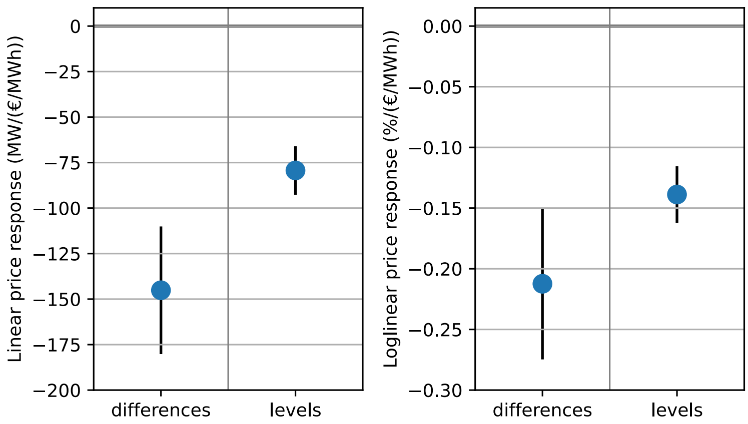

Figure 10: Estimates of linear (left) and log-linear (right) demand elasticity obtained using the 2SLS model based on first differences compared to the main estimates based on levels. The whiskers indicate the 95% confidence interval.

6 Discussion and conclusion

Summary. We estimate that a 1 €/MWh increase in German wholesale prices triggers a reduction in aggregate demand of 67–80 MW (linear estimates using the 2SLS/2SGAM) or 0.12–0.14% (log-linear estimates). In the following, we put these numbers into perspective, compare them with estimates in the literature, discuss their relevance, and draw conclusions.

Absolute demand response. While our estimated demand elasticity might seem small at first glance – just 0.13% for a one-unit price change – this is not the case, for the simple reason that wholesale electricity prices fluctuate widely over short time scales. To put this into perspective, we derive the absolute price response for the expected range of wind-induced fluctuations in wholesale prices. We take wind-induced price variations as a benchmark because this best reflects our estimation technique. More precisely, we consider the 5–95th percentile of wind energy generation, which corresponds to a range of 27.3 GW. Using our (first-stage) estimate of a 0.94 €/MWh decrease in wholesale electricity prices per 1 GW increase in wind energy generation, 27.3 GW of wind variation corresponds to a 25.7 €/MWh variation in wholesale prices. Using the demand response estimates from our linear model specification (80 MW per €/MWh), this means that the absolute demand response to wind-induced changes in wholesale prices is about 2 GW, which is 4% of average demand.

Implications. This result has important consequences for power markets as systems. One example is the power system integration of variable renewable energy sources. A change in demand of 2 GW per 27 GW of wind energy means that the integration of about 8% of the additional wind energy into electricity systems is facilitated through adjustment in demand, without the need for curtailment of renewables or energy storage. This may reduce the need for other integration options such as energy storage and fossil back-up plants as well as related system costs by about 8%, although further analysis is needed to quantify potential non-linear substitution effects between the different integration options. Another implication of demand response would be the substitution for costly firm supply capacity, independent of the share of variable renewables in the system. In our case, the estimated 2 GW reduction demand is about 2% of firm capacity in Germany. However, our estimate is based on only moderately varying prices during our period of observation. When prices are more extreme in times of scarcity, the absolute demand response may be larger. More generally, our finding of a significant demand elasticity weakens the justification for government-mandated capacity remuneration mechanisms and electricity price subsidies (as implemented, for instance, during the energy crisis in 2022 in Europe).

Comparison with previous estimates. To make our results comparable to previous literature, we convert our estimates to a dimensionless price elasticity parameter. We do so by dividing our estimated absolute price response by the ratio of the average demand and price in our sample. This yields a price elasticity between −0.051 and −0.045. This parameter range is consistent with estimates of Knaut and Paulus (2016) of −0.02 to −0.13, who used a similar method. Bönte et al. (2015) found an elasticity that is an order of magnitude larger (−0.43), which is likely explained by the fact that they examined volumes at the power exchange, not aggregate demand (see Footnote 4). The estimate from Lijesen (2007) is an order of magnitude smaller (−0.0014), which is probably because lagged prices, which they us as an instrument, do not fulfill the exclusion restriction (see Footnote 3). Kulakov and Ziel (2019) and Damien et al. (2019) also found smaller or even positive estimates, possibly because the simultaneity problem of price and demand was not properly addressed.

Regulatory framework. When interpreting our estimates, two more points are worth keeping in mind. First, only a fraction of customers in Germany are currently exposed to wholesale prices. The percentage change in demand per €/MWh of the exposed consumers must be higher than our estimates, given that the responsiveness of those with flat retail tariffs is zero. Second, our estimates are conditional on the current regulatory situation in Germany. Industrial customers receive a discount on grid fees if they consume a constant amount of electricity from the grid, which likely dampens their response to wholesale prices (Richstein and Hosseinioun, 2020). If more customers were exposed to wholesale prices and regulatory barriers to flexibility were reduced, the price responsiveness of the aggregate demand would likely increase.

Further research. We focused on the demand response to hourly fluctuations in wholesale prices. Further research may expand on this by analyzing the demand response at different time scales. For example, the recent exogenous increase in fuel prices may be used as an instrument to analyze price elasticity at a monthly resolution. In addition, future research could look at estimating the intertemporal price elasticity of demand, that is, how a price increase in one hour affects demand in adjacent hours.

Acknowledgements

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Appendix A: Data

A1 Electricity demand

Aggregate demand. We use the "Total Load" data series published by the European Network of Transmission System Operators (ENTSO-E) for measuring the aggregate electricity demand in Germany (for details, see Schumacher and Hirth, 2015; Hirth et al., 2018). This is calculated as "Net Generation – Exports + Imports – Absorbed Energy," where the absorbed energy is the electricity used to charge storage.[11]

Completeness of demand data. By definition, the "Total Load" data should include demand that is met by behind-the-meter generation (self-generation). However, we are not entirely sure that this part of the load is completely and correctly estimated. We suspect that the data may be incomplete because of a gap between the annual sum of the "Total Load" time series by ENTSO-E and the annual "Final Consumption" statistics from EUROSTAT, although both follow the same definition for load/consumption; the gap, however, declines over time.[12] While the ENTSO-E time series are the best source we know for hourly demand data, the annual EUROSTAT data are presumably more complete. We expect the cause of this gap to be related to the load served by behind-the-meter generators, which can be distinguished into two groups: rooftop solar photovoltaics and industrial fossil self-generation, the latter of which often comes with heat cogeneration. We discuss below how uncertainty regarding the self-generation of these two groups could affect our identification strategy.

Small-scale solar. Just like wind generation, solar energy depresses electricity prices and hence, in principle, could be used as an additional instrument. We have decided not to do so in our main specification for the following reason. Much of the solar capacity represents small-scale, decentralized generation. These generators are usually not metered at hourly resolution. To calculate "Total Load," system operators estimate the hour-by-hour solar generation. Estimation errors that are correlated with prices could induce a relationship between prices and observed demand that is not due to the demand response. This would violate the exclusion restriction, inflating our estimates of demand elasticity. In all our regressions, however, we do control for solar to account for any possible correlation with wind generation and demand. In addition, we run a sensitivity test of solar energy as an additional instrument (Section 5.1).

Industrial self-generation. Industrial self-generation could be positively correlated with prices if industrial consumers decided to shut down their power plants at low prices and buy from wholesale markets instead. If this was not properly accounted for in the total load data, such a dispatch decision on self-generation would introduce an upward bias in our demand-response estimates. Because the gap between the ENTSO-E and EUROSTAT data decreases over time, while our estimates remain consistent over the years (see Section 4.2), we are confident that the demand responsiveness that we are measuring is not entirely due to industrial self-generation. In addition, we conducted the following analysis: the German regulator (Bundesnetzagentur) maintains a public list of power plants containing 1,980 units. A manual review resulted in 366 units that could potentially be industrial behind-the-meter plants, according to the reported names of the operators. Of those, 28 have a nameplate capacity of 100 MW or larger, meaning they should report hour-by-hour generation on the ENTSO-E Transparency Platform. We were able to identify such time series for nine units. On the aggregate of these nine time series, we ran the same 2SLS model as the one we present and apply below for our main analysis. In doing so, we found that a 1 €/MWh price increase leads to a 2.6 MW increase in

[11] https://transparency.entsoe.eu/content/static_content/Static%20content/knowledge%20base/data-views/load-domain/Data-view%20Total%20Load%20-%20Day%20Ahead%20-%20Actual.html

[12] From about 50 TWh in 2015 to about 20 TWh in 2019.

production, with a confidence interval of 2.0 MW to 3.3 MW. Scaling the estimated price response of our sample by the total annual output of industrial self-generation in Germany[13] yields a price response of the German-wide industrial self-generation of around 8 MW per €/MWh, just over a tenth of the price elasticity we estimate in our main analysis. In other words, this assessment suggests that at least 90% of our main estimate of demand response occurs due to adjustment of electricity consumption, while about 10% could be due to an increase in industrial behind-the-meter generators.

Temporal patterns in aggregate demand. Figure A1 illustrates the temporal patterns of the aggregate German electricity demand used in our analysis. There are two distinct diurnal peaks in electricity consumption, one in the morning at 11 a.m. and the other in the evening at 6 p.m., and demand is significantly lower on weekends compared to weekdays, reflecting lower commercial and industrial demand. Electricity consumption is also higher during the winter months compared to other times of the year. The aggregate demand for Germany was relatively stable across the years considered in our analysis. There is only a marginal underlying positive trend from 2015 to 2018 and a decline in 2019. A linear least squares model with demand as the dependent variable shows that the hourly, monthly, weekday, annual, and time trends together explain 83% of the variation in hourly aggregate demand in Germany.

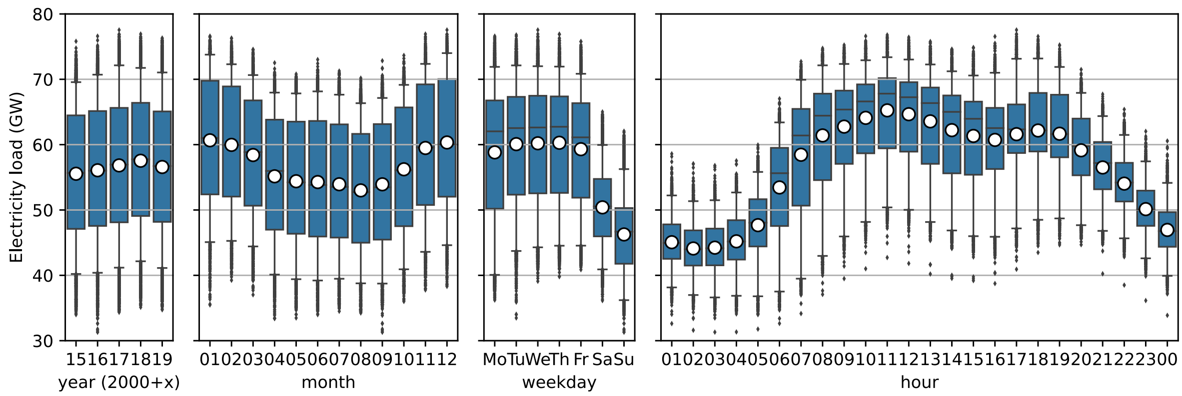

Figure A1: Boxplots of the electricity demand by year, month, weekday, and hour[14]

A2 Prices

Day-ahead wholesale prices. We use data of the German day-ahead auction of the EPEX SPOT power exchange to measure electricity prices, the dominant wholesale market for the physical delivery of electricity. The auction clears supply and demand for each hour of the next day separately, yielding 24 electricity prices. Although not all electricity consumed is traded in the day-ahead market, the day-ahead prices are the relevant benchmark for bilateral trades and self-generation because they reflect the opportunity costs of not trading in the power exchange. Furthermore, our analysis based on day-ahead prices will capture demand response to market prices at other lead times, such as intraday and balancing prices, to the extent that these prices are correlated with the day-ahead prices.

Temporal patterns in electricity prices. The nature of the time-series data of day-ahead spot prices in electricity markets has been previously studied (Knittel and Roberts, 2005; Kosater and Mosler, 2006; Huisman et al., 2007; Liebl, 2013). Usually, time series of electricity spot prices are assumed (i) to have

[13] The nine plants have a joint annual output of about 8 TWh compared to the total industrial self-generation of about 25 TWh (according to the German Association of Energy and Water Industries).

[14] The black lines in the middle of the boxes indicate the median; the boxes extend from the first to the third quartile (inter-quartile range), and the whiskers include the 5–95% confidence interval of the observations. Observations outside of this confidence interval are depicted as black dots, and the white points represent the mean of the distribution.

deterministic annual variations and also monthly, weekly, and hourly patterns, (ii) to show price-dependent volatilities, and (iii) to be stationary (after controlling for seasonal patterns). These temporal trends are clearly visible in our data as well (Figure A2). The average spot price of electricity changes over time in our data, with prices falling slightly in 2016 from 2015 before increasing to a peak in 2018 and sharply falling in the first quarter of 2019. Besides this trend over the years, there are the expected intra-annual patterns. Electricity prices change over the course of the year, depending on the month. Prices are higher during the weekdays and lower over the weekends, reflecting lower demand from industrial and commercial activity. Over the course of a day, there are two distinct peaks: a morning and an evening peak around 8 a.m. and 7 p.m., respectively. Fitting a nonparametric generalized additive model (GAM) to electricity prices reveals that the nonlinear coal and gas prices and the seasonal time patterns together explain about 48% of the variation in the hourly spot price of electricity. The residual spot prices, once the deterministic seasonal and time trends are accounted for, seem stochastic.

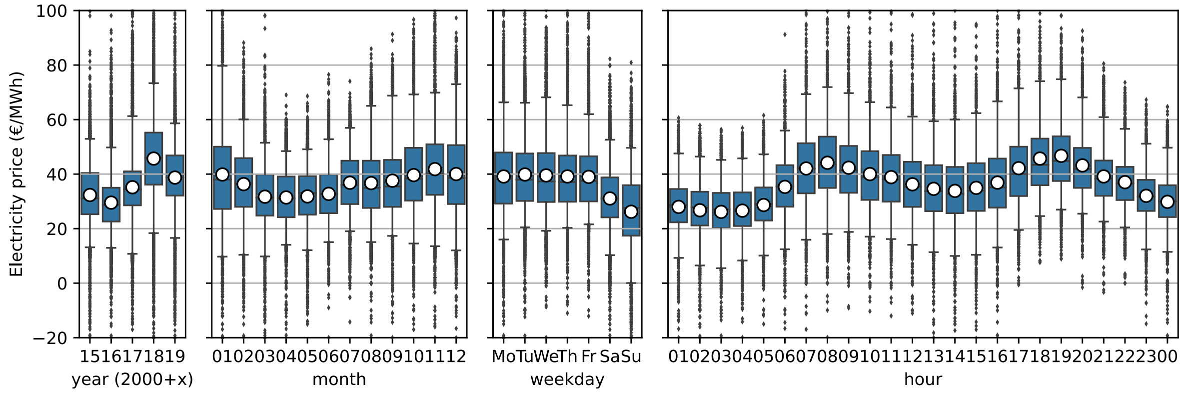

Figure A2: Boxplots of the electricity price by year, month, weekday, and hour[15]

Correlation with fuel prices. The monthly averages of wholesale electricity prices reflect the underlying cost of electricity generation, closely following the prices of natural gas and coal (Figure A3).[16] We therefore include monthly fuel prices converted to €/MWh as control variables in our models. In some of our model specifications, we also control for a nonparametric time trend (see Section 3).

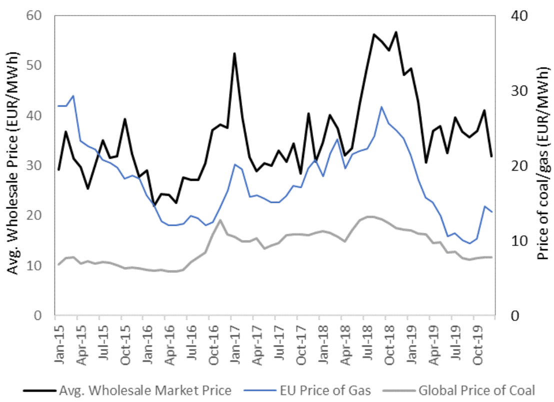

Figure A3: Day-ahead prices in wholesale markets in Germany vs. global prices of coal and gas

[15] Note that some extreme prices are not visible because they exceed the limits of the ordinate. See Footnote 3 for an explanation of the boxplot elements.

[16] We use the data series “Global price of Coal, Australia, U.S. Dollars per Metric Ton, Monthly, Not Seasonally Adjusted” and “Global price of Natural gas, EU, U.S. Dollars per Million Metric British Thermal Unit, Monthly, Not Seasonally Adjusted” published by the International Monetary Fund for coal and gas prices, respectively.

A3 Other data series

Wind and solar generation. Our time series for wind and solar energy originate from the ETNSO-E Transparency Platform. They represent actual electricity generation, which has two implications. First, renewable energy is traded in the day-ahead market based on forecasts such that it is the predicted rather than the actual electricity generation that impacts day-ahead prices. We argue, however, that the actual electricity generation can still be used as an explanatory variable for day-ahead prices, given the high correlation with predicted values. Second, the actual generation may differ from the potential generation due to curtailment at negative electricity prices or grid congestion. The implications of curtailment for our identification strategy are discussed in Section 2.2. Furthermore, part of the solar generation is not individually metered at hourly resolution, which may introduce estimation errors. Therefore, we decided to use only wind energy as an instrument and to include solar energy as a control variable. The temporal patterns of wind energy are displayed in Figure A4.

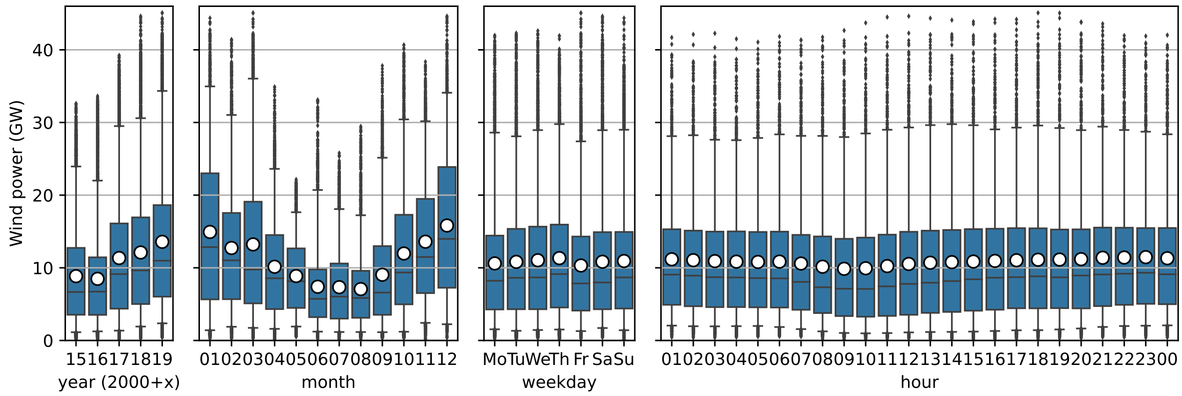

Figure A4: Boxplots of the wind energy generation by year, month, weekday, and hour[17]

Further control variables. In addition to fuel prices, we use the daily carbon price from the European Union Emissions Trading Scheme, which we retrieved from the Intercontinental Exchange (ICE).[18] Furthermore, we use hourly time series for ambient temperature from renewables.ninja.[19] They provide population-weighted averages of spatial temperature data across Germany. For the linear models, we derived the hourly heating and cooling degrees from the ambient temperature using 15°C as a threshold.

[17] Note that some extreme prices are not visible because they exceed the limits of the ordinate. See Footnote 3 for an explanation of the boxplot elements.

[18] https://www.theice.com/

[19] https://www.renewables.ninja/

Appendix B: Additional results

B1 Control variables

Overview. This section briefly discusses the estimated linear coefficients of our control and dummy variables in the first and second stages. Those are not directly linked to our research question but might yield interesting insights for readers. We also present the estimated nonparametric effects of our main control variables, solar energy, and ambient temperature. Overall, the estimated coefficients and nonparametric relationships are plausible, which increases our confidence in the validity of our methodology.

First-stage solar and temperature effects. In the first stage, the effect of solar power is very similar to that of wind energy for both linear and nonparametric specifications (compare Table 3, Figure 2, and Figure B1a). This makes sense, as wind and solar power equally constitute additional supply at low variable costs, shifting the supply curve outward and leading to a decline in prices. The linear coefficients of the heating and cooling degrees are both positive, which is in line with our expectation that prices increase with heating and cooling due to an increase in demand. The nonparametric specification suggests a nonlinear relationship, with the effect of temperature on price being higher at temperatures above 20°C and below 0°C, which may reflect that both heat pumps and air conditioning become less efficient at more extreme temperatures (Figure B1b).

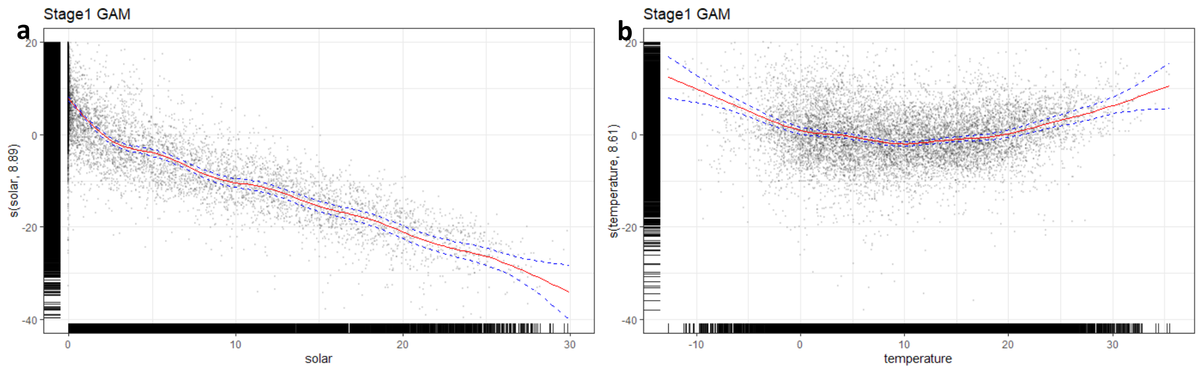

Figure B1: Nonparametric covariates in the first stage: solar (left) and temperature (right)

First-stage fuel and carbon price effects. The coefficients of the carbon price in both linear and nonparametric specifications indicate that electricity prices increase by about 1 €/MWh per 1 €/t increase in carbon prices, which seems plausible given that the specific emissions of European power plants are in the range of 0.4–1.2 t/MWh (Ruhnau et al., 2022). The relationship between fuel and power prices depends on the efficiency of different power plants and the share of hours when those plants are marginal, price-setting plants. The efficiency of coal-fired power plants is in the range of 38–46% (Hirth et al., 2021), such that we would expect that a 1 €/MWh increase in coal prices would cause a 2.4 €/MWh increase in electricity prices during those hours when coal-fired power plants are setting the price. The fact that our estimate is lower (about 1.7) seems reasonable because coal-fired power plants were setting the prices only during some hours of our observed period. Our estimated coefficient for the gas price is even smaller (0.35), which may reflect the fact that modern gas-fired power plants are more efficient (up to 60%) and that gas-fired power plants were setting electricity prices during fewer hours of our observed period. The nonparametric specification for coal and gas prices also shows a plausible positive relationship with electricity prices.

Time dummies and trends in the first stage. The estimated dummies for hour, week, month, and year in the first-stage regression are displayed in Figure B2. Both the 2SLS model and the GAM match well with the temporal price patterns described in Appendix A. The nonparametric time trend in the GAM is also significant, capturing exceptional price movements, such as the spike at the beginning of 2017 (Figure A3).

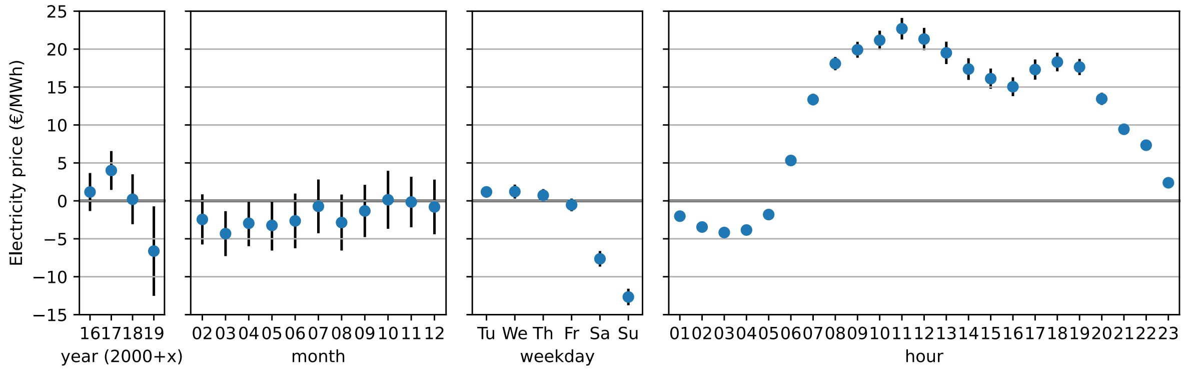

Figure B2: 2SLS time dummies in the first stage (year, month, weekday, and hour)

Second-stage solar and temperature effects. In the second stage of the 2SLS model, solar has a negative effect on demand. This supports the hypothesis that our demand data may not fully include demand that is served by behind-the-meter solar; therefore, an increase in behind-the-meter production may appear in our demand data as a decrease in demand. The GAM indicates that this effect is most pronounced at low solar levels (Figure B3a). The coefficients of heating and cooling degrees are both positive, as expected, with the coefficient of heating being larger than that of cooling. This matches well with the U-shape of the estimated nonparametric relationship between temperature and demand. The vertex of the curve coincides with our assumed heating and cooling threshold of 15°C (Figure B3b). In the range of 0–10°C, the spline is almost linear, with a slope that is similar to the 2SLS estimate (310 MW/°C). Below 0°C, the slope increases (but fewer observations are available).

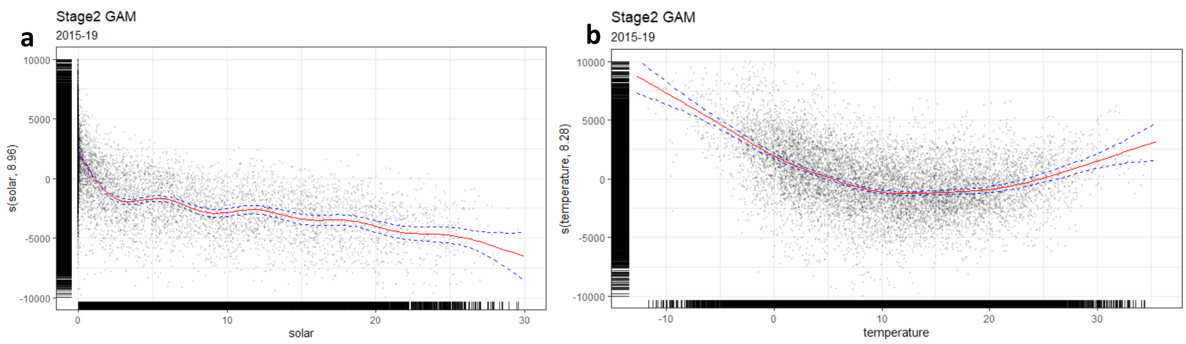

Figure B3: Nonparametric covariates in the second stage: solar (left) and temperature (right)

Time dummies and nonparametric time trends in the second stage. As in the first stage, the second-stage time dummies are displayed in Figure B4 and reflect the time temporal patterns presented in Appendix A. The nonparametric time variable features very large confidence intervals, indicating weak time trends on top of the yearly, monthly, daily, and hourly variations.

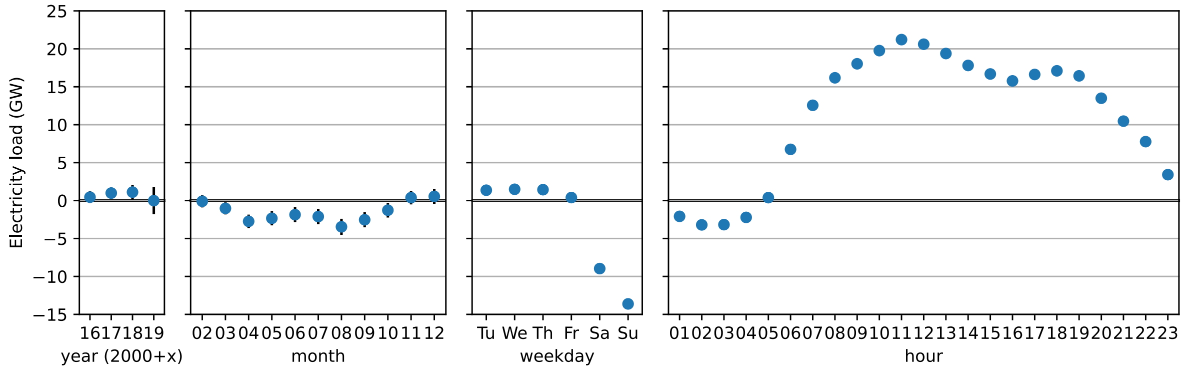

Figure B4: 2SLS time dummies in the second stage (year, month, weekday, and hour)

B2 Temporal heterogeneity of log-linear estimates

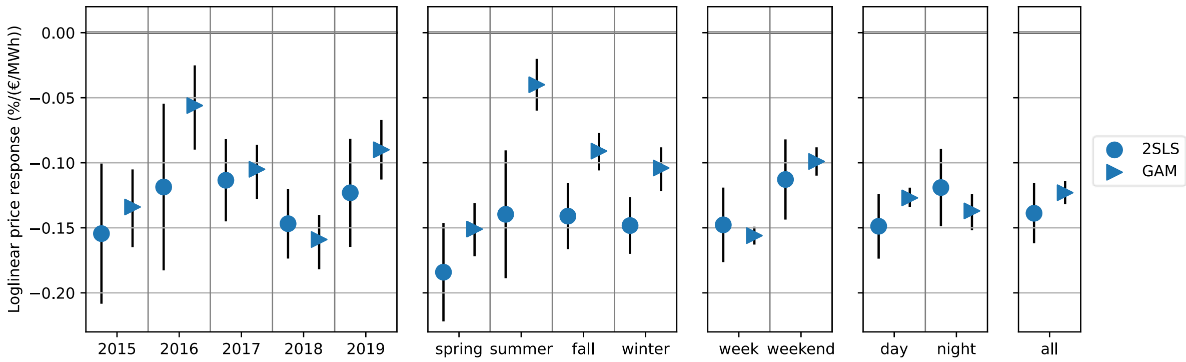

Figure B5: Estimates of log-linear demand elasticity based on the dataset being split into years, seasons, weekdays, weekends, and daytime and nighttime hours compared to the estimate based on the entire dataset ("all"). The whiskers indicate the 95% confidence interval.

B3 Model diagnostics

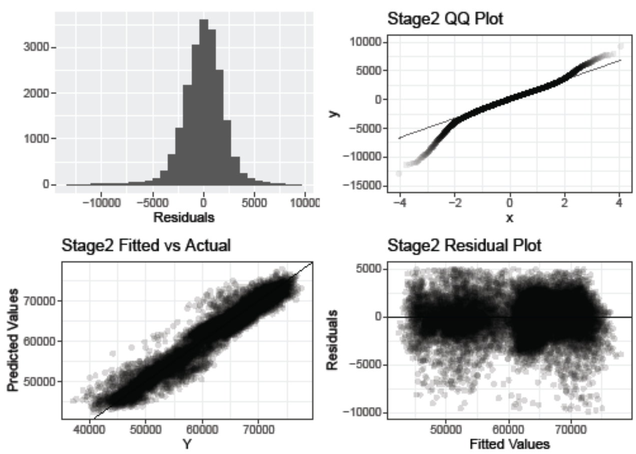

Figure B6: Model diagnostics for the linear model specification in 2SLS for **daytime** hours. The model overall shows a good fit: the residuals exhibit normal distribution, the residuals vs. fitted values plots appear randomly scattered and the predicted vs. actual plots are as expected.

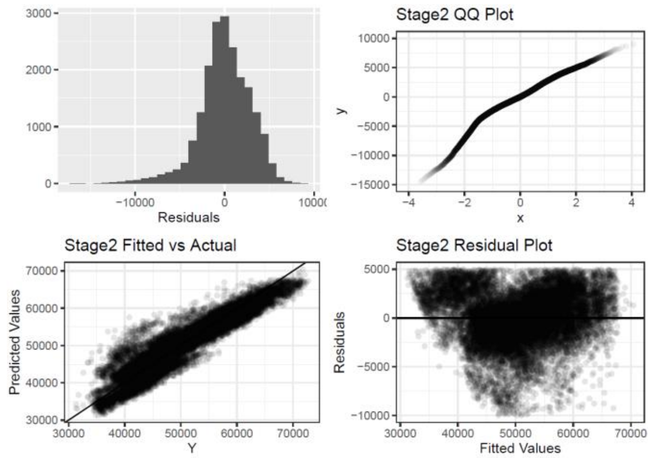

Figure B7: Model diagnostics for the linear model specification in 2SLS for **nighttime** hours. The model fir is considerably weaker compared to daytime hours: the residuals are left-skewed, the residuals vs. fitted values plots appear show distinct pattern and the QQ plots show large deviances.

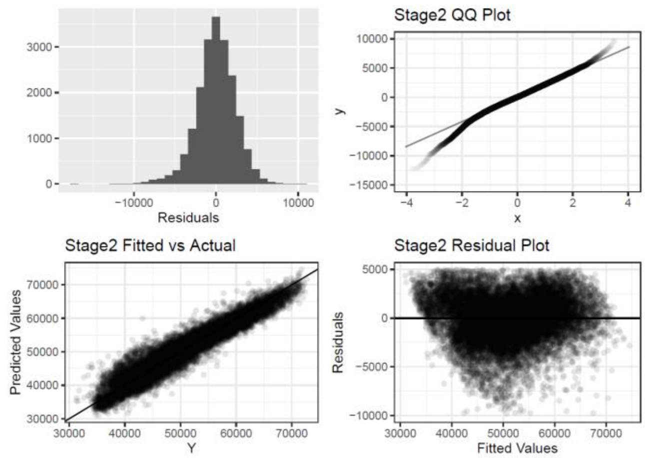

Figure B8: Model diagnostics for the nonparametric model specification in 2SGAM for **nighttime** hours. The model overall shows a better fit: the residuals exhibit normal distribution, the residuals vs. fitted values plots appear randomly scattered, the QQ plot shows lower deviance and the predicted vs. actual plots are as expected.

Appendix C: Seasonal correlation

Serial correlation. The time series data for electricity price, demand, wind energy and our weather-related control variables show serial correlation. This serial correlation can arise on account of both seasonal patterns in the time series data, and correlation between hourly and daily values of these data. Although we control for seasonal dummy variables, the residuals from 2SLS models are also serially correlated. Figure A7 displays the serial correlation in residuals from the first and (linear) second stage of the 2SLS model without any correction for serial correlation. Presence of serial correlation can result in incorrect standard errors. To correct for serial correlation, all confidence intervals reported for the 2SLS estimates in Table 4 are based on HAC standard errors that are robust to serial correlation and heteroscedasticity. The HAC confidence intervals (95% CI = [−91.3, −67.8]) are wider than those from the 2SLS model (95% CI = [−83.6, −75.5]) but are statistically significant. We also calculated the confidence intervals using the Cochrane–Orcutt or FGLS estimator, which results in a confidence interval that is higher than that obtained from the HAC standard errors (95% CI = [−125.1, −98.2]). The estimates reported by us in Table 4 are thus conservative.

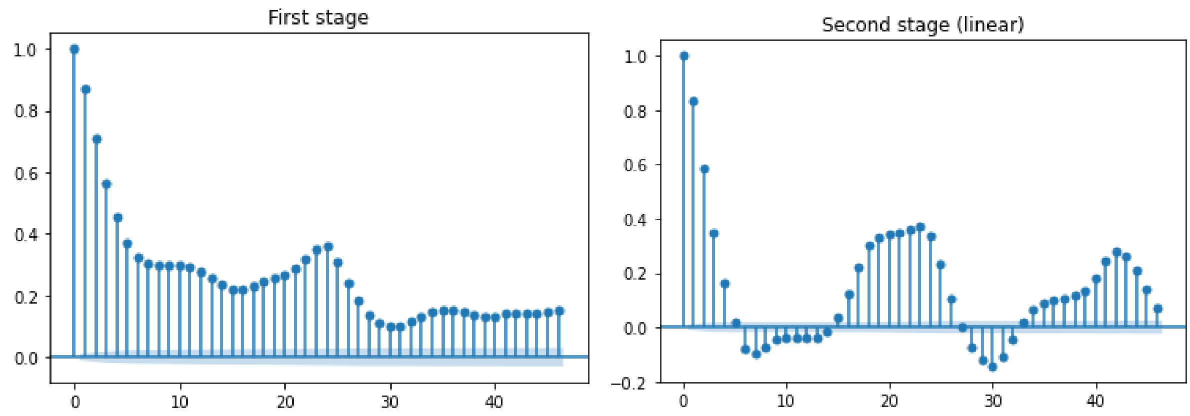

Figure C1: ACF plots for the linear first stage specification (left) and the linear second stage specification (right). As expected, serial correlation shows a strong 24-hour seasonality. The residuals of the loglinear second stage behave similarly to the linear second stage.

First differences. Another way to address persistence in the linear specification of the 2SLS models is the first differences approach, which is presented in Subsection 5.4. Figure A8 confirms that the serial correlation in the residuals of the model with first differences is lower than the model with level variables. Note that, however, the adjusted R^2 is also lower: 0.45 instead of 0.76 for the first stage and 0.69 instead of 0.89 for the linear second stage (0.73 instead of 0.90 for the loglinear second stage). The partial R^2 of wind energy in the first stage is also lower (0.03 instead of 0.46), but the corresponding F-statistic has a value of 115, which is still above the thresholds below which wind energy would be considered a weak instrument.

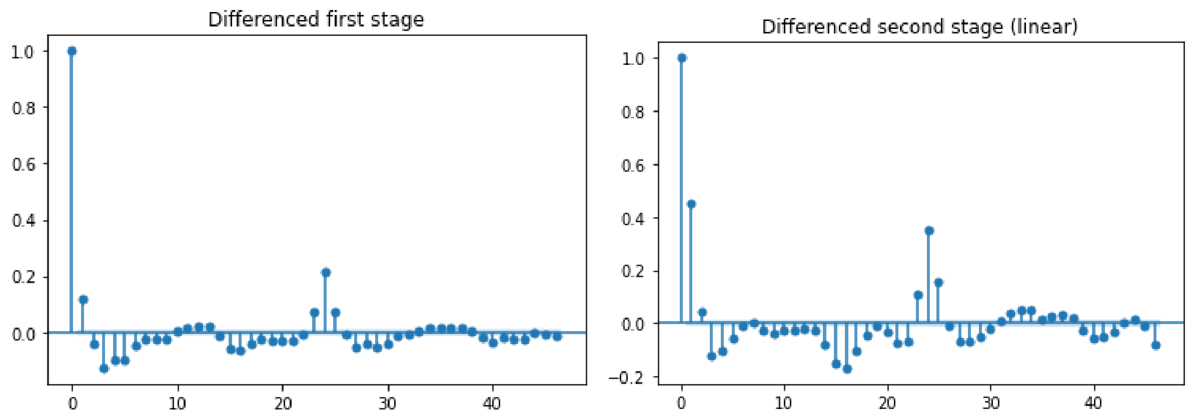

Figure C2: Autocorrelation of the 2SLS residuals with the differenced first stage specification (left) and the differenced linear second stage specification (right). The residuals of the differenced loglinear second stage behave similarly to the differenced linear second stage.

Seasonally differenced estimates. In addition to the first differences approach explained above, we differenced each by different lags: 24th lag (corresponding to the number of observations in a day), 168th lag (corresponding to the number of observations in a week) and 8736th lag (corresponding to the number of observations in 52 weeks of a year). We take the differences of all the time series variables with the 24th lag, leaving the time-related dummy variables as level variables. Differencing with the 24th lag, the 168th lag, and the 8736th lag results in estimates of −76, −71, and −65 respectively, which are close to the estimate from the main model specification. The residuals from the 24th lag difference estimate show high serial correlation up to the fourth lag and the overall pattern is similar to that shown for the main specification in Figure A7 except that the cyclical peaks in correlation occur around the 20th lag and not the 24th lag. The residuals from the 168th and the 8736th lag difference estimate show a very high degree of correlation even up to the 50th lag.

These results indicate that, in addition to the seasonal patterns captured by the time dummy variables in the main model specification, there is no persistence in the series arising from seasonality (correlation in time series data across 24 hours, over the week or the year) that significantly affects our estimates. However, the serial correlation arising from persistence between consecutive hours is mitigated by taking the first differences. However, since the estimates from the first difference model are actually higher than those from our main model specification, our main results continue to remain conservative.

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