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How aggregate electricity demand responds to hourly wholesale price fluctuations

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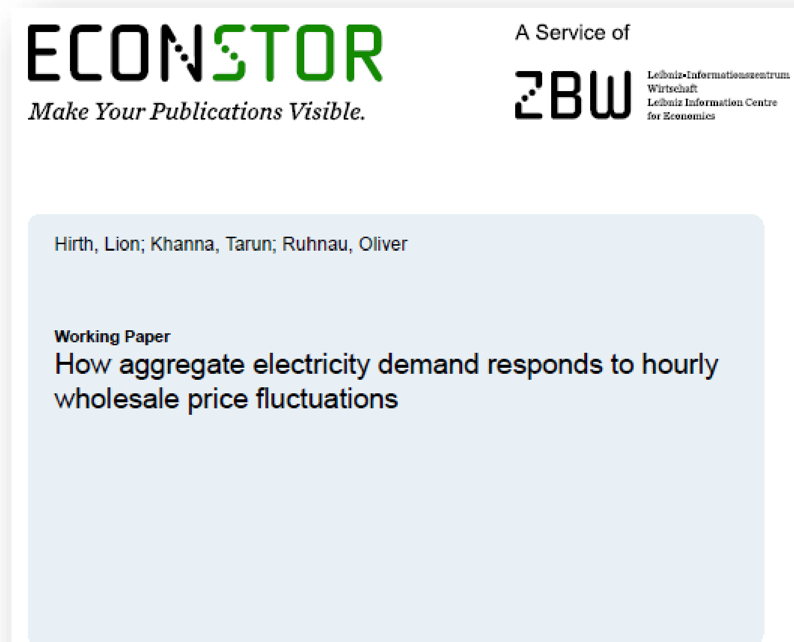
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Hirth, Lion; Khanna, Tarun; Ruhnau, Oliver

Working Paper
How aggregate electricity demand responds to hourly wholesale price fluctuations

Research question and motivation

Research question

How much does hourly aggregate electricity demand respond to changes in day-ahead prices in the wholesale markets of electricity?

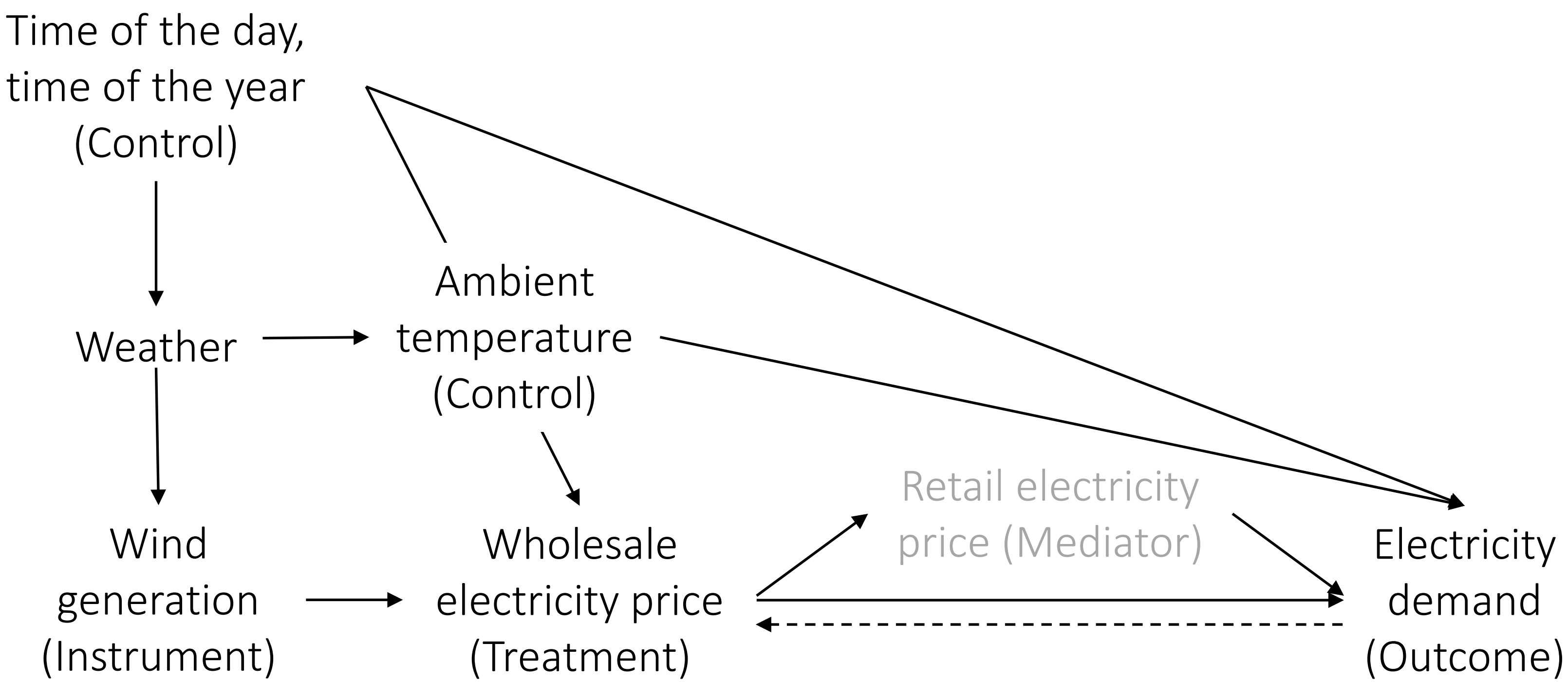
Hourly price response of electricity demand is relevant

- Important input to electricity market models and analyses
- Integration of wind and solar power
- Substitute for firm/back-up generators
- Mitigate market power

Previous studies

- Bottom-up flexibility *potential* of existing and future electricity demand
- Empirical work based on annual/quarterly/monthly data

Identification strategy



We also control for other variables (fuel and CO_2 prices) and more time dummies (weekday and year)

Using wind energy as an instrument

- Weather has a long history of being used as instrument
- Meets the three important criteria to serve as an instrument
    - **Relevance:** wind energy generation should impact wholesale electricity price
    - **Exogeneity:** wind energy generation should note be endogenously impacted by demand (or by a confounder impacting both wind energy and demand)
    - **Exclusion restriction:** wind energy should impact demand only through electricity price
- Variation in wind energy generation is highly correlated with variation in electricity prices
- Robustness checks for potential challenges to exogeneity of wind generation

Potential challenges using wind generation as instrument

	Identification challenge	Direction of bias	How addressed / tested?
Economic curtailment *Exogeneity/ confounders*	Low wind generation due to economic curtailment at negative prices is correlated with low load; this may be falsely attributed to price response	*Overestimate*	Exclude negative prices Use wind speed as an instrument
Demand disruption *Exclusion restriction*	If extremely high wind speeds (▲ wind generation, ▼ prices) cause electricity-consuming infrastructure to break down (e.g., railroads) > would be erroneously attribute to price response	*Underestimate*	Exclude times of very high wind speeds → estimates do not change

We discuss and address further challenges in the paper

Model specification and estimation

- Five different model specifications that capture:
  - Linear, loglinear and nonparametric relationships between price and demand
  - Linear and nonparametric relationships between demand/price and control variables
- Estimated using the 2 Stage Least Squares (2SLS) or 2 Stage Generalized Additive Models (2SGAM)

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	Loglinear	Linear	Loglinear	Non-parametric

Parametric models

$$Price_t = \alpha_0 + \alpha_1 I_t + \boldsymbol{\alpha_C C_t} + \boldsymbol{\alpha_D D_t} + v_t \qquad (1)$$

$$Demand_t = \beta_0 + \beta_1 \widehat{Price}_t + \boldsymbol{\beta_c C_t} + \boldsymbol{\beta_D D_t} + u_t \qquad (2)$$

$Price_t$	Wholesale price of electricity in hour t
$\widehat{Price}_t$	Predicted electricity price based on Eq. (1)
$Demand_t$	Electricity demand in hour t
β_1	Linear demand response to electricity price
I_t	Instrument: wind energy generation
$\boldsymbol{C}_t$	Controls: solar generation, HDD, CDD, coal, gas and CO_2 prices
$\boldsymbol{D}_t$	Dummies: hour of day, weekday, month of year, year

- Estimated using the 2 Stage Least Squares (2SLS) estimator
- Heteroskedasticity-and-Autocorrelation-Consistent Standard Errors

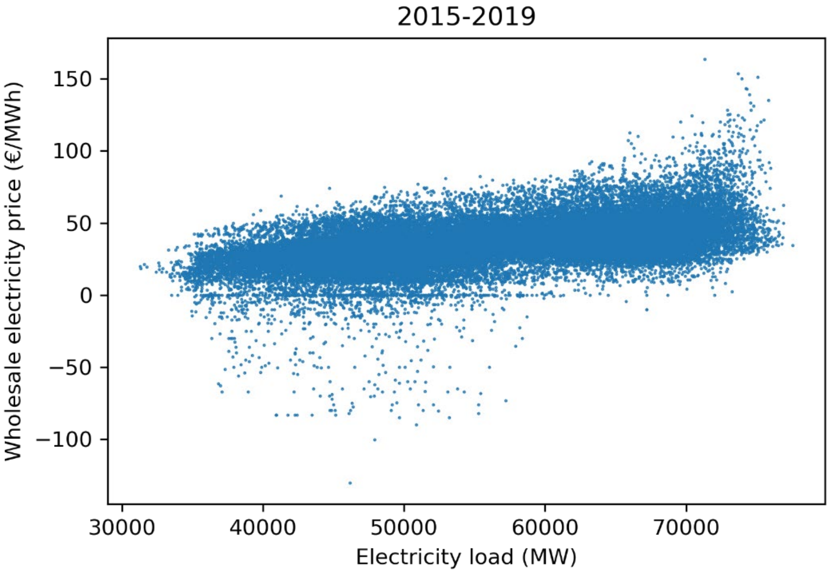
Data

Time series (via the Open Power System Data platform):

- Hourly “Total Load” from ENTSO-E Transparency Platform
- Hourly day-ahead wholesale electricity price from EPEX
- Hourly actual wind generation from ENTSO-E Transparency Platform
- Daily and national average ambient temperature from NASA MERRA-2
- Daily EUA prices; monthly coal and gas fuel prices from IMF data

Scope

- Germany
- 2015-2019 (no energy crisis)
- No holydays, bridge-days, Christmas period



Parametric results

First stage: effect of wind on price

	2SLS	GAM
Adjusted R^2	0.76	0.79
Partial R^2 of wind energy	0.46	-
Partial F-statistic	930	-
Wind energy (GW)	-0.94 ***	Spline***
	[-1.01, -0.88]	

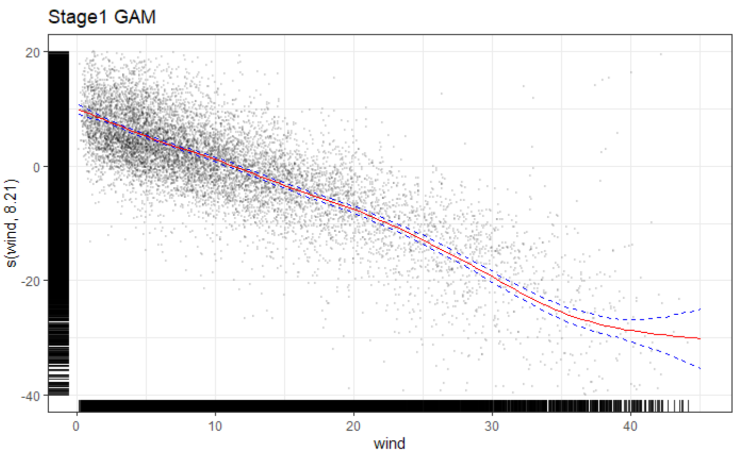
Second stage: effect of price on demand

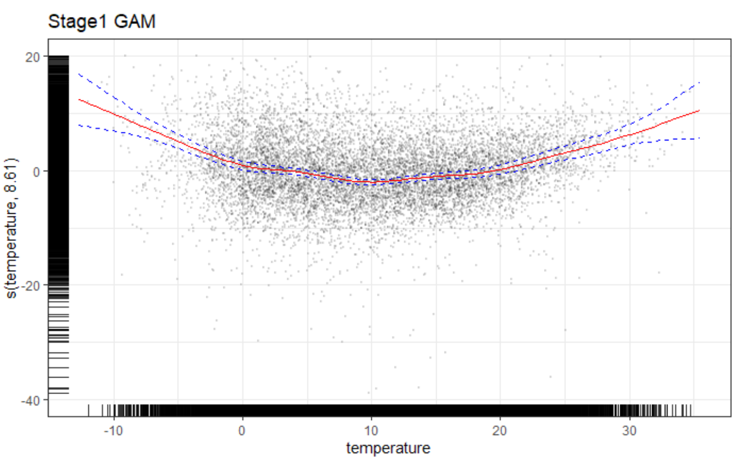
	Linear		Log-linear [a]	
	2SLS	GAM	2SLS	GAM
Adjusted R^2	0.89	0.94	0.90	0.94
Price (€/MWh)	−79.6 ***	−67.3 ***	−0.14 ***	−0.12 ***
	[−91.3, −67.8]	[−72.2, −62.7]	[−0.16, −0.12]	[−0.13, −0.11]

- Plausible coefficients of covariates
- Statistically significant and robust to model specifications and sensitivity checks
- Temporal and spatial heterogeneity suggests that industry is responding to prices

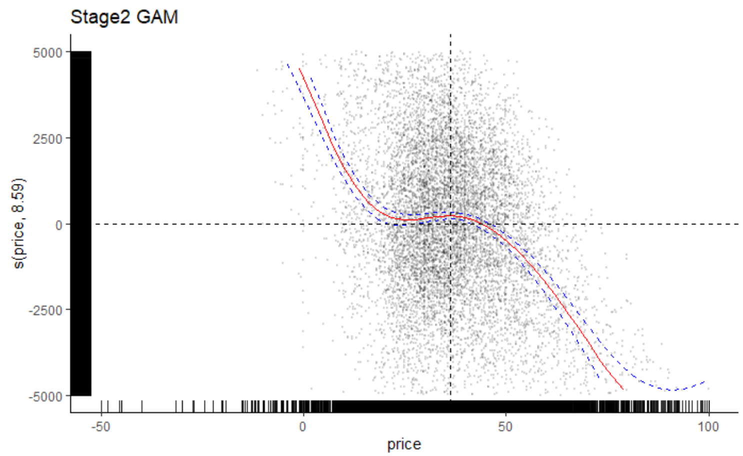
Nonparametric results

First stage





Second stage



- 1st stage non-linear results are plausible
- 2nd stage non-linear results are less clear & demand seems linear when only looking at day hours

Results in perspective

- 1 €/MWh increase in wholesale prices → reduction in aggregate demand of 70-80 MW (linear estimates) or 0.12-0.14% (log-linear estimates)
- For the avg. price and demand, the dimensionless elasticities is about -0.05
  - Knaut and Paulus (2016): -0.02 to -0.13 (similar approach)
  - Bönte et al. (2015): -0.43 (bids at the power exchange, not aggregate demand)
  - Lijesen (2007): -0.0014 (lagged price as instrument)
- For 27 GW variation in wind generation (5-95% percentile) → variation of 26 €/MWh in prices → about 2 GW demand response
  - 4% of avg. demand
  - 7% of wind generation
  - Studies on the future potential of industrial demand response: 2-5 GW (Klobasa 2007, Paulus and Borggrefe 2011, Gils 2015, Gruber 2017, SynErgie 2018, Kochems 2020) (often bottom-up estimates and surveys)

Conclusions & outlook

Conclusions

- Electricity demand responds to hourly wholesale price variations already today
- These are average values for a period with relatively flat electricity prices (no scarcity prices, no energy crisis) and little price exposure (only industry)
- More demand response expected with increasing price exposure (smart meters & tariffs) and new technologies (EVs, heat pumps, electrolyzers)

Outlook

- Demand response during the energy crisis
  (upcoming WP at EWI)
- Implications of autocorrelation in the treatment variable
  (upcoming WP at the Hertie School)

Thank you!

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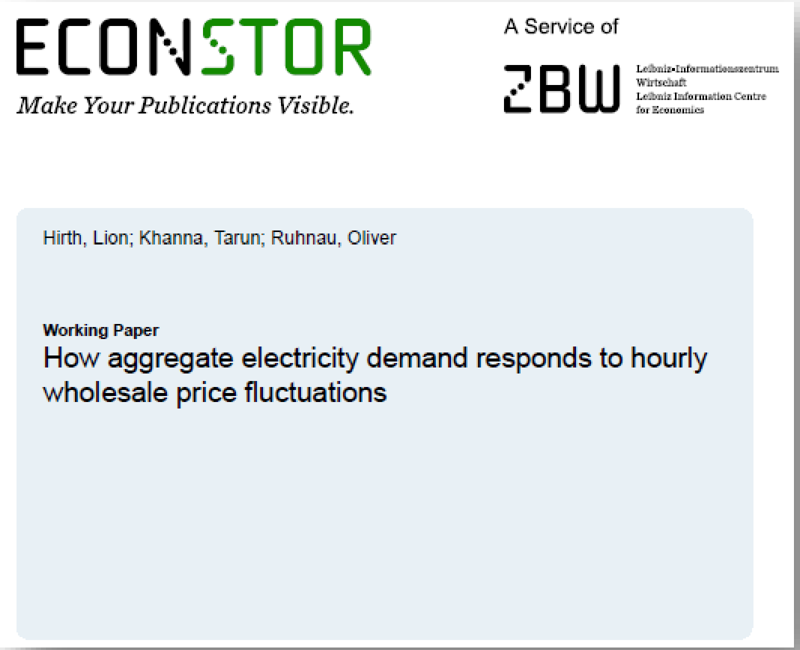

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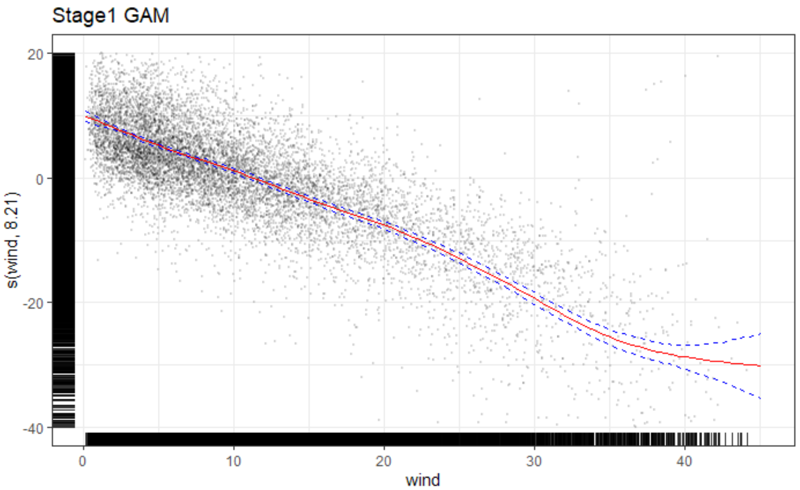
Detailed results

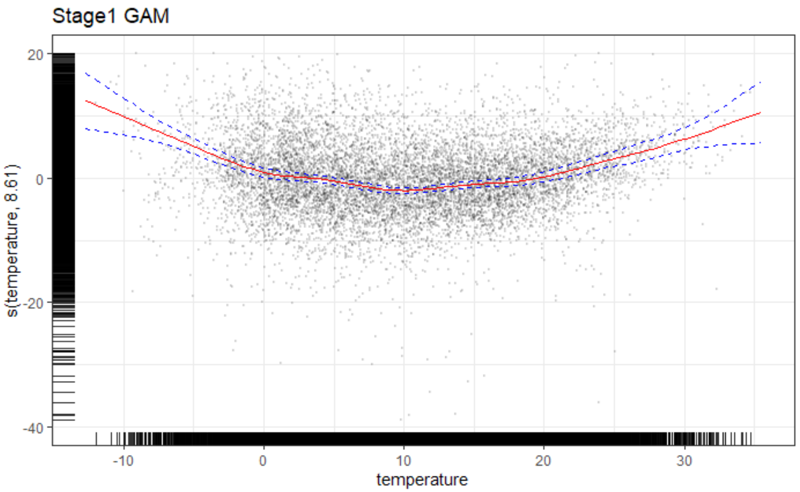
Results from first stage regression

	2SLS	GAM
Adjusted R^2	0.76	0.79
Partial R^2 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***
Heating degrees (°C)	0.36 *** [0.22, 0.49]	-
Cooling degrees (°C)	0.45 *** [0.33, 0.58]	-
Temperature (°C)	-	Spline***
EUAs (€/t)	1.08 *** [0.84, 1.32]	0.75 *** [0.68, 0.83]
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 *** 0.001 ** 0.01 * 0.05
The significance of the dummy variables can be read from Figure A1 in the Appendix.

Results from first stage regressions: nonparametric





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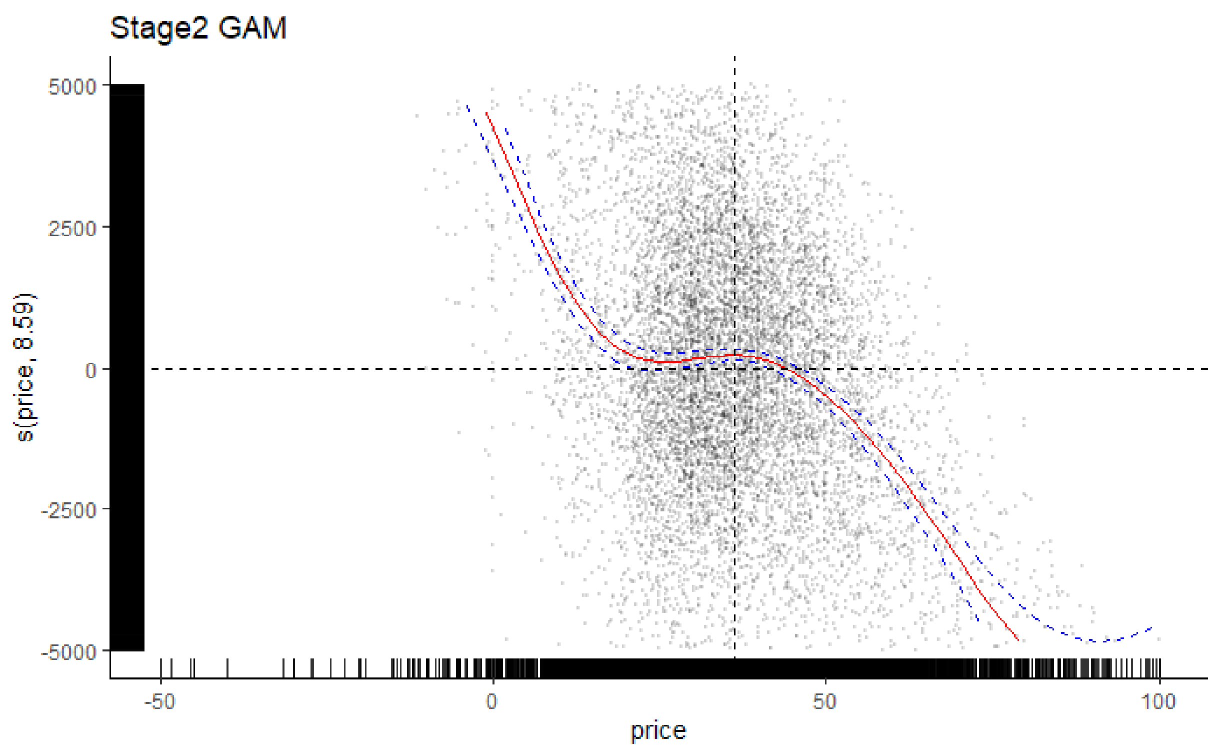
Results from second stage regressions

	Linear		Log-linear [a]	
	2SLS	GAM	2SLS	GAM
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
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]	-
Temperature (°C)	-	Spline ***	-	Spline ***
EUAs (€/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 ***

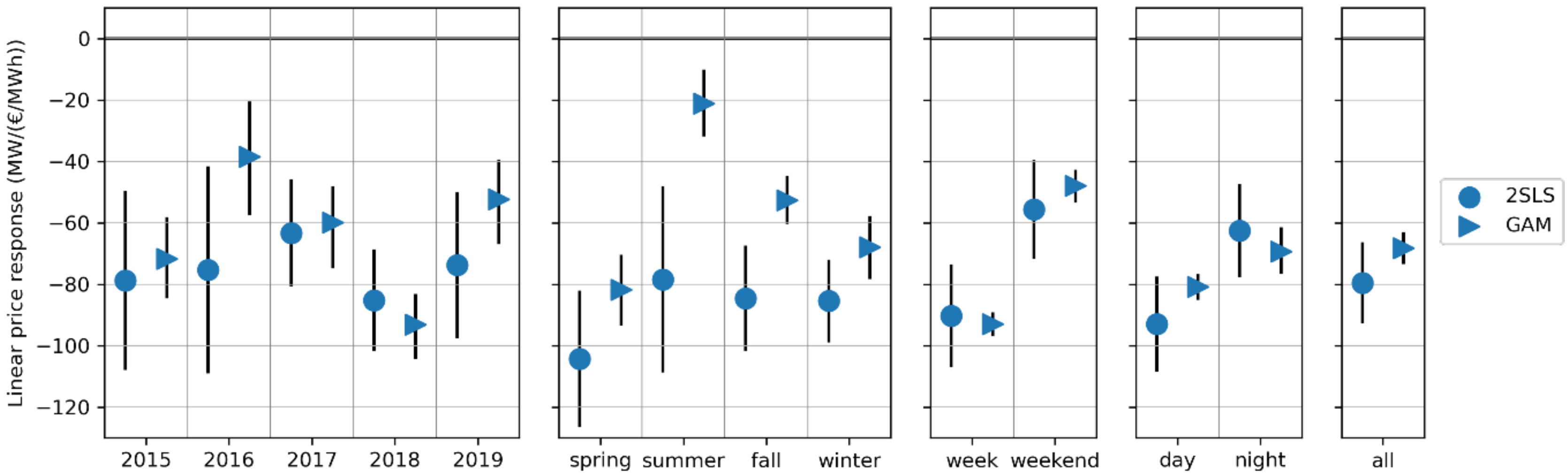
[a] All estimated parameters of the log-linear model are reported as percentages.
95% confidence intervals are reported in brackets; significance levels: *** 0.001 ** 0.01 * 0.05.
The significance of the dummy variables can be found in Figure A2 in the Appendix.

Non-linear relationship between price and demand?



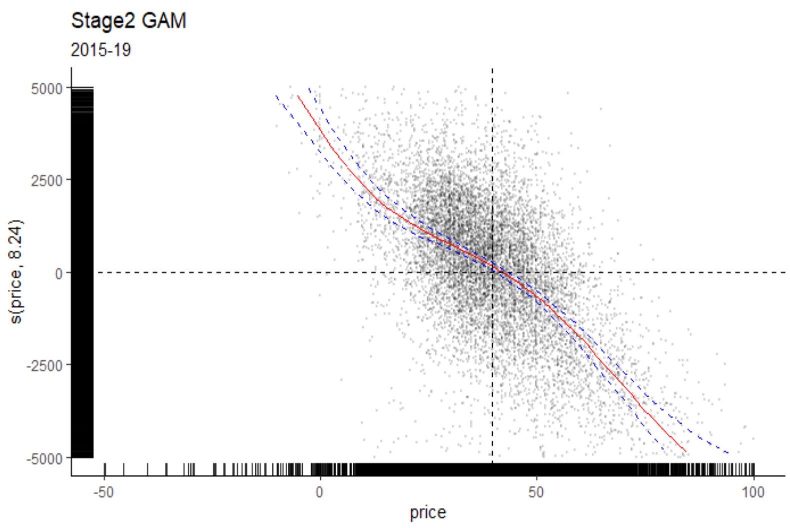
- Relationship between price and demand is statistically significant. Appears to be a kink in the otherwise linear relationship around the median price
- However, we cannot think of a plausible fundamental explanation

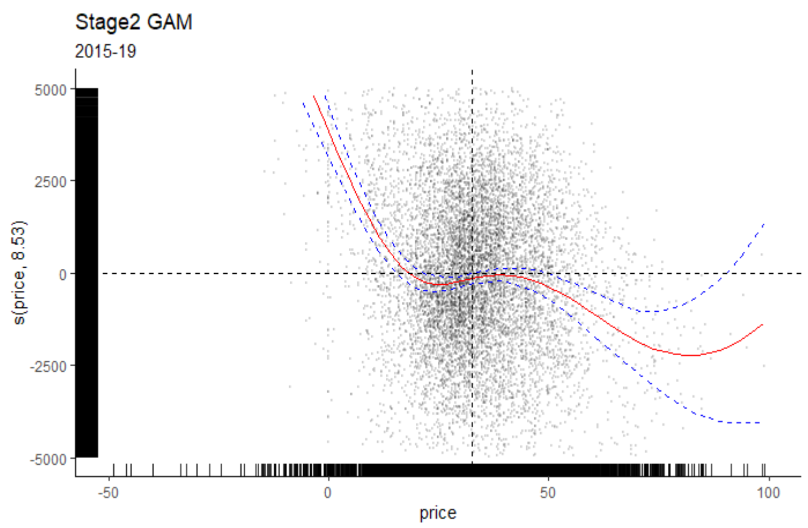
Temporal variation in estimates of demand elasticity



- Results are quite robust across years; no time trend
- Price elasticity significantly lower during weekends and nighttime hours – because only industry can respond to wholesale prices?

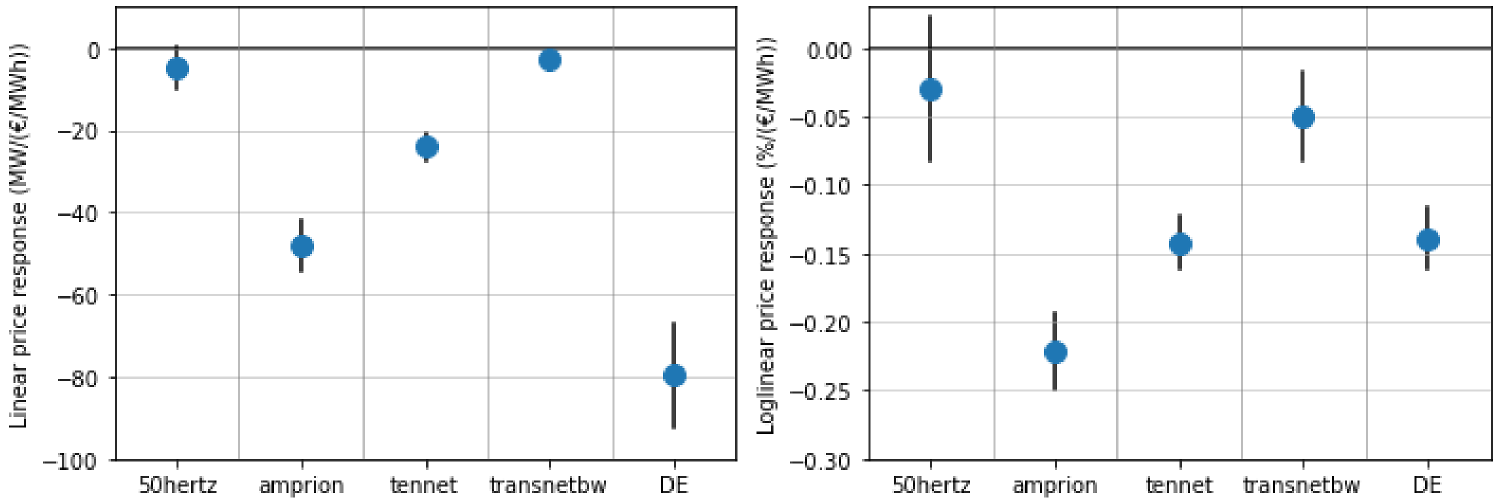
Day vs. Night





- When only looking at daytime hours, we find a mostly linear demand curve
- The nonlinearity seems to stem from nighttime hours. This is also supported by model diagnostics.
- Industrial consumers tend to be more responsive during weekdays?

Regional differences across Germany



- % change in demand per 1 €/MWh change in electricity price is close to zero for 50Hertz and TransnetBW, similar to the national estimate for TenneT, and about twice as large for Amprion
- As Amprion is home to most of Germany's heavy industry, this supports the idea that most of the demand response is from industrial consumers

Robustness checks

Potential challenges using wind generation as instrument

	Identification challenge	Direction of bias	How addressed / tested?
Seasonality *Exogeneity/ confounders*	If wind energy generation and electricity consumption are both seasonal (year, day, other time scales) and hence correlated, which is the case at least over the year, we would attribute this erroneously to price response	*Underestimate/ Overestimate (annual seasonality)*	Control for seasonality (time dummies / nonparametric time trend)
Temperature *Exogeneity/ confounders*	If wind energy generation and demand are both correlated with temperature, we would attribute this erroneously to price response	*Underestimate/ Overestimate*	Control for temperature (heating / cooling degrees, nonparametric)
Economic curtailment *Exogeneity/ confounders*	Low wind generation due to economic curtailment at negative prices is correlated with low load; this may be falsely attributed to price response	*Overestimate*	Exclude negative prices Use wind speed as an instrument
Grid curtailment *Exogeneity/ confounders*	Low wind generation due to grid curtailment is correlated with high load; this may bias our price response estimate	*Underestimate*	Use wind speed as an instrument

Potential challenges using wind generation as instrument

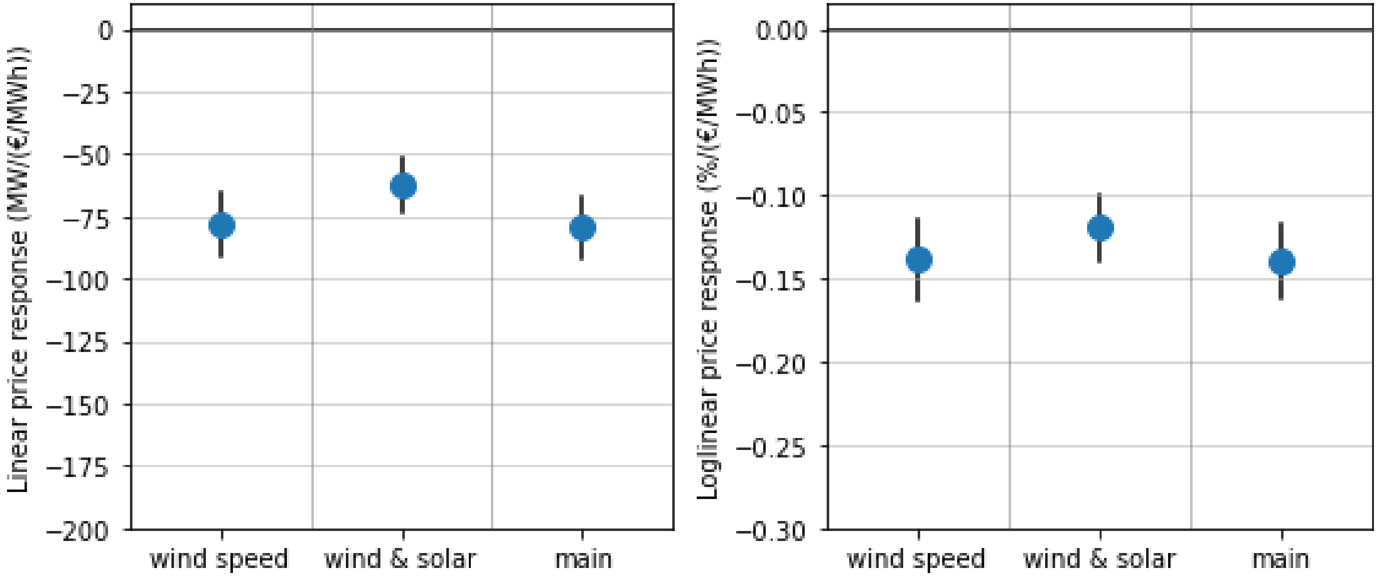
	Identification challenge	Direction of bias	How addressed / tested?
Heating *Exclusion restriction*	If high wind speeds (▲ wind generation, ▼ prices) increase demand for (electric) heating, high wind generation will be associated with higher demand > would be erroneously attributed to price response	*Overestimate*	Data split by season → estimates do not differ between high heating season (winter) and low heating (summer) season
Cooling *Exclusion restriction*	If high wind speeds (▲ wind generation, ▼ prices) decrease demand for (electric) cooling, high wind generation will be associated with lower demand > would be erroneously attributed to price response	*Underestimate*	Data split by season → estimates do not differ between high cooling season (summer) and low cooling (winter) season
Demand disruption *Exclusion restriction*	If extremely high wind speeds (▲ wind generation, ▼ prices) cause electricity-consuming infrastructure to break down (e.g., railroads) > would be erroneously attribute to price response	*Underestimate*	Exclude times of very high wind speeds → estimates do not change

Potential challenges using solar generation as instrument

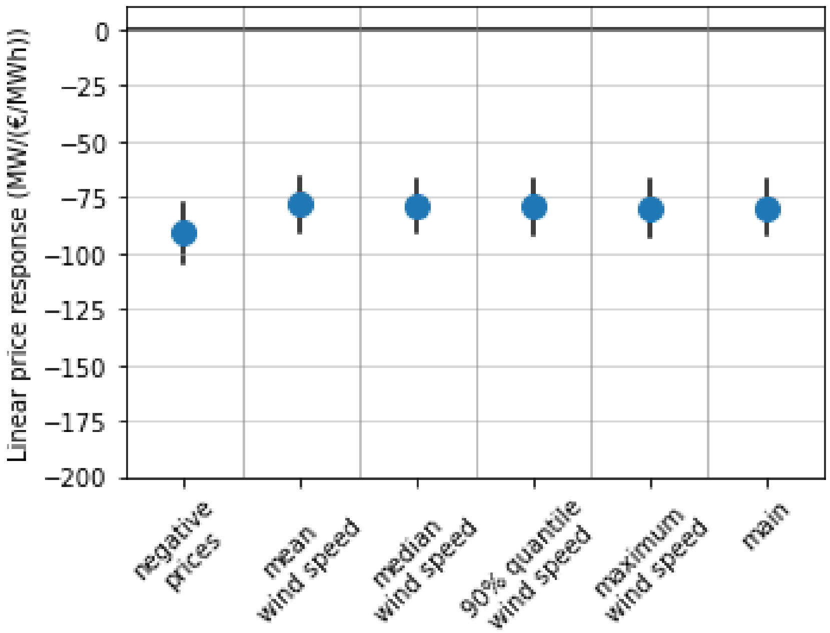
	Identification challenge	Direction of bias	How addressed / tested?
Incomplete measurement *Exclusion restriction*	Solar generation is estimated, not always metered. If it is not estimated accurately, more generation could mean less (observed) load, this could be erroneously attributed to price response	*Underestimate*	• Solar not used as instrument in main specification • When solar is added as instrument, estimate changes only slightly - and becomes *smaller*

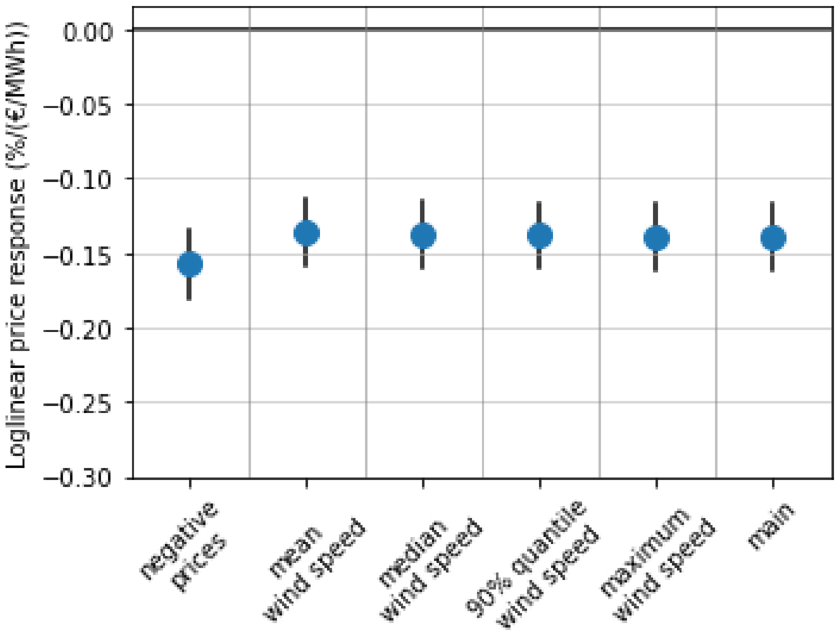
Other instruments

- Wind speed instead of wind energy generation as an instrument avoids some exogeneity concerns regarding congestion etc.
- Use both wind and solar energy generation as an instrument to better estimate $\widehat{Price}$ in the first stage



Robustness to extreme events



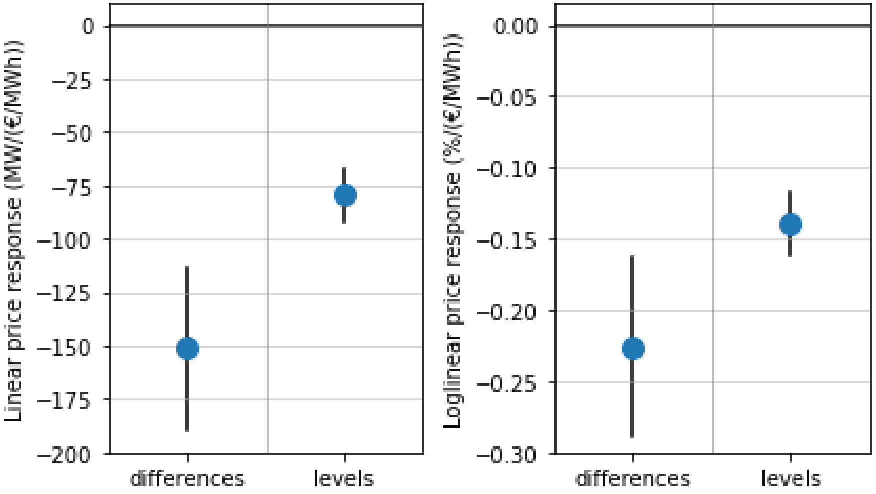


- Excluding 1% highest wind speeds based on different wind speed data

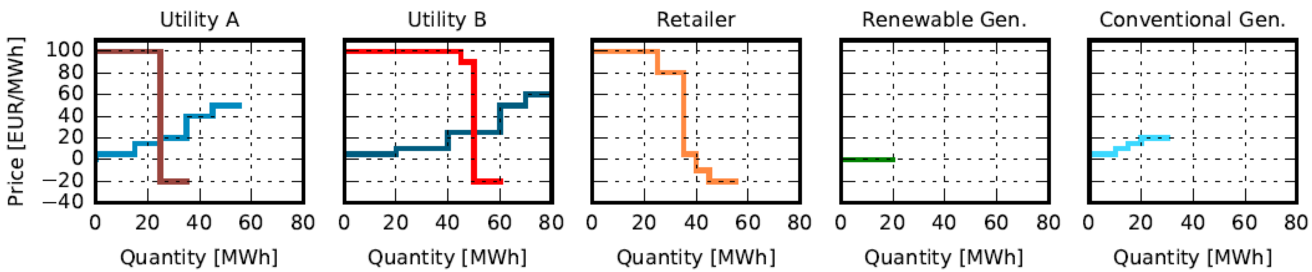
Serial correlation

Both the price and demand time series exhibit serial correlation. Main model specifications use HAC standard errors (parametric) and simulated CI (nonparametric) to overcome this. Other options:

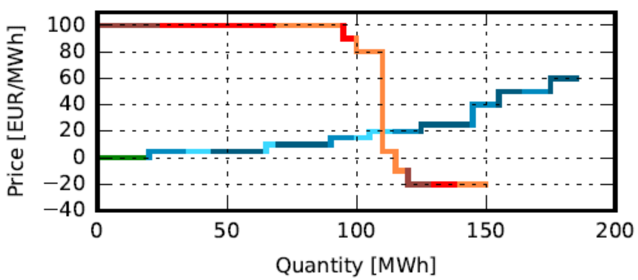
- FGLS or Cochrane–Orcutt (CORC) estimator for the parametric models. The FGLS estimator on stage 2 estimation returns a smaller estimate (-72 MW per 1 €/MWh increase in price vs. -79 MW) and CI are slightly larger (14 vs. 10)
- Estimate the first difference model (keeping time and seasonal dummies level) to remove correlation in errors.



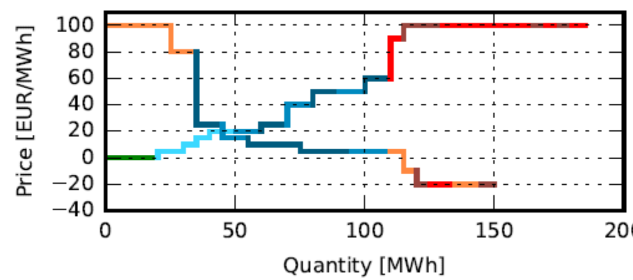
System demand (load) ≠ wholesale demand (EPEX)



(i) Wholesale market players



(ii) Supply and demand aggregation



(iii) Supply and demand in the wholesale market

From Knaut and Paulus (2016)

Because of utility portfolios and OTC contracts,

- wholesale demand includes generators buying instead of producing
- wholesale supply includes consumers selling instead of consuming

Hourly price response ≠ short-term price elasticity

Economists usually investigate yearly data

- Short-term: response to a price change in the same year
- Long-term: response to a price change in the previous year

Examples

- Eskeland and Mideska 2010 and Azevedo et al. 2011
  - Europe: -0.2
- Cialani and Mortazavi 2018. Household and industrial electricity demand in Europe. *Energy Policy*
  - Europe: -0.03…-0.05
- Csereklyei 2020. Price and income elasticities of residential and industrial electricity demand in the European Union. *Energy Policy*
  - Europe: -0.08

Empirical literature on hourly price response

Lijesen 2007. Energy Economics Paper

- NL 2003: -0.0014 (exponential demand curve)
- Lagged price as instrumental variable

Knaut and Paulus 2016. EWI Working Paper

- DE 2015: -0.02…-0.12 (linear demand curve)
- Wind energy as instrumental variable

Kulakov and Ziel 2019. HEMF Working Paper

- DE 2017: -0.0001 (nonparametric curve)
- Decomposition of wholesale demand and supply

In summary: single years and countries, different approaches & results

Why Germany?

Germany combines several factors:

- High domestic wind share
- Imports and exports do not matter so much
- Not so much (hydro) storage
- Diverse conventional generation mix (many steps in the merit order)
- Highly competitive market with competitive price formation (no regulated prices)

Hence, wind power has a strong explanatory power for wholesale prices (strong instrument)

Who "sees" wholesale price fluctuations?

Residential consumers

- Virtually no real-time pricing

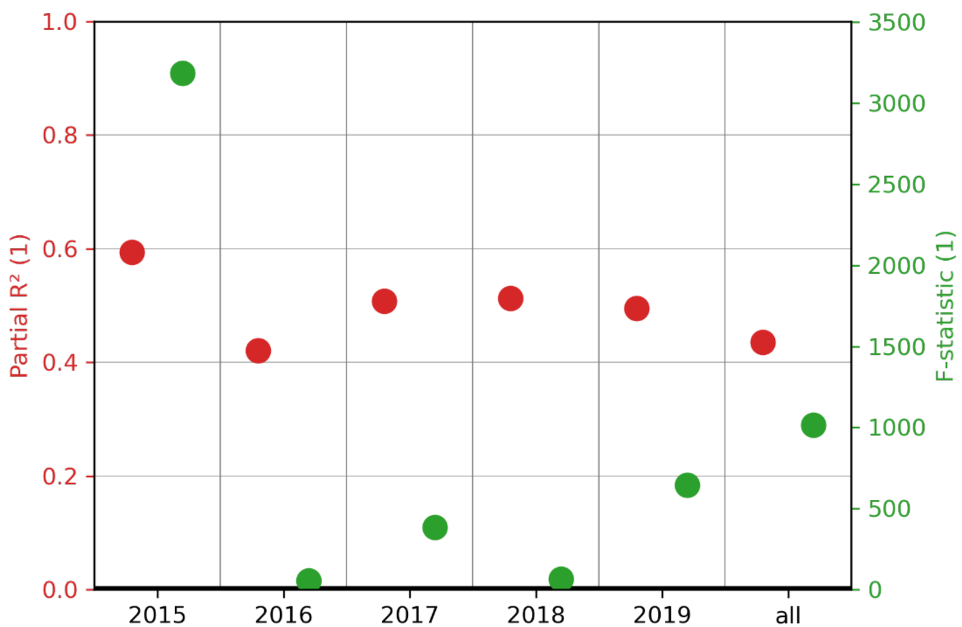
Large-scale consumers

- Partial price exposure (real-time tariffs or own market access)

Additional tariff components

- Time-invariant surcharges (taxes, etc.) on top of wholesale price
  → their true price elasticity (in %) is higher than the one we estimate here
- Incentives *against* flexibility (reduced grid fees for continuous consumption)

Weak instruments?



- Substantial partial R^2 for the instrument (wind power) in the 1^{st} stage
- Corresponding F-statistic varies substantially, but always > 10
- Smallest R^2 and F-statistic for 2016, where GAM estimate is quite low

Nonparametric models

$$Price_t = \alpha_0 + s(I_t) + \boldsymbol{s}(\boldsymbol{C_t^s}) + \boldsymbol{\alpha_D D}_t + \ v_t \qquad (3)$$

$$Demand_t = \beta_0 + s(Price_t) + \boldsymbol{s}(\boldsymbol{C_t^s}) + \boldsymbol{\beta_D D}_t + s(\hat{v}_t) + u_t \qquad (4)$$

$Price_t$	Wholesale price of electricity in hour t
$Demand_t$	Electricity demand in hour t
I_t	Instrument: wind energy generation
$\boldsymbol{C_t^s}$	Non-linear controls: solar generation, CO_2 price, ambient temperature, coal and gas prices, time
$\boldsymbol{D}_t$	Dummies: hour of day, weekday, month of year, year
$s(\cdot)$	Modeled splines

- Estimated using a 2 Stage Generalized Additive Model (2SGAM) approach (Radice and Marra 2011)

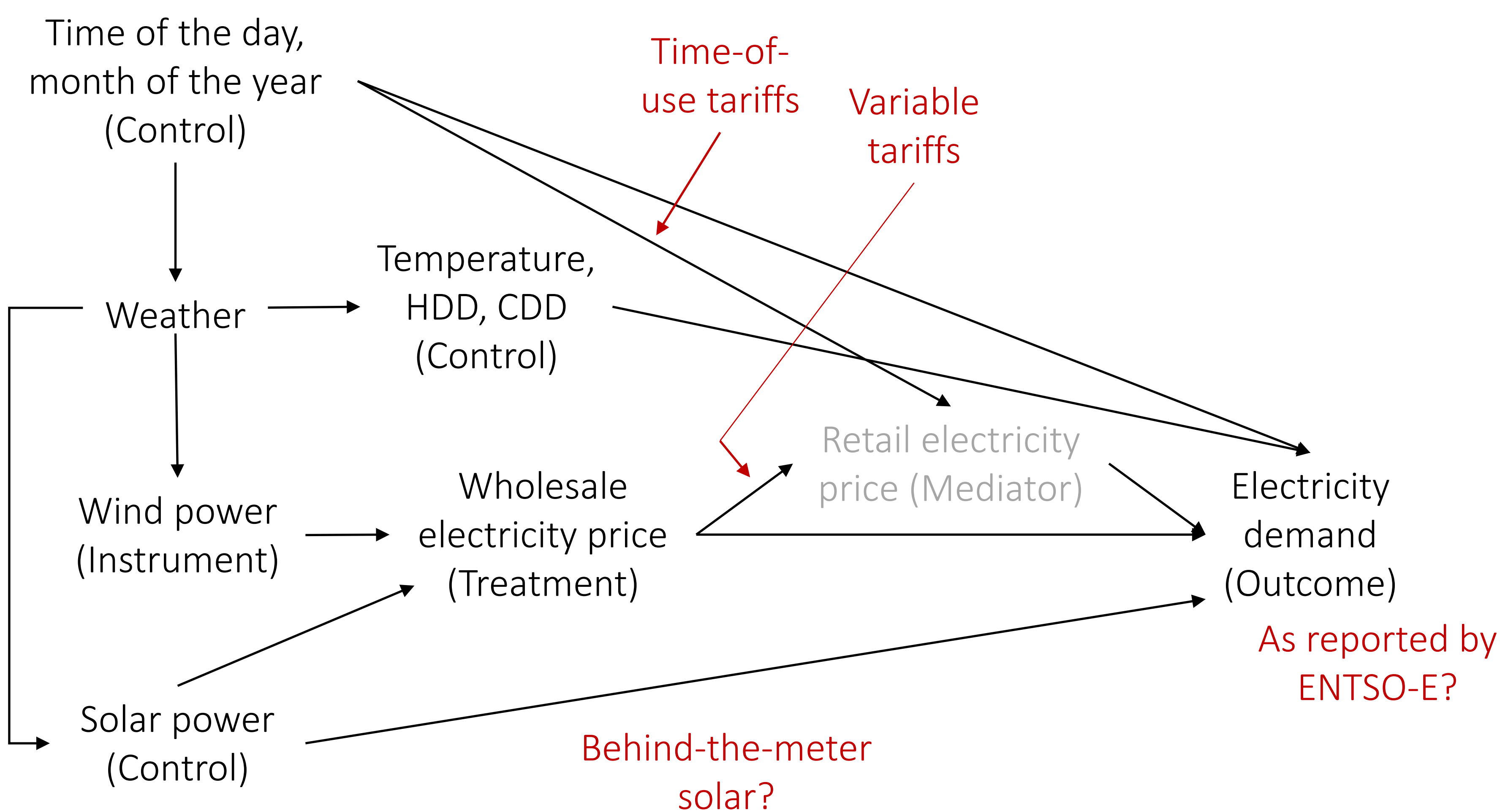
2-stage generalized additive model (GAM) estimation

$$Price_t = \alpha_0 + s(I_t) + \alpha_{lin} C_t^{lin} + \boldsymbol{s}(\boldsymbol{C_t^s}) + \boldsymbol{\alpha_D D}_t + \ v_t \qquad (1)$$

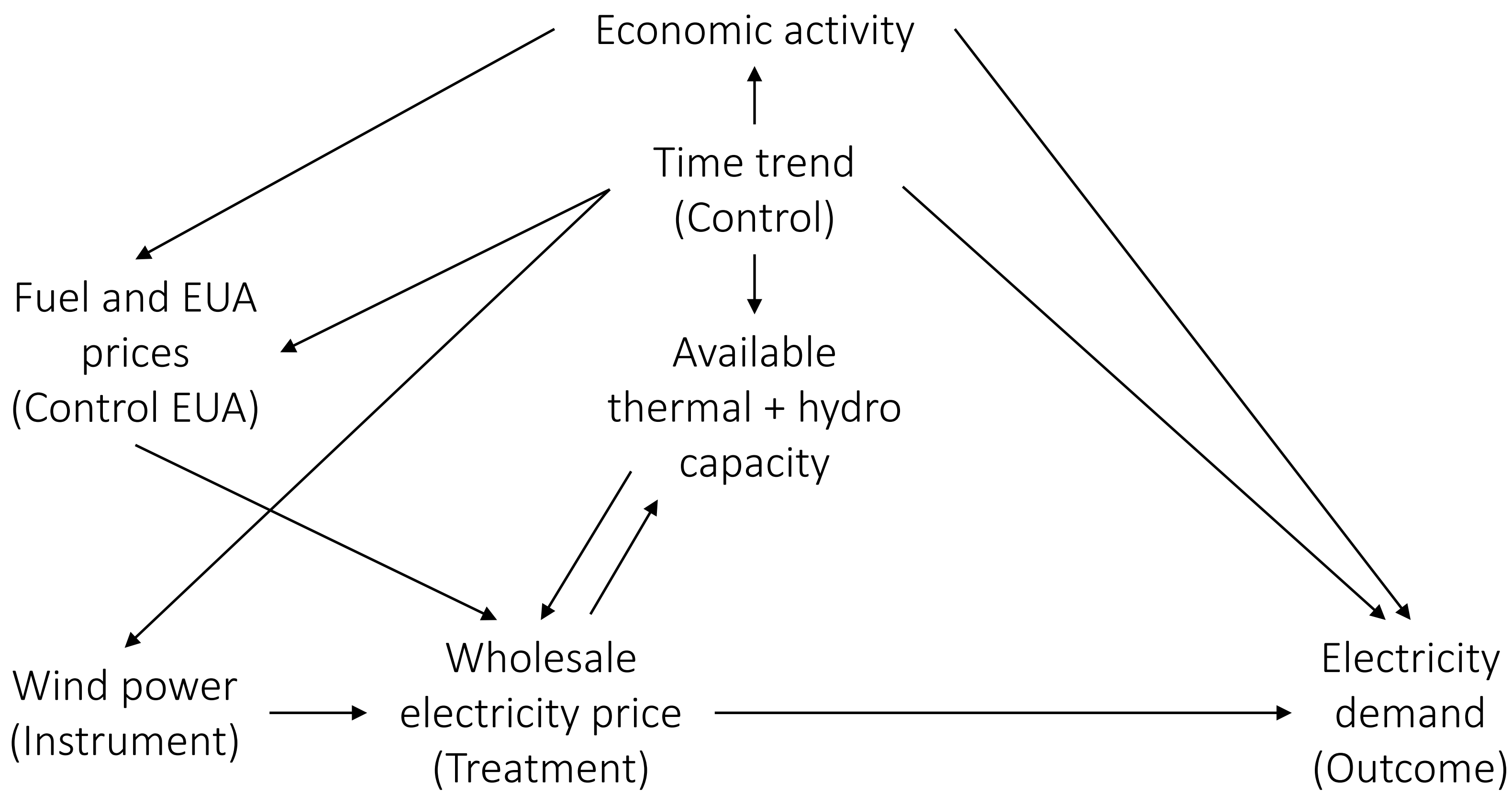
$$Demand_t = \beta_0 + \beta_1 Price_t \text{ (or } s(Price_t)) + \beta_{lin} C_t^{lin} + \boldsymbol{s}(\boldsymbol{C_t^s}) + \boldsymbol{\beta_D D}_t + s(\hat{v}_t) + u_t \qquad (2)$$

- The approach is based on work done by Marra and Radice (2011) and Zanin, Radice and Marra (2015)
- GAMs extend linear models by allowing the determination of possible nonlinear effects of predictors on the response variable. A GAM has a model structure y = g−1(η) + e, where g−1(η) = μ = E(y|X), with g(·) being a suitable link function
- The presence of an endogenous relationship between the demand and price can lead to inconsistent estimates. But because $\boldsymbol{s}(\hat{v}_{t)})$ in Eq. 2 allows us to flexibly account for endogeneity, the linear/nonlinear effects of the endogenous regressors can be estimated consistently.

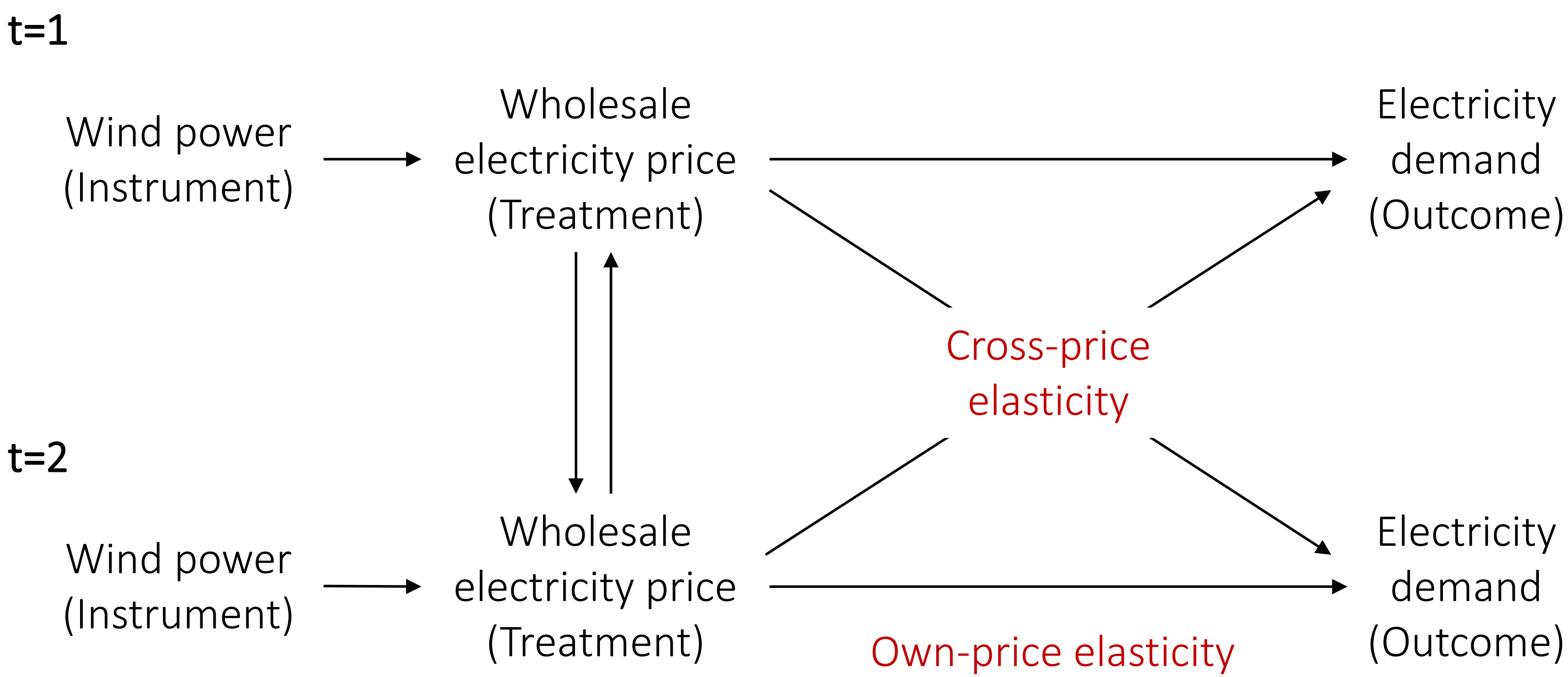
Causal relationships: instruments, exclusion restriction



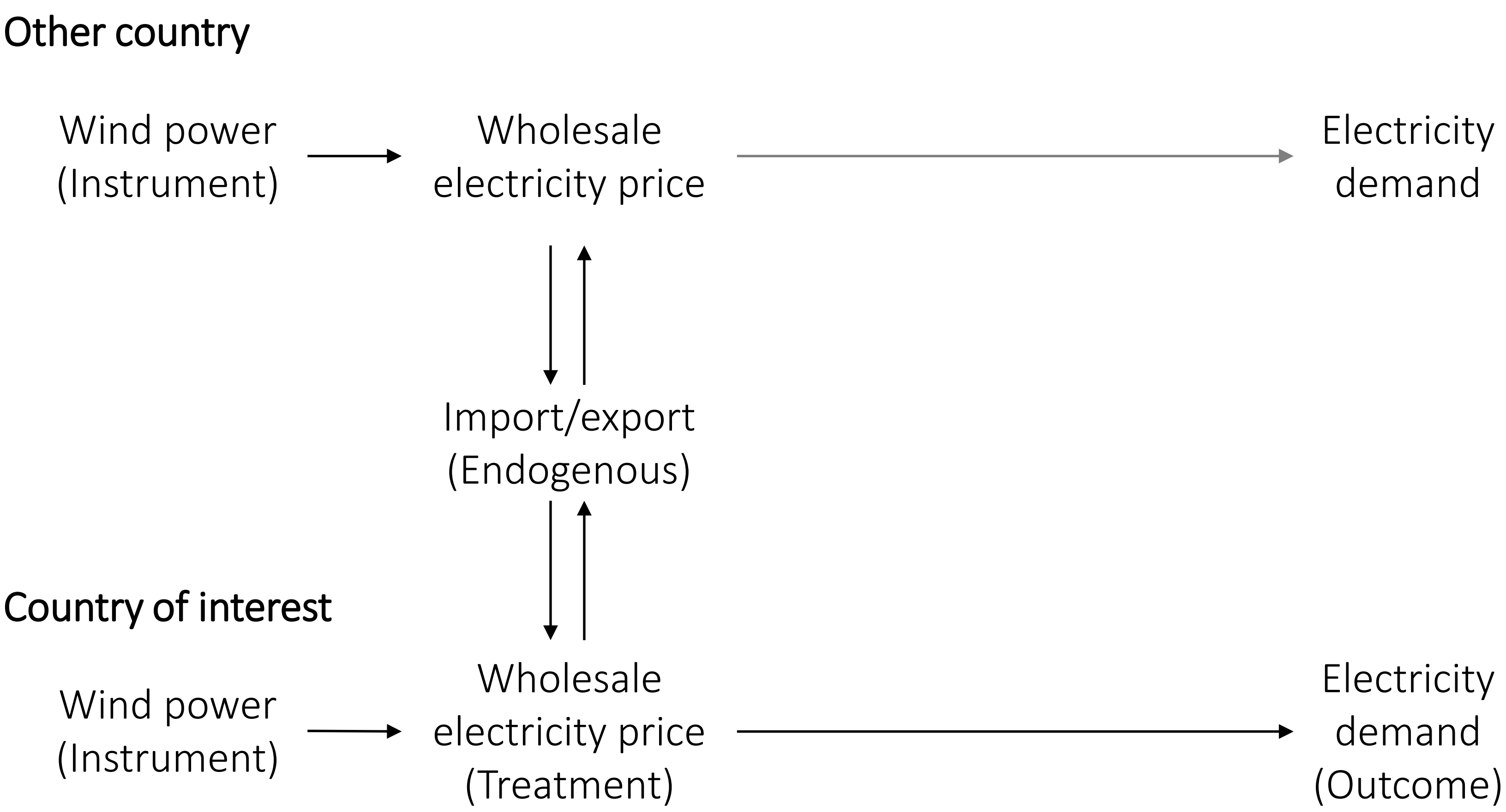
Causal relationships: time trend and further controls



Causal relationships: the role of lagged prices (Granger Causality)



Causal relationships: import/export



Statistical Appendix

Stationarity checks

1. All time series in OLS regressions need to be stationary. If a time series is non-stationary, then all the typical results of OLS analysis are not valid
2. If there are inherent trends in a series then its non-stationary. Trends can be either 1) deterministic or 2) stochastic.
3. Deterministic trends are the type that we have been looking at – seasonal, daily, annual trends. Detrending the series or including a trend variable in the regression solves this problem.
4. Usually, time series of electricity spot prices are assumed (i) to have deterministic daily, weekly and yearly seasonal patterns, (ii) to show price dependent volatilities, and (iii) to be stationary (after controlling for the seasonal patterns); see Huisman and De Jong (2003), Knittel and Roberts (2005), Kosater and Mosler (2006), Huisman, Huurman and Mahieu (2007) and many others.
5. A stochastic trend is random and varies over time. Example: highly persistent time series. $Y_t = p * Y_{t-1} + u_t$ or $Y_t = Y_{t-1}$ + time trend + $u_{t.}$ This is also called presence of a unit root. If $|p| <1$ then the series is weakly stationary or unit root is absent and series can be used in regressions. ADF tests with lags confirms the absence of a unit root in our time series.

Autocorrelation checks

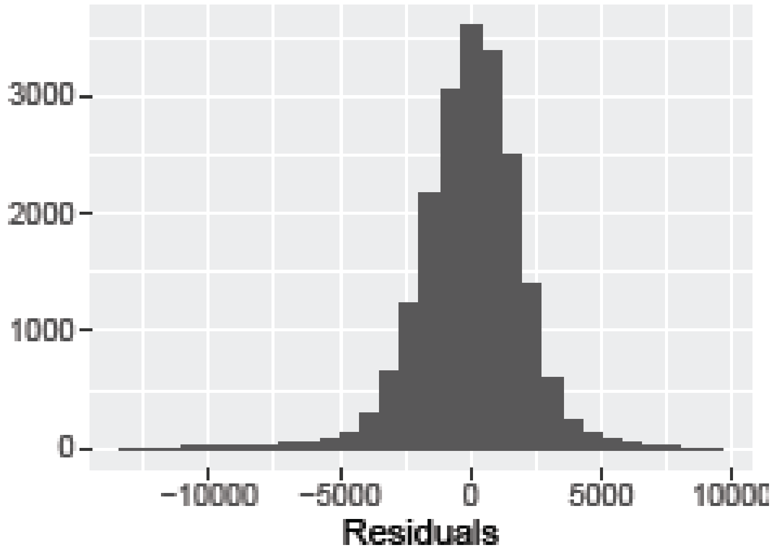
- Another problem is autocorrelation of errors. This is similar to 4 except that autocorrelation can exist even in stationary series. So serial correlation problems exist with or without stationarity problems.

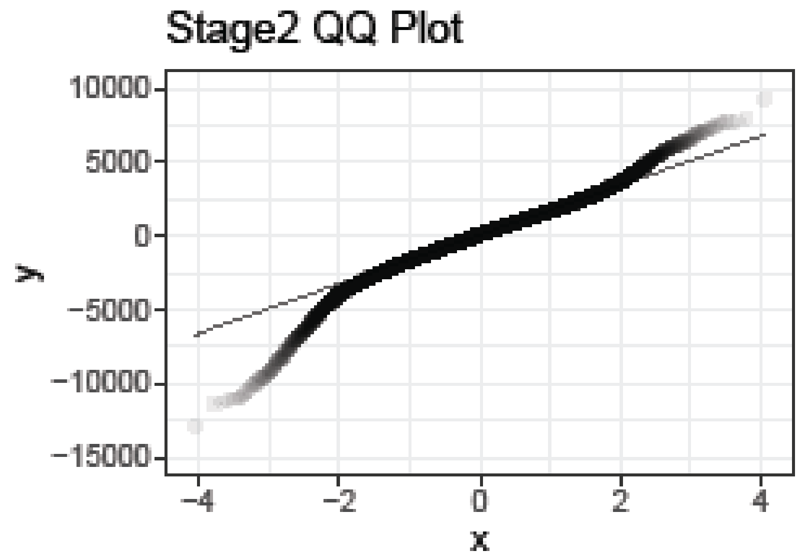
- This is a problem for the standard errors mostly. Serial correlation in the errors can make them appear smaller than they should be (type I error) but the coefficient estimates are usually still unbiased or at least consistent.

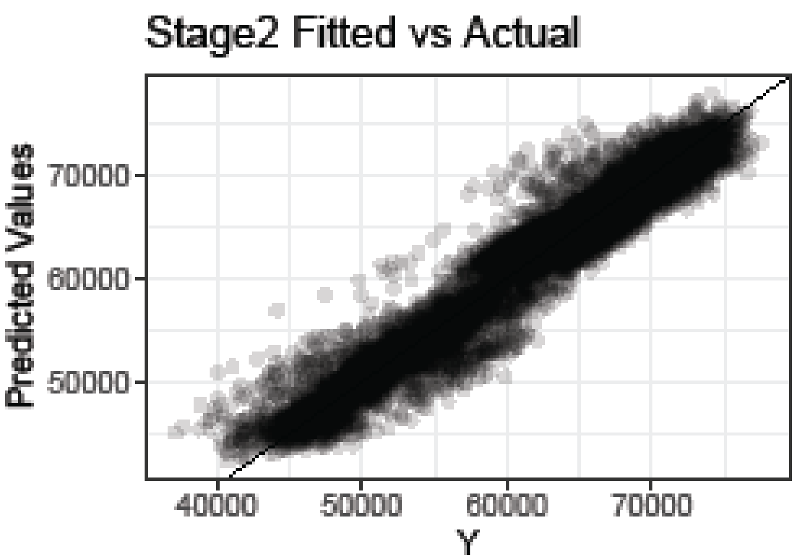
- GMM that corrects for serial correlation is useful. We can also just test for errors coming from the regression for correlation.

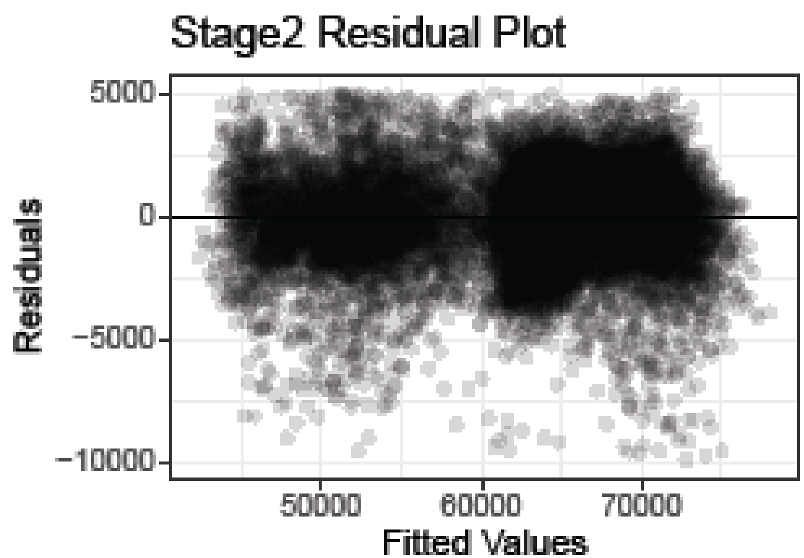
- Dynamically incomplete models, where the lags are not taken into account will also result in autocorrelation in the series. Not sure how this impacts our case. What also complicates our case is that not only is demand at t related to lead and lag prices but the relationship is endogenous, i.e., prices at t can also be caused by demand at t +/-h. How this impacts the model is uncertain and we cannot really take this into account. We should be looking at things like Granger causality etc.

Model diagnostics: Daytime hours (2SLS)

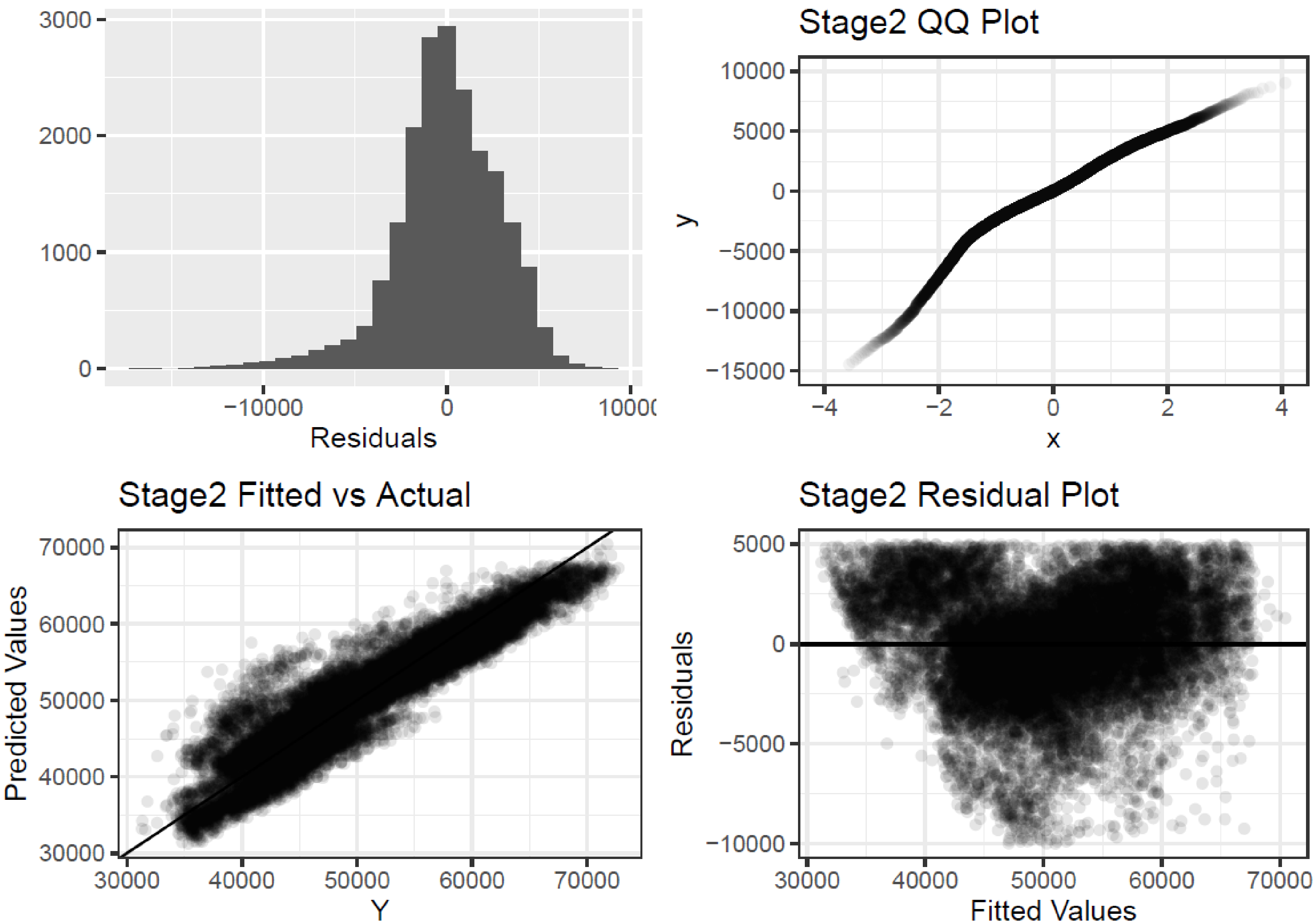




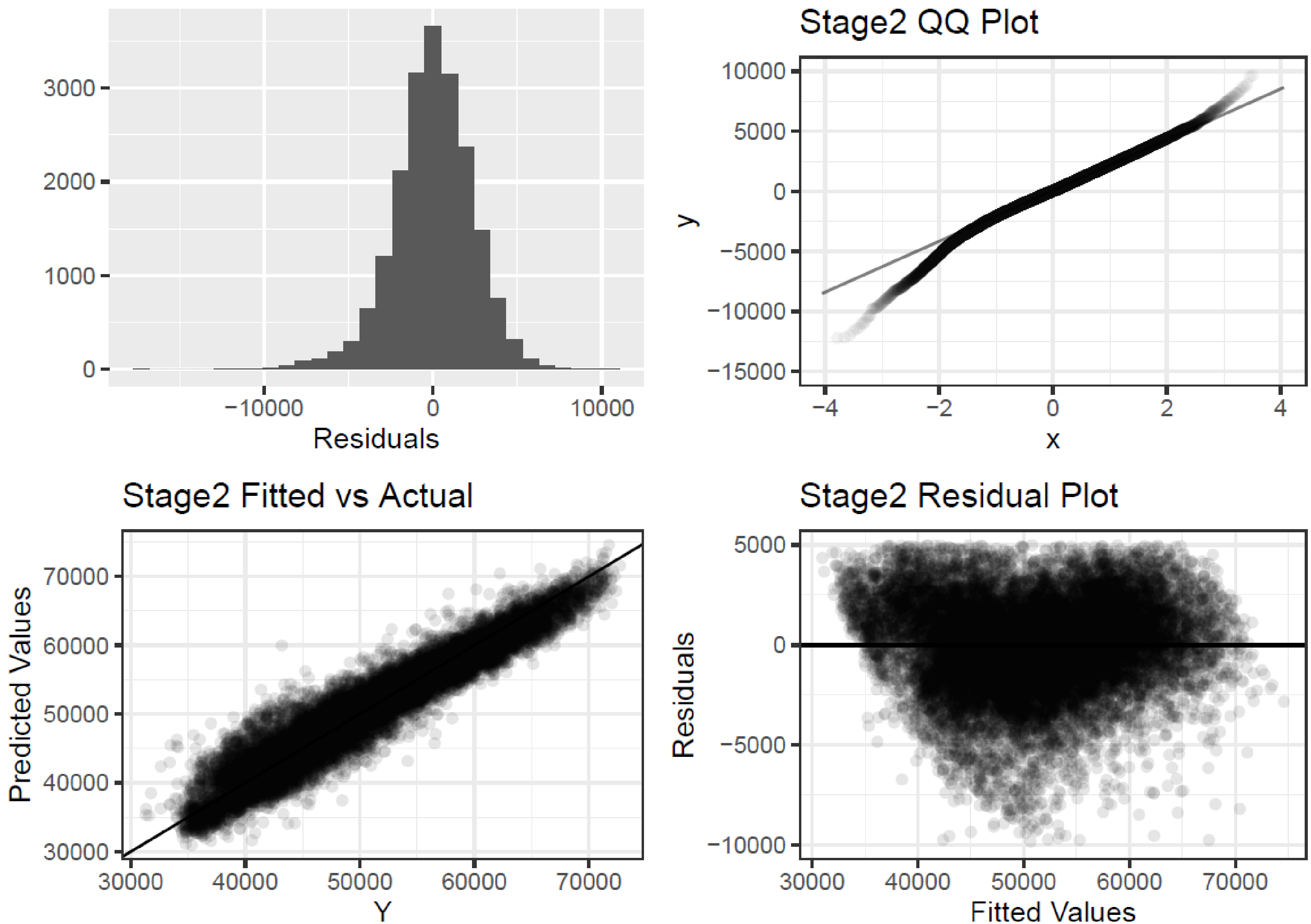




Model diagnostics: Night time hours (2SLS)

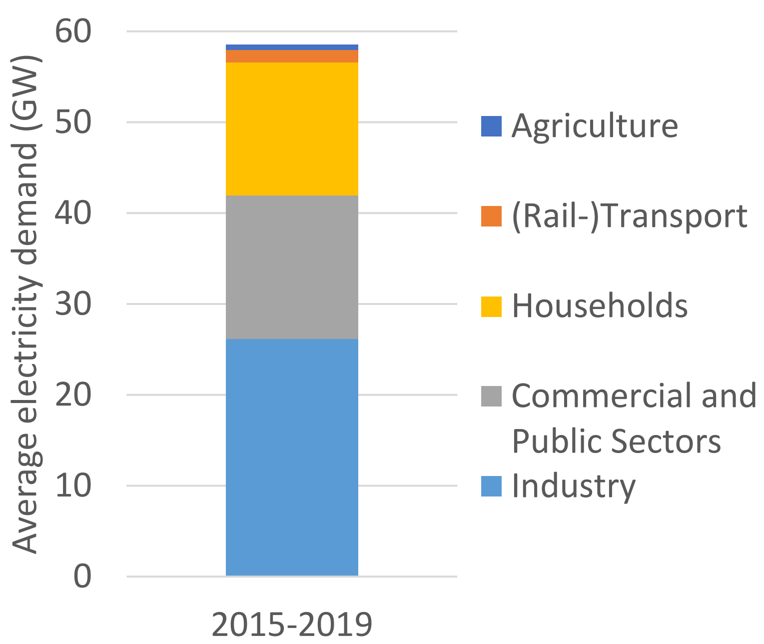


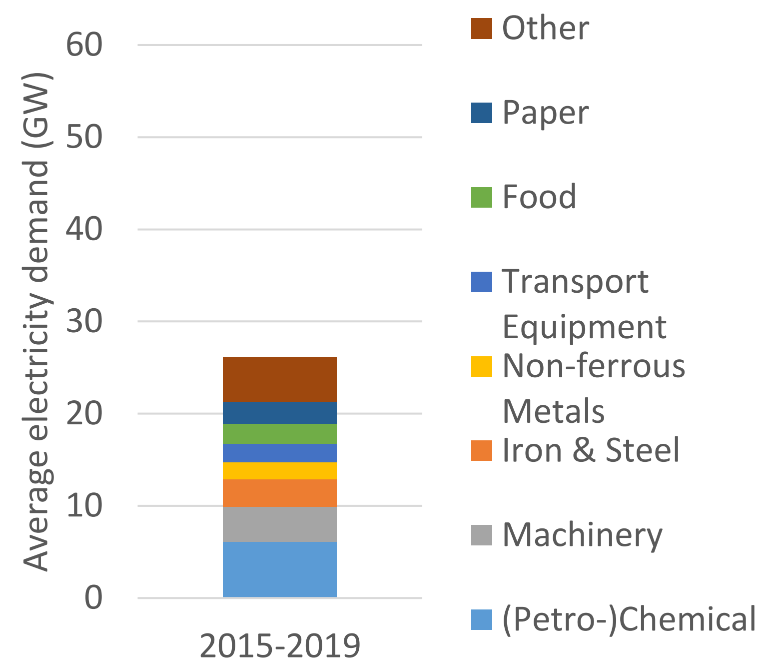
Model diagnostics: Night time hours (2SGAM)



Interpretation of German estimates

How much electricity demand from the different sectors





- Most of the demand comes from industry, thereafter commercial and public sectors → when only looking at weekdays these sectors will be even larger
- Within industry, (petro-)chemical, machinery, iron & steel, other metals, food, and paper are the largest sectors
- On top of final energy demand: power-to-heat in district heating?

Households

Germany

- Lack of smart meters (numbers?)
- Few household aggregators:
  - Pebbles: < 1 MW
  - Sonnen: focus on balancing market
  - RegEE (Thüga): < 1 MW
- Few tariffs:
  - Octopus: > 2.5m customers but smart tariffs are not yet launched in DE
  - Awattar

Other EU countries have more of this

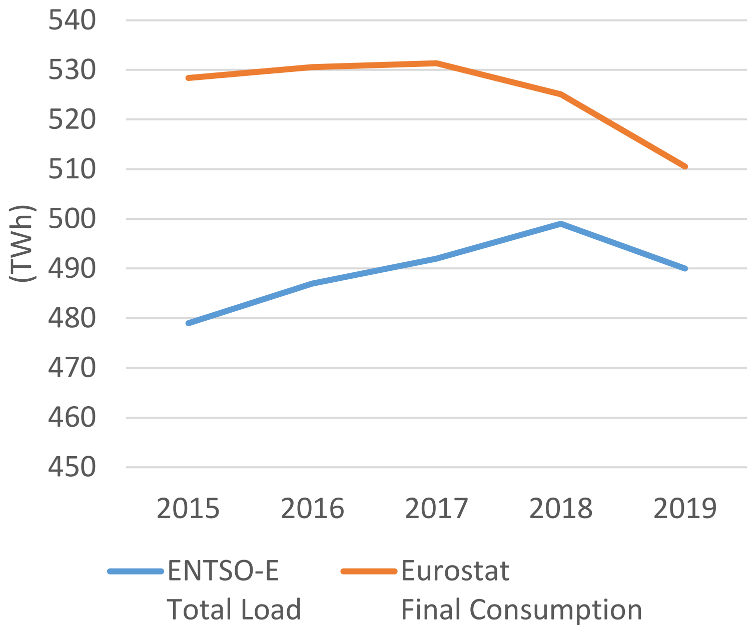
- Octopus energy has smart tariffs operating in UK
- McKenna et al. 2021 on Austria, 1500 consumers
- Spain?

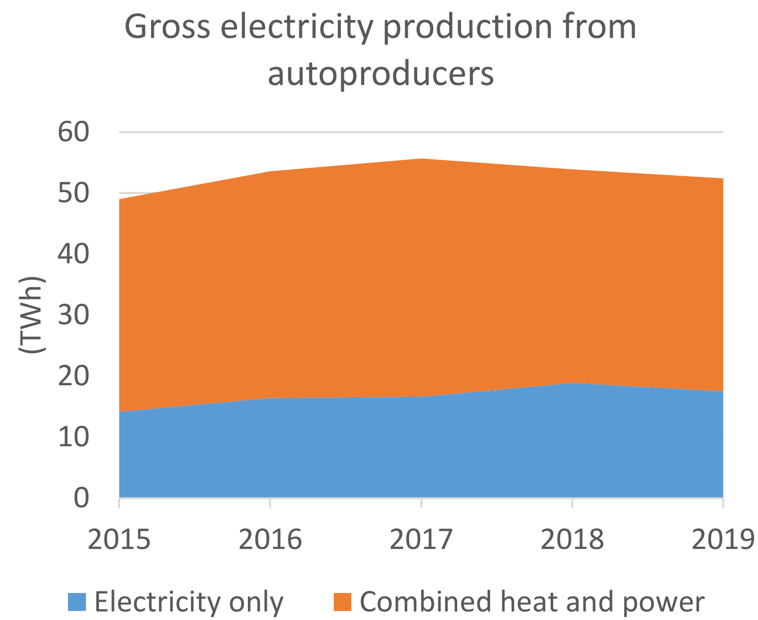
Industry

The theoretical demand response potential

- Klobasa 2007, Paulus and Borggrefe 2011, Gruber 2017: 2.3–4.3 GW
- Gils 2014: about 5 GW
- Kochems 2020: 5 GW
    - Paper: 2 GW
    - Steel: 1 GW
    - Non-ferrous metals: 1 GW
    - Chlor-alkali electrolysis: 0.5 GW
    - Process cold: 0.5 GW
- SynErgie 2018: 2.2 GW (mostly glas, chemical, metal)

Or is it just a measurement error?





- There is a substantial difference between ENTSO-E and EUROSTAT, but this difference decreases
- The difference decreases even though auto-production remains constant
- Despite the decrease in difference, our estimates stay the same