How (In)Elastic is the Short-Run Demand for Electricity?

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Abstract

This paper examines how the aggregate demand for electricity responds to changes in hourly wholesale market prices. I focus on a hydropower-rich country and use data on imported wind energy and accumulated precipitation as instruments for price. Using data from Switzerland from 2016 to 2023, I find that both instruments have a strong and significant price-depressing effect, and I estimate the price elasticity of aggregate demand to be -0.1. However, this responsiveness is entirely driven by the consumption of storage systems and power plants, while end-user demand remains perfectly inelastic to price fluctuations in the short-run.

Keywords: elasticity, electricity demand, storage, hydroelectricity, wind energy.

JEL codes: D12, L94, Q25, Q41.

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1 Introduction

Electricity demand and supply must be balanced at all times. Hence, wholesale electricity markets typically clear multiple times a day. Although prices can vary substantially from one hour to the next, the amount of electricity consumed does not respond much to price fluctuations in the short-run.

The literature is increasingly concerned with the short-term elasticity of electricity demand (Bönte et al., 2015; Knaut and Paulus, 2016; Fabra et al., 2021; Blonz, 2022; Hirth et al., 2024), since responsiveness to prices reduces the need for excess generation capacity, lowers average production costs, limits market power, and helps mitigate renewable curtailment and react to extreme weather events. In practice, data-validated estimates of short-run elasticity are scarce, due to the difficulty of identifying relevant exogenous price shifters (Kellogg and Reguant, 2021, Section 4.4).

In this paper, I use a 2SLS approach to estimate the hourly price elasticity of total demand, of demand by end-users, and of demand by power plants (which is largely driven by consumption for storage purposes). To my knowledge, this is the first attempt to separately estimate the responsiveness of these two components of aggregate demand.

Firstly, I estimate the elasticity of aggregate demand to be -0.1. This is in line with the consensus that electricity demand tends to be very inelastic in the short-run. The result aligns with the findings of Knaut and Paulus (2016) and Hirth et al. (2024), the two prior studies that credibly estimate the response of aggregate electricity demand to hourly price changes using similar empirical settings. Both studies focus on Germany and use wind energy as an instrument for price. Knaut and Paulus find a price elasticity of -0.02 to -0.13 in 2015, while Hirth et al. estimate an elasticity of -0.05 for 2015 to 2019.

Secondly, I explore the mechanism behind aggregate demand responses by separately analyzing the reactions of end-users and power plants. The end-user group comprises residential, service, and industrial sectors. Real-time price exposure for residential consumers remains uncommon in Switzerland, as in most countries, despite the gradual deployment of smart meters (Mari et al., 2025). Even when exposed to real-time electricity prices, residential consumers' demand may be unresponsive because of the relatively high costs of monitoring prices and adjusting behavior (Fabra et al., 2021). Very energy-intensive industrial consumers are directly exposed to market prices if they procure electricity directly from the wholesale market. Industries capable of self-producing electricity are also exposed to variations in prices, as the wholesale price represents the opportunity cost of consumption. Moreover, in Switzerland, the retail market was partially liberalized in 2009, allowing end users with an annual consumption above 100 MWh to freely choose their suppliers. It is possible that large service and industrial consumers are exposed to wholesale prices through their tariffs, although the exact incidence of dynamic pricing is unknown.

Power plant demand comprises the energy consumed for power plants' own requirements and for operating the pumps in pumped-storage hydropower plants. Since the power plants' owners trade in the wholesale market, the market price is the opportunity cost of self-consumption. Moreover, the profitability of storage depends on buying energy during low-price periods and selling it during high-price periods, making these operations price-sensitive by nature. Although pumped-storage units accounted for only about 2% of Swiss electricity production in 2023, their maximum nominal power consumption has grown over time, from approximately 1.8 GW in 2016 to 3.8 GW in 2023.[1]

My findings indicate that the price elasticity of aggregate demand in the short-run can be entirely attributed to consumption by power plants and storage systems. Power plants' demand is approximately unit elastic, while end-user demand is perfectly inelastic. This underscores the need to boost consumer exposure to wholesale prices, first and foremost for large commercial and industrial users. Furthermore, it confirms that even limited storage capacity can significantly impact the elasticity of aggregate demand.

2 Empirical Strategy

Quantity and price are equilibrium outcomes, and are simultaneously determined. I use a 2SLS approach to identify the causal effect of wholesale prices on aggregate electricity demand, using exogenous supply shifters to instrument for price.

I specify the second stage as

$$\ln(Quantity_t) = \beta_0 + \beta_1 \cdot \ln(Price_t) + \beta_2' \cdot X_t + \beta_3' \cdot D_t + \epsilon_t, \tag{1}$$

where β_1 indicates the price elasticity of demand. X_t is a vector of control variables that are possibly correlated with *Quantity* and *Price*: temperature (including a squared term to capture the effect of both heating and cooling on electricity consumption), natural gas spot market prices, EU carbon permit prices,[2] realized solar energy generation. D_t is a vector of dummy variables accounting for the hour of the day, the day of the week, the month, the year, and whether the day is a public holiday.

[1] https://www.bfe.admin.ch/bfe/de/home/versorgung/digitalisierung-und-geoinformation/geoinformation/geodaten/wasser/statistik-der-wasserkraftanlagen.html. Accessed in September 2024.

[2] Switzerland has its own emission trading system, whose size is about 0.4% the size of the EU market. The two markets have been tied since 2020, meaning that anyone obliged to participate in the Swiss or EU ETS can use emission allowances from either system.

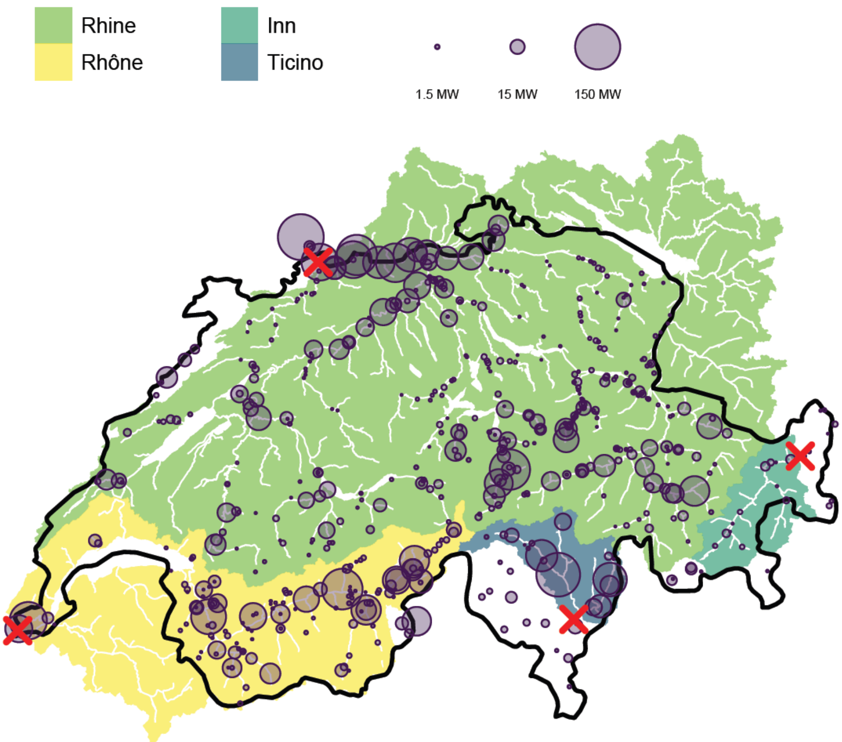

Figure 1: *Location and nominal capacity of all the ROR plants in Switzerland with respect to the catchment areas of the Rhine, Rhône, Inn, and Ticino rivers. The four red* × *mark the position of the downstream hydrometric stations that monitor discharge of the four rivers in Basel, Chancy, Tarasp, and Bellinzona, respectively.*

Wind energy is commonly used as an instrument for electricity prices. However, the contribution of wind turbines to electricity generation within Switzerland is negligible: approximately 0.2% of production in 2023. Since Switzerland is a net importer of electricity from Germany,[3] higher realized wind energy generation in Germany tends to lower Swiss prices, making it a viable instrument. Additionally, relying on imported wind energy strengthens the credibility of the exclusion restriction, as it is unlikely that wind speeds in Germany would influence Swiss electricity demand, except through prices. One limitation of this instrument is that trade between the German and the Swiss markets is subject to transmission constraints.[4] Therefore, I complement this instrument by exploiting precipitation as an exogenous driver of run-of-river (ROR) hydroelectricity generation. ROR generation, responsible for 24% of domestic production in 2023 (BFE, 2024), is the energy supplied by power plants with little or no storage capacity: generation depends solely on flowing waters. I do not use ROR generation as an instrument for two reasons. First, even though the lack of storage limits the chances to exercise market power, most ROR units lie downstream with respect to conventional reservoirs and pumped-storage plants, so their inflow of water may not be exogenous with respect to the market outcomes. Second, hourly generation data from my main data source, the ENTSO-E Transparency Platform, is severely

[3] In 2023 net imports from Germany were approximately 3.8 TWh, or 6% of total consumption.
[4] Hellwig et al. (2020) find that trade at the Swiss-German border was congested 84% of the hours in 2015-2016.

under-reported, as it likely only covers large (i.e. $\geq$100 MW) ROR plants.[5]

Instead of generation, I rely on the exogenous variation of the rivers' discharge as driven by accumulated precipitation. I compute the average hourly precipitation over the catchment area of the four hydrometric stations of Basel - Rheinhalle (Rhine), Chancy - Aux Ripes (Rhône), Tarasp (Inn), and Bellinzona (Ticino), weighted by each area's ROR nominal capacity. These catchment areas contain 91% of the national ROR capacity and they overlap with most of the country (Figure 1).

For each hour t I then calculate the precipitation accumulated over the previous week as

$$\mathit{Weekly\ Precipitation}_t = \sum_{s=t-180}^{t-12} \mathit{Precipitation}_s .$$

I exclude hours between $t - 11$ and t to rule out violations of the exclusion restriction, were precipitation to alter concurrent consumption.

In Table A1 in Appendix A I regress the hourly discharge of each river as monitored by the four hydrometric stations, against precipitation accumulated over the previous seven weeks. These models validate the choice of aggregating precipitation on a weekly basis.

One concern with this instrument is that it might not satisfy the exclusion restriction if precipitation affects pumped-storage plants' demand other than through the electricity prices. Considerations about water inflows into the reservoirs might be part of a plant's decision process, and therefore affect its consumption of electricity. To address this issue, I control for the filling rate of the Swiss water reservoirs.

I specify the first stage as

$$\begin{aligned} \ln(\mathit{Price}_t) =& \gamma_0 + \gamma_1 \cdot \ln(\mathit{Weekly\ Precipitation}_t) + \\ & \gamma_2 \cdot \ln(\mathit{German\ Wind\ Energy}_t) + \gamma_3' \cdot X_t + \gamma_4' \cdot D_t + \nu_t. \end{aligned} \tag{2}$$

Both weather and electricity demand exhibit serial correlation. Additionally, the weekly precipitation instrument is constructed as a rolling sum, which yields auto-correlated residuals. To address this, I compute heteroskedasticity-and-autocorrelation-consistent (HAC) standard errors, using the Bartlett kernel by Newey and West (1987).

Table 1: *Summary statistics.*

Statistic	Mean	St. Dev.	Min	Max
Price (€ /MWh)	97.6	101.3	0.02	871.6
Load (MW)	7,268.5	1,031.4	4,203.9	10,556.4
End-User Demand (MW)	6,390.7	1,206.1	3,628.9	9,966.9
Power Plant Demand (MW)	877.8	565.9	238.7	3,541.2
Temperature (K)	282.4	8.0	259.7	305.9
Carbon Price (€ /t)	38.3	31.9	4.0	96.8
Gas Price (€ /MWh)	39.8	42.9	7.1	302.0
Reservoirs (GWh)	4,762.4	2,305.8	757	8,187
Solar Energy (MW)	170.7	407.7	0	2,875
German Wind Energy (GW)	51.7	39.8	0.3	210.3
Weekly Precipitation (mm)	33.1	23.9	0.01	144.6

3 Data

Table 1 reports the summary statistics. I collect hourly data from 1 January 2016 to 31 December 2023. I exclude all hours in 2020 from the main analysis due to restrictions induced by the COVID-19 pandemic on social and economic activities.[6]

Since the Swiss power market consists of a series of sequential markets, I use the hourly day-ahead market price at the EPEX power exchange. Not all load is traded in the day-ahead market, but a significant share is. In addition, the day-ahead price is used as a benchmark for forward contracts. It also represents the opportunity cost of self-generation and bilateral trades (such as PPA's), and it correlates with intraday and balancing prices. Hourly day-ahead prices are reported by the ENTSO-E Transparency Platform. I exclude from the sample 196 hours during which prices are zero or negative.

Load refers to the total consumed energy in the control block, whereas end-user demand excludes grid losses, plant self-consumption, and energy used for pumped-storage operations. These data are reported by the Swiss transmission system operator, Swissgrid.[7] I derive power plant demand as the difference between load and end-user demand.

I obtain data on hourly generation of onshore and offshore German wind power stations from the ENTSO-E Transparency Platform. Data on the energy content of Swiss reservoirs per calendar week are provided by the Swiss Federal Office of Energy.[8] Hourly precipitation and temperature data come from the ERA5-Land database (Muñoz Sabater et al., 2021). I use hourly air temperature at two meters above land surface, weighted by population density.

[5] For example, the reported total ROR generation for 2023 was 2.1 TWh, but the actual figure was about 17.5 TWh (BFE, 2024).

[6] The inclusion of the observations from 2020 does not alter the results.

[7] https://www.swissgrid.ch/en/home/operation/grid-data/load.html. Accessed in September 2024.

[8] https://www.bfe.admin.ch/bfe/en/home/supply/statistics-and-geodata/energy-statistics/electricity-statistics.html. Accessed in September 2024.

4 Results

Table 2 reports the results of the first stage. Model (1) includes one week of accumulated precipitation as the instrument. Model (2) uses only wind energy. Model (3) includes both. Both instruments are always significant at the 0.1% level, and both precipitation and wind exhibit a price-depressing effect, as expected. A one percent increase in accumulated precipitation (0.33 mm at the mean value) is expected to decrease prices by approximately 0.04% (4 cents at the mean price). A one percent increase in imported wind energy (0.5 GW at the mean) decreases prices by approximately 0.08% (8 cents at the mean). In all three models, the F-statistic for the joint significance of the instruments is above the critical value of 13.91 suggested by Stock and Yogo (2005) for a maximum accepted bias of the 2SLS estimator relative to OLS of 5%.

Table 3 reports the results for the second stage. In the first three models, total load is used as the dependent variable, with the only difference being the choice of instruments. All three models yield very similar results. The estimated value of β_1 ranges between -0.10 and -0.13, and is always significant at the 1% level.

Models (4) and (5) follow the same specification of model (3), but with the two alternative dependent variables: end-user demand and power plant demand, respectively. The effect of short-term price changes on end-user consumption is not significantly different from zero. End users, whether residential, commercial, or industrial, do not react to hourly price changes. This is in contrast with the findings of Hirth et al. (2024), who suggest that large retail and industrial consumers are price sensitive, to some extent. The estimated price coefficient in model (5), on the other hand, is statistically significant at the 0.1% level and equal to -0.93. This implies that power plant demand is almost unit elastic, and that it is responsible for any responsiveness of aggregate demand to hourly price fluctuations.

Figure C1 in Appendix C reports the β_1 estimates for each individual year. I find no evidence of responsive end-user demand in any year (C1a), nor of any clear trend in the elasticity of power plant demand (C1b).

5 Discussion and Conclusion

This study contributes to the literature in three ways. First, it addresses a shortage in the literature of credible estimates of the short-run elasticity of aggregate electricity demand. I find that the price elasticity in Switzerland is -0.1 for aggregate demand, zero for end-user demand, and -0.9 for power plant demand. To my knowledge, this is the first study precisely identifying one mechanism that drives

Table 2: *First stage results.*

Dependent variable	ln(Price)		
	(1)	(2)	(3)
ln(Weekly Precipitation)	-0.046^{***}		-0.043^{***}
	(0.008)		(0.007)
ln(German Wind Energy)		-0.085^{***}	-0.082^{***}
		(0.009)	(0.008)
Controls	✓	✓	✓
Time Dummies	✓	✓	✓
Adjusted R^2	0.84	0.84	0.84
Partial F-statistic	37.2	99.8	55
Observations	61,124	61,124	61,124

Notes: HAC standard errors. ***(**,*) indicates statistical significance at the 0.1% (1%, 5%) level. The complete results are reported in Appendix B.

Table 3: *Second stage results.*

Dependent variable	ln(Quantity)				
	(1)	(2)	(3)	(4)	(5)
	Load	*Load*	*Load*	*End Users*	*Power Plants*
ln(Price)	-0.10^{**}	-0.13^{***}	-0.12^{***}	0.01	-0.93^{***}
	(0.03)	(0.02)	(0.02)	(0.01)	(0.09)
Controls	✓	✓	✓	✓	✓
Time Dummies	✓	✓	✓	✓	✓
IV: Weekly Precipitation	✓	-	✓	✓	✓
IV: German Wind Energy	-	✓	✓	✓	✓
Adjusted R^2	0.73	0.7	0.71	0.87	0.45
Observations	61,124	61,124	61,124	61,124	61,124

Notes: HAC standard errors. ***(**,*) indicates statistical significance at the 0.1% (1%, 5%) level. The complete results are reported in Appendix B.

the limited responsiveness of total demand. Moreover, if compared to the findings of Hirth et al. (2024), my study implies that the mechanism through which demand responds is market specific. Therefore, one should exercise caution when calibrating models based on estimates from dissimilar settings.

Second, I demonstrate that even limited storage capacity can significantly enhance the responsiveness of electricity demand to price fluctuations, thereby improving economic efficiency in an otherwise unresponsive market while also complementing the integration of renewables into electricity production.

Finally, my findings carry important implications for policymakers. In the studied scenario, large industrial and commercial end users remain unresponsive to hourly price fluctuations. As these consumers have shown some price sensitivity in other contexts (Blonz, 2022), prioritizing their exposure to real-time prices might effectively enhance aggregate demand responsiveness. Determining the best approach to achieve this is left to future research.

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Supplementary Tables and Figures

A Weekly precipitation and river discharge

Table A1: *OLS model of each river's discharge, as a function of weekly precipitation over the river basin over seven weeks. All hours between 2016 and 2023.*

Dependent variable	Discharge			
	(1)	(2)	(3)	(4)
	Rhine	*Rhône*	*Inn*	*Ticino*
Weekly Precipitation$_t$	10.366***	2.553***	0.212***	0.803***
	(0.604)	(0.183)	(0.045)	(0.072)
Weekly Precipitation$_{t-168}$	5.275***	0.972***	0.104**	0.226***
	(0.492)	(0.181)	(0.035)	(0.036)
Weekly Precipitation$_{t-336}$	4.611***	0.791***	0.107**	0.104***
	(0.490)	(0.161)	(0.034)	(0.031)
Weekly Precipitation$_{t-504}$	3.394***	0.770***	0.136***	0.143***
	(0.462)	(0.160)	(0.036)	(0.037)
Weekly Precipitation$_{t-672}$	2.063***	0.559***	0.084**	0.100*
	(0.433)	(0.152)	(0.030)	(0.050)
Weekly Precipitation$_{t-840}$	1.356***	0.553***	0.087*	0.082*
	(0.393)	(0.155)	(0.034)	(0.033)
Weekly Precipitation$_{t-1008}$	1.066**	0.580***	0.048	0.053
	(0.387)	(0.163)	(0.032)	(0.034)
Constant	96.290*	99.683***	−3.098	5.364
	(40.612)	(14.408)	(2.035)	(2.750)
Adjusted R^2	0.65	0.28	0.13	0.29
Observations	69,671	69,671	69,671	69,671

Notes: HAC standard errors. ***(**,*) indicates statistical significance at the 0.1% (1%, 5%) level.

Table A1 reports the results of regressing discharge of each river as monitored by the four hydrometric stations (see Figure 1), against precipitation accumulated over the previous seven weeks. Precipitation from the previous week has the largest impact on discharge, while older precipitation has a progressively smaller effect. The R^2 seems to increase with the size of the catchment area, with the *Rhine* model explaining 65% of the variation in discharge. As the Rhine catchment area is about 73% of the area over which I monitor precipitation, this gives me confidence in the relevance of the instrument. Historical data from hydrometric stations was provided by the Swiss Federal Office for the Environment - Hydrology Division.[9]

B Complete results

Tables B1 and B2 report the complete first and second stage results, respectively. As *Solar Energy* has value zero for many observations, I transform it using the inverse hyperbolic sine instead of the logarithm.

C Temporal heterogeneity

Following the Russian invasion of Ukraine in early 2022, electricity prices have been higher and more volatile. This may have increased the incentive to respond to prices, even for (large) end users. Moreover, the nominal capacity for power consumption of the Swiss storage plants more than doubled between 2016 and 2023. If storage plants' consumption is severely constrained, a capacity expansion could result in a more responsive demand. Figure C1 reports the results of a temporal heterogeneity analysis. Neither end-user demand nor power plant demand seem to have become more responsive over time.

[9] https://www.bafu.admin.ch/bafu/en/home/topics/water/state/data/obtaining-monitoring-data-on-the-topic-of-water/hydrological-data-service-for-watercourses-and-lakes.html. Requested in August 2024.

Table B1: *First stage results.*

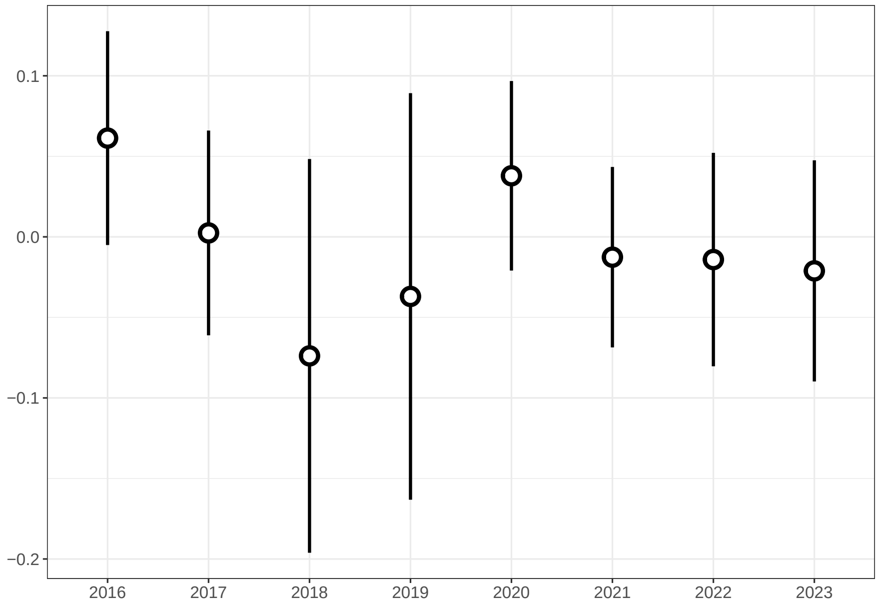
Dependent variable	ln(Price)		
	(1)	(2)	(3)
ln(Weekly Precipitation)	−0.046***		−0.043***
	(0.008)		(0.007)
ln(German Wind Energy)		−0.085***	−0.082***
		(0.009)	(0.008)
ln(Temperature)	−489.058***	−463.530***	−364.214***
	(100.308)	(94.350)	(92.738)
ln(Temperature)^2	42.905***	40.732***	31.861***
	(8.860)	(8.337)	(8.195)
ihs(Solar Energy)	0.307***	0.339***	0.328***
	(0.063)	(0.063)	(0.060)
ln(Carbon Price)	0.677***	0.692***	0.671***
	(0.031)	(0.030)	(0.030)
ln(Gas Price)	0.100*	0.087*	0.097*
	(0.042)	(0.041)	(0.040)
ln(Reservoirs)	−0.017***	−0.017***	−0.018***
	(0.002)	(0.002)	(0.002)
Constant	1,393.913***	1,319.220***	1,041.373***
	(283.917)	(266.970)	(262.399)
Time Dummies	✓	✓	✓
Adjusted R^2	0.84	0.84	0.84
Partial F-statistic	37.2	99.8	55
Observations	61,124	61,124	61,124

Notes: HAC standard errors. ***(**,*) indicates statistical significance at the 0.1% (1%, 5%) level. The time dummies were excluded for reasons of space.

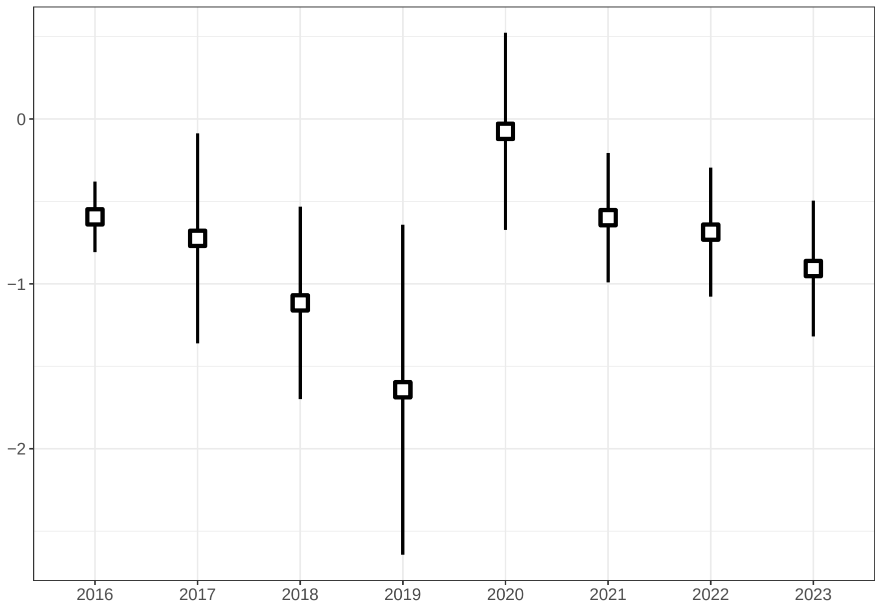
Table B2: *Second stage results.*

Dependent variable	ln(Quantity)				
	(1)	(2)	(3)	(4)	(5)
	Load	*Load*	*Load*	*End Users*	*Power Plants*
ln(Price)	-0.10^{**}	-0.13^{***}	-0.12^{***}	0.01	-0.93^{***}
	(0.03)	(0.02)	(0.02)	(0.01)	(0.09)
ln(Temperature)	-326.50^{***}	-341.48^{***}	-336.17^{***}	-313.34^{***}	-697.90^{***}
	(27.11)	(25.76)	(24.12)	(19.02)	(103.78)
ln(Temperature)^2	28.72^{***}	30.04^{***}	29.58^{***}	27.53^{***}	61.85^{***}
	(2.39)	(2.28)	(2.13)	(1.68)	(9.17)
ihs(Solar Energy)	0.03	0.04^{*}	0.03^{*}	-0.0003	0.23^{***}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.06)
ln(Carbon Price)	0.09^{***}	0.11^{***}	0.10^{***}	0.01	0.67^{***}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.07)
ln(Gas Price)	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)
ln(Reservoirs)	-0.001	-0.001	-0.001	-0.002^{**}	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Constant	936.51^{***}	979.08^{***}	964.00^{***}	899.97^{***}	$1{,}976.27^{***}$
	(76.76)	(72.84)	(68.19)	(53.74)	(293.66)
Time Dummies	✓	✓	✓	✓	✓
IV: Weekly Precipitation	✓	-	✓	✓	✓
IV: German Wind Energy	-	✓	✓	✓	✓
Adjusted R^2	0.73	0.7	0.71	0.87	0.45
Observations	61,124	61,124	61,124	61,124	61,124

Notes: HAC standard errors. ***(**,*) indicates statistical significance at the 0.1% (1%, 5%) level. The time dummies were excluded for reasons of space.



(a) *End-user demand.*



(b) *Power plant demand.*

Figure C1: *Estimates of the elasticity of demand by year.*