How aggregate electricity demand responds to hourly wholesale price fluctuations

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Tarun Khanna
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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
We also control for other variables (fuel and CO₂ 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
  o **Relevance:** wind energy generation should impact wholesale electricity price
  o **Exogeneity:** wind energy generation should not be endogenously impacted by demand (or by a confounder impacting both wind energy and demand)
  o **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

<table>
<thead>
<tr>
<th>Identification challenge</th>
<th>Direction of bias</th>
<th>How addressed / tested?</th>
</tr>
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<tbody>
<tr>
<td>Economic curtailment</td>
<td><strong>Overestimate</strong></td>
<td>Exclude negative prices</td>
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<td><strong>Exogeneity/confounders</strong></td>
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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)

<table>
<thead>
<tr>
<th>Model</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model class</td>
<td>Parametric models</td>
<td></td>
<td>Nonparametric models</td>
<td>Linear/Nonparametric</td>
<td></td>
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<tr>
<td>Specification of controls</td>
<td>Linear</td>
<td></td>
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</tr>
<tr>
<td>Estimator</td>
<td>Two-stage least squares (2SLS)</td>
<td></td>
<td>Two-stage generalized additive model (2SGAM)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demand-price relationship</td>
<td>Linear</td>
<td>Loglinear</td>
<td>Linear</td>
<td>Loglinear</td>
<td>Non-parametric</td>
</tr>
</tbody>
</table>
Parametric models

\[ Price_t = \alpha_0 + \alpha_1 I_t + \alpha_C C_t + \alpha_D D_t + \nu_t \]  \hspace{1cm} (1)

\[ Demand_t = \beta_0 + \beta_1 \hat{Price}_t + \beta_C C_t + \beta_D D_t + \mu_t \]  \hspace{1cm} (2)

- \( Price_t \): Wholesale price of electricity in hour \( t \)
- \( \hat{Price}_t \): Predicted electricity price based on Eq. (1)
- \( Demand_t \): Electricity demand in hour \( t \)
- \( \beta_1 \): Linear demand response to electricity price
- \( I_t \): Instrument: wind energy generation
- \( C_t \): Controls: solar generation, HDD, CDD, coal, gas and CO\(_2\) prices
- \( D_t \): 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

<table>
<thead>
<tr>
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<th>2SLS</th>
<th>GAM</th>
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</thead>
<tbody>
<tr>
<td>Adjusted R²</td>
<td>0.76</td>
<td>0.79</td>
</tr>
<tr>
<td>Partial R² of wind energy</td>
<td>0.46</td>
<td>-</td>
</tr>
<tr>
<td>Partial F-statistic</td>
<td>930</td>
<td>-</td>
</tr>
<tr>
<td>Wind energy (GW)</td>
<td>-0.94 ***</td>
<td>Spline***</td>
</tr>
<tr>
<td></td>
<td>[−1.01, −0.88]</td>
<td></td>
</tr>
</tbody>
</table>

Second stage: effect of price on demand

<table>
<thead>
<tr>
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<th>GAM</th>
</tr>
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<tbody>
<tr>
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<td>Price (€/MWh)</td>
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<td>Price (€/MWh)</td>
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<tr>
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- 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

• 1\textsuperscript{st} stage non-linear results are plausible
• 2\textsuperscript{nd} 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 $\rightarrow$ 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) $\rightarrow$ variation of 26 €/MWh in prices $\rightarrow$ about 2 GW demand response
  • 4% of avg. demand
  • 7% of wind generation
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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University of Cologne

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Institute of Energy Economics (EWI)

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Detailed results
## Results from first stage regression

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<tr>
<td>Solar energy (GW)</td>
<td>-1.12 ***</td>
<td>Spline***</td>
</tr>
<tr>
<td></td>
<td>[-1.19, -1.05]</td>
<td></td>
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<tr>
<td>Heating degrees (°C)</td>
<td>0.36 ***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>[0.22, 0.49]</td>
<td></td>
</tr>
<tr>
<td>Cooling degrees (°C)</td>
<td>0.45 ***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>[0.33, 0.58]</td>
<td></td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>-</td>
<td>Spline***</td>
</tr>
<tr>
<td>EUAs (€/t)</td>
<td>1.08 ***</td>
<td>0.75 ***</td>
</tr>
<tr>
<td></td>
<td>[0.84, 1.32]</td>
<td>[0.68, 0.83]</td>
</tr>
<tr>
<td>Coal price (€/MWh)</td>
<td>1.67 ***</td>
<td>Spline***</td>
</tr>
<tr>
<td></td>
<td>[1.33, 2.01]</td>
<td></td>
</tr>
<tr>
<td>Gas price (€/MWh)</td>
<td>0.35 ***</td>
<td>Spline***</td>
</tr>
<tr>
<td></td>
<td>[0.12, 0.57]</td>
<td></td>
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<tr>
<td>Hour</td>
<td>Dummies</td>
<td>Dummies</td>
</tr>
<tr>
<td>Weekday</td>
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<tr>
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<td>Dummies</td>
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<tr>
<td>Year</td>
<td>Dummies</td>
<td>Dummies</td>
</tr>
<tr>
<td>Time</td>
<td>-</td>
<td>Spline***</td>
</tr>
</tbody>
</table>

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
## Results from second stage regressions

<table>
<thead>
<tr>
<th></th>
<th>Linear 2SLS</th>
<th>Linear GAM</th>
<th>Log-linear 2SLS</th>
<th>Log-linear GAM</th>
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<td>0.90</td>
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<td>Price (€/MWh)</td>
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<td>−67.3 ***</td>
<td>−0.14 ***</td>
<td>−0.12 ***</td>
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<td></td>
<td>[−91.3, −67.8]</td>
<td>[−72.2, −62.7]</td>
<td>[−0.16, −0.12]</td>
<td>[−0.13, −0.11]</td>
</tr>
<tr>
<td>Solar energy (GW)</td>
<td>−125.3 ***</td>
<td>Spline</td>
<td>−0.14 ***</td>
<td>Spline</td>
</tr>
<tr>
<td></td>
<td>[−153.6, −97.1]</td>
<td></td>
<td>[−0.19, −0.10]</td>
<td></td>
</tr>
<tr>
<td>Heating degrees (°C)</td>
<td>310.9 ***</td>
<td>-</td>
<td>0.55 ***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>[279.8, 342.0]</td>
<td></td>
<td>[0.49, 0.61]</td>
<td></td>
</tr>
<tr>
<td>Cooling degrees (°C)</td>
<td>149.9 ***</td>
<td>-</td>
<td>0.32 ***</td>
<td>-</td>
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<tr>
<td></td>
<td>[113.0, 186.8]</td>
<td></td>
<td>[0.25, 0.38]</td>
<td></td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>-</td>
<td>Spline ***</td>
<td>-</td>
<td>Spline ***</td>
</tr>
<tr>
<td>EUAs (€/t)</td>
<td>98.1 ***</td>
<td>Spline ***</td>
<td>0.19 ***</td>
<td>Spline ***</td>
</tr>
<tr>
<td></td>
<td>[37.5, 158.7]</td>
<td></td>
<td>[0.06, 0.31]</td>
<td></td>
</tr>
<tr>
<td>Coal price (€/MWh)</td>
<td>299.8 ***</td>
<td>Spline ***</td>
<td>0.53 ***</td>
<td>Spline ***</td>
</tr>
<tr>
<td></td>
<td>[221.0, 378.7]</td>
<td></td>
<td>[0.37, 0.68]</td>
<td></td>
</tr>
<tr>
<td>Gas price (€/MWh)</td>
<td>14.1</td>
<td>Spline ***</td>
<td>0.03</td>
<td>Spline ***</td>
</tr>
<tr>
<td></td>
<td>[−39.4, 67.7]</td>
<td></td>
<td>[−0.08, 0.14]</td>
<td></td>
</tr>
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<td>-</td>
<td>Spline ***</td>
<td>-</td>
<td>Spline ***</td>
</tr>
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*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

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<th>Identification challenge</th>
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<tr>
<td><strong>Seasonality</strong></td>
<td><strong>Underestimate/ Overestimate</strong></td>
<td>Control for seasonality (time dummies / nonparametric time trend)</td>
</tr>
<tr>
<td>Exogeneity/confounders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>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</td>
<td><strong>Underestimate/ Overestimate</strong> (annual seasonality)</td>
<td></td>
</tr>
<tr>
<td><strong>Temperature</strong></td>
<td><strong>Underestimate/ Overestimate</strong></td>
<td>Control for temperature (heating / cooling degrees, nonparametric)</td>
</tr>
<tr>
<td>Exogeneity/confounders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If wind energy generation and demand are both correlated with temperature, we would attribute this erroneously to price response</td>
<td><strong>Underestimate/ Overestimate</strong></td>
<td></td>
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<tr>
<td><strong>Grid curtailment</strong></td>
<td><strong>Underestimate</strong></td>
<td>Use wind speed as an instrument</td>
</tr>
<tr>
<td>Exogeneity/confounders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low wind generation due to grid curtailment is correlated with high load; this may bias our price response estimate</td>
<td><strong>Underestimate</strong></td>
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<tr>
<td>Exclusion restriction</td>
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</tr>
<tr>
<td>If high wind speeds (↑ wind generation, ↓ prices) increase demand for (electric) heating, high wind generation will be associated with higher demand &gt; would be erroneously attributed to price response</td>
<td><strong>Overestimate</strong></td>
<td>Data split by season → estimates do not differ between high heating season (winter) and low heating (summer) season</td>
</tr>
<tr>
<td><strong>Cooling</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exclusion restriction</td>
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</tr>
<tr>
<td>If high wind speeds (↑ wind generation, ↓ prices) decrease demand for (electric) cooling, high wind generation will be associated with lower demand &gt; would be erroneously attributed to price response</td>
<td><strong>Underestimate</strong></td>
<td>Data split by season → estimates do not differ between high cooling season (summer) and low cooling (winter) season</td>
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<td><strong>Demand disruption</strong></td>
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<td>If extremely high wind speeds (↑ wind generation, ↓ prices) cause electricity-consuming infrastructure to break down (e.g., railroads) &gt; would be erroneously attribute to price response</td>
<td><strong>Underestimate</strong></td>
<td>Exclude times of very high wind speeds → estimates do not change</td>
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Potential challenges using solar generation as instrument

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<tr>
<td>Incomplete measurement</td>
<td></td>
<td>- Solar not used as instrument in main specification</td>
</tr>
<tr>
<td>Exclusion restriction</td>
<td><strong>Underestimate</strong></td>
<td>- When solar is added as instrument, estimate changes only slightly - and becomes <em>smaller</em></td>
</tr>
<tr>
<td>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</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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 $\hat{\text{Price}}$ 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.
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
  - Europe: -0.03…-0.05
  - Europe: -0.08
Empirical literature on hourly price response

- 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

- 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 1st 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

\[ \text{Price}_t = \alpha_0 + s(I_t) + s(C_t^s) + \alpha_D D_t + \nu_t \]  

\[ \text{Demand}_t = \beta_0 + s(\text{Price}_t) + s(C_t^s) + \beta_D D_t + s(\hat{\nu}_t) + \eta_t \]  

- \text{Price}_t \quad \text{Wholesale price of electricity in hour } t
- \text{Demand}_t \quad \text{Electricity demand in hour } t
- I_t \quad \text{Instrument: wind energy generation}
- C_t^s \quad \text{Non-linear controls: solar generation, CO}_2 \text{ price, ambient temperature, coal and gas prices, time}
- D_t \quad \text{Dummies: hour of day, weekday, month of year, year}
- s(\cdot) \quad \text{Modeled splines}

- Estimated using a 2 Stage Generalized Additive Model (2SGAM) approach (Radice and Marra 2011)
2-stage generalized additive model (GAM) estimation

\[ \text{Price}_t = \alpha_0 + s(I_t) + \alpha_{\text{lin}} C_{t}^{\text{lin}} + s(C_t^s) + \alpha_D D_t + \nu_t \quad (1) \]

\[ \text{Demand}_t = \beta_0 + \beta_1 \text{Price}_t \text{ (or } s(\text{Price}_t)) + \beta_{\text{lin}} C_{t}^{\text{lin}} + s(C_t^s) + \beta_D D_t + s(\hat{v}_t) + u_t \quad (2) \]

- 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 \( y = g^{-1}(\eta) + e \), where \( g^{-1}(\eta) = \mu = \text{E}(y|X) \), with \( g(\cdot) \) being a suitable link function
- The presence of an endogenous relationship between the demand and price can lead to inconsistent estimates. But because \( s(\hat{v}_t) \) 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

- Wind power (Instrument)
- Weather
  - Temperature, HDD, CDD (Control)
- Time of the day, month of the year (Control)
- Solar power (Control)
- Retail electricity price (Mediator)
- Wholesale electricity price (Treatment)
- Time-of-use tariffs
- Variable tariffs
- Electricity demand (Outcome)
- As reported by ENTSO-E?

Behind-the-meter solar?
Causal relationships: time trend and further controls

- Economic activity
  - Time trend (Control)
  - Available thermal + hydro capacity
- Fuel and EUA prices (Control EUA)
- Wind power (Instrument)
- Wholesale electricity price (Treatment)
- Electricity demand (Outcome)
Causal relationships: the role of lagged prices (Granger Causality)

- Wind power (Instrument) at \( t=1 \) influences Wholesale electricity price (Treatment)
- Wholesale electricity price (Treatment) at \( t=1 \) influences Cross-price elasticity
- Cross-price elasticity influences Electricity demand (Outcome)
- Wind power (Instrument) at \( t=2 \) influences Wholesale electricity price (Treatment)
- Wholesale electricity price (Treatment) at \( t=2 \) influences Own-price elasticity
- Own-price elasticity influences Electricity demand (Outcome)

Own-price elasticity
Cross-price elasticity

\( t=1 \)
\( t=2 \)
Causal relationships: import/export

Other country

Wind power (Instrument) → Wholesale electricity price → Import/export (Endogenous) → Electricity demand

Country of interest

Wind power (Instrument) → Wholesale electricity price (Treatment) → Electricity demand (Outcome)
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. \( Y_t = p \cdot Y_{t-1} + u_t \) or \( Y_t = Y_{t-1} + \text{time trend} + u_t \). 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