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Price Response in Residential Electricity Demand: Evidence from Danish Smart Meter Data

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Real-time and time-of-use electricity pricing is based on the premise that consumers reduce demand when prices are high. This paper tests this assumption empirically, using a large, high-frequency smart meter dataset from Denmark, estimating the short-run (hourly) price elasticity of electricity demand at the household level. Although most households show no significant responsiveness to price signals, we find that nearly one third reduce their consumption significantly when prices rise. On average, a one Danish Krone increase in electricity prices leads to a 2.6% decrease in demand. By linking smart meter data to administrative records, we further examine how price responsiveness varies across socio-demographic groups.

Keywords

Climate
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Price Response in Residential Electricity Demand: Evidence from Danish Smart Meter Data

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Abstract

Real-time and time-of-use electricity pricing is based on the premise that consumers reduce demand when prices are high. In this paper, we test this assumption empirically using a large, high-frequency smart meter dataset from Denmark, estimating the short-run (hourly) price elasticity of electricity demand at the household level. Although most households show no significant responsiveness to price signals, we find that nearly one third reduce their consumption significantly when prices rise. On average, a one Danish krone increase in electricity prices leads to a 2.6% decrease in demand. By linking smart meter data to administrative records, we further examine how price responsiveness varies across socio-demographic groups. We find that the price sensitivity is higher among households with higher educational attainment and overall electricity consumption, but lower among those aged 35 to 54.

Keywords: Energy Demand; Prices; Energy Policy; Instrumental Variables (IV) Estimation
JEL-Codes: Q41, C26, Q48

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1 Introduction

Using a large dataset of hourly residential electricity demand in Denmark, we estimate how individual households adjust their electricity consumption in response to price signals. The dataset is based on a nationwide roll-out of smart electricity meters. We find that almost one third of households significantly reduce demand in response to higher prices. Heterogeneity in the price response among households is large. Highly educated consumers and those with high overall electricity consumption react most strongly to prices. The demand response of households to price signals is important as it contributes to stabilizing the electricity grid.

The price elasticity of electricity demand, such as empirically estimated in this paper, is a key premise in the design of both real-time and time-of-use pricing schemes. In both models, fluctuating prices are intended to incentivize consumers to shift demand away from peak hours. If residential demand is price-elastic, households will reduce consumption when prices rise, helping to stabilize the load on the electricity grid. This mechanism is especially important in energy systems with a high share of renewables, where supply is inherently less flexible, more dependent on weather conditions and thus more volatile, as flexible pricing schemes allow demand to be aligned with short-term supply (ACER & CEER, 2024; European Parliament, 2025).

The Danish retail electricity market design builds both on elements from real-time and time-of-use pricing: Retail electricity prices are set at an hourly frequency, one day ahead, and are based on wholesale electricity spot prices that reflect supply and demand conditions (real-time pricing). In addition, grid tariffs vary by the time of the day (time-of-use pricing), to discourage consumption during peak load hours, such as evenings (see Kahn-Lang et al., 2025; Schittekatte et al., 2022, for a detailed discussion of pricing models). Consumers know the final hourly price per kWh one day ahead.

Despite the increasing importance of these flexible pricing models, there is so far only relatively sparse and inconclusive evidence from actual, large scale consumption data on whether or not households actually adjust electricity demand in response to short term price signals. Although varying prices are designed to provide economic incentives for consumers to adjust usage, actual behavioral responses may be muted due to rational inattention: For many households, electricity accounts for only a small share of expenditures, and the perceived costs of monitoring prices and shifting usage may outweigh potential savings.

In line with this reasoning, we find that for the majority of households, estimated price elasticities are statistically indistinguishable from zero. For these households, we can therefore not reject the hypothesis that they do not adjust their electricity demand with varying prices. However, for nearly one-third of the sample, we document significant negative elasticities. The consumption data from these households reveal that they reduce consumption when prices increase, contributing to a stabilization of electricity markets. We document that these households – for which the estimated elasticity is significantly below 0 – are more likely to be older and have a high educational attainment. We also document substantial heterogeneity in the magnitude of elasticities. On average, a 1 Danish krone (DKK) increase in the hourly electricity price leads to a 2.6% reduction in consumption (2.1% for the median household).

Our empirical analysis draws on a large dataset of hourly residential electricity consumption recorded by smart electricity meters in Denmark between 2020 and 2023. Smart electricity meters transmit the consumption of an individual household to electricity providers, at a high, hourly frequency. By matching each observation to its corresponding hourly marginal price based on time and geographic location, we construct a household-level panel. For this paper, we consider a subset of almost 25,000 households across two grid areas, the *Radius* grid in the Greater Copenhagen area and the *Trefor* grid in Jutland. Unlike most previous studies, which estimate aggregate elasticities using national-level demand data, our dataset enables us to estimate household-specific price elasticities. This granular approach provides a more nuanced view of electricity demand and its responsiveness to price, highlighting heterogeneity across the population.

The endogeneity between prices and demand is a well-known problem in the estimation of demand elasticities. Since prices often respond to shifts in demand, failing to account for this two-way relationship can lead to biased estimates of how demand adjusts in response to price changes. For example, in electricity markets, higher prices during peak hours may coincide with increased usage due to external factors, making it hard to isolate the true effect of price on consumption. In our application, to address the endogeneity between electricity prices and demand, we employ an instrumental variable strategy. Specifically, we instrument electricity prices using hourly wind power production, which is largely driven by exogenous wind speed. Following the reasoning in Hirth et al. (2024), we assume that household electricity consumption is exogenous to fluctuations in wind-based electricity generation.

Due to a unique linkage between electricity consumption data and Danish administrative registers, we are able to explore heterogeneity in price responsiveness across households. We find that highly educated households, as well as those with relatively high electricity consumption, exhibit stronger responses to price signals. These findings are consistent with rational inattention frameworks (e.g., Gabaix, 2014) and also provide insight into the role of electricity as a necessity good within household consumption.

Firstly, rational inattention models suggest that households are only partially informed about electricity prices due to the cognitive or time costs associated with tracking them. Limited attention to prices can amplify equilibrium price volatility, but it also opens up opportunities for targeted policy interventions aimed at enhancing consumer responsiveness. Indeed, evidence from a randomized controlled trial by Jessoe and Rapson (2014) demonstrates that low demand elasticities are partly driven by inattention to price information. Similarly, Harding and Sexton (2017) emphasize the role of informational frictions in shaping residential electricity demand elasticities.

Secondly, the observed increase in price responsiveness with higher total electricity consumption suggests that electricity behaves as a necessity good. Households that use electricity beyond essential needs-—such as for leisure or discretionary appliances-—are better able to adjust consumption in response to prices. This is in line with prior research, including Meier et al. (2013) and Baffes et al. (2021), who document income elasticities for electricity demand below one.

Our results are important in the context of the green transition and help to inform policy debates. Electricity markets play a central role on the path toward a carbon-neutral economy. As households and firms increasingly electrify activities previously reliant on fossil fuels, aggregate electricity demand is expected to grow. At the same time, reducing carbon emissions requires a shift from fossil energy sources (e.g., coal and natural gas) to renewables on the supply side (e.g., Edenhofer et al., 2011; Tsiropoulos et al., 2020). While renewable energy can lower costs due to its low marginal cost, its intermittency may affect price volatility.[1] Because electricity cannot be stored economically at scale and renewable energy sources are less flexible to short term load adjustments (e.g., ACER & CEER, 2024), prices must continuously balance supply and demand. In this context, price signals play a critical role in managing scarcity and

[1] While the high-frequency volatility of electricity prices might increase due to the exposure to weather fluctuations (e.g., Branner and Ingholt, 2023), renewable energy sources might at the same time reduce the low frequency price volatility, due to a reduced exposure to fossil energy spikes (e.g., Simon and Anadon, 2025).

promoting energy-saving behavior on the demand side, as illustrated during the 2022 energy crisis following Russia's invasion of Ukraine. Policy communication might potentially help increase inattentive households' awareness of price signals.

In that context, recent policy discussions in other European countries have emphasized more flexible electricity pricing—exposing consumers to short-term price fluctuations instead of fixed long-term rates—and new taxation schemes designed to curb demand during peak hours. While our results demonstrate that some households indeed react to price signals, our results with regards to socio-demographic heterogeneity in the price response might also inform the design of communication strategies or behavioral nudges to enhance demand-side flexibility in electricity markets.

Related literature Closest to our study, Fabra et al. (2021) investigate the introduction of real-time electricity pricing on Spanish households, using household specific smart meter data as well as projected wind energy production as an instrument. In contrast to our findings, Fabra et al. (2021) document that Spanish consumers do not adjust consumption in response to price signals. At the same time, using a different methodological approach, Enrich et al. (2024) finds in the case of Spanish retail consumers that time-of-use pricing causes households to shift consumption to off-peak hours. Blomquist et al. (2018) find similar socio-demographic heterogeneity in the price responsiveness of electricity demand as our paper, relying on survey data and causal tree and causal forest algorithms. The meta-study by Harding and Sexton (2017) summarizes experimental evidence on real time pricing of electricity to consumers, finding that while the price response is generally low, this is partly due to an information problem.

A number of studies focus on residential electricity demand elasticities, based on aggregated time series data. Closest to this analysis, Hirth et al. (2024) estimates the response of German electricity demand to spot price variations, relying on wind energy production as an instrument. The meta-study by Labandeira et al. (2017) summarizes the consumer demand response to low-frequency changes in several energy prices, including the price of electricity. The study finds that energy demand is inelastic, at a price elasticity of -0.231. Interestingly, Labandeira et al. (2017) find that absolute elasticities tend to be higher for studies relying on residential and micro data.

Danish electricity market Between 2020 and 2022, household electricity demand accounted for around 2.3% of total household expenditures in Denmark (Statistics Denmark, 2022). Electricity consumers in Denmark receive electricity under a private contract with an electricity supplier. Prices can either be fixed in advance, for a given period of time (e.g., monthly or quarterly), or fluctuate on an hourly basis. In the latter case, the price of electricity within an hour is known to the consumer one day in advance and can be accessed either online or via mobile phone applications. This is the most common type of contract, used by the majority of electricity consumers (Green Power Denmark, 2024). While consumers typically pay a fixed base price independent of consumption, the marginal price of electricity depends on the spot price as well as several tariffs, fees and taxes. The tariffs vary throughout the day, also for consumers on fixed-price contracts. The hourly spot price is determined daily, for the next day, on the NordPool electricity market, between energy suppliers and electricity retailers. There are two separate markets and prices for electricity zones, covering West Denmark (DK1), to the west of the Great Belt and East Denmark (DK2) to the east of the Great Belt (e.g., Forsyningstilsynet, 2022).

The remainder of the paper is structured as follows: Section 2 describes the data and Section 3 introduces the econometric approach. Section 4 discusses estimation results. Section 5 links estimated elasticities to demographic characteristics. A final Section concludes.

2 Data

The empirical analysis within the paper is based on a number of data sources. In the following we will describe the electricity data on electricity prices and residential consumption, as well as our data on household characteristics.

2.1 Electricity prices

Electricity prices for residential consumption in Denmark feature both regional and hourly variation. Let $P_{i,a,t}$ denote the price of one kWh electricity for household i, located in grid area a, at time t:

$$P_{i,a,t} = (1 + \tau) \left[E_{i,t} + G_t^T + G_{a,t}^D + T_i \right] \tag{2.1}$$

Here, the variable $E_{i,t}$ is the net price for the electricity *(eltarif)*, usually equal to a markup over the Nordpool market price. The variable G_t^T is the transmission grid tariff, set by the grid provider (Energinet: grid + system tariff).[2] There is some low frequency variation over time, but not within days. $G_{a,t}^D$ is the distribution grid tariff *(local nettarif)*[3] This tariff varies depending on the time of day and time of year and is set by the local grid operator who serves as an intermediary between the national grid and local residential consumers. For the observed grid areas in our sample, Radius and Trefor, the tariffs vary throughout the day, peaking between 5 p.m. and 9 p.m. and being the lowest between 0 a.m. and 6 a.m. The within-day tariff structure is set and changes only at low-frequency, usually on a yearly basis. These tariffs vary for all electricity customers, regardless of whether or not they are on a fixed price contract, thereby creating an incentive to move to electricity consumption out of peak hours. Table 5 in the Appendix provides an overview over time-of-day dependent grid tariffs in both grid areas. The variable T_i denotes a set of consumption taxes.[4] The parameter $\tau = 0.25$ denotes the value added tax that is constant over our sample period. Additionally, we do not observe and therefore do not take into account reduced consumption tax when electricity is used for heating of homes, which can come into effect when the annual household electricity consumption is above 4,000 kWh. Table 4 in the Appendix provides an overview of data sources.

The monthly payment $Y_{i,a}$ is then equal to the hourly price times the hourly consumption, $C_{i,a,t}$, and a number of charges (supply contract charge *(elabonnement)*, distribution grid access charge). We denote the sum of consumption invariant charges as $X_{i,a,t}$. While there is some variability in these changes, they tend to be stable over time.

$$Y_{i,a,t} = (1 + \tau)X_{i,a,t} + \sum_t P_{i,a,t}C_{i,a,t} \tag{2.2}$$

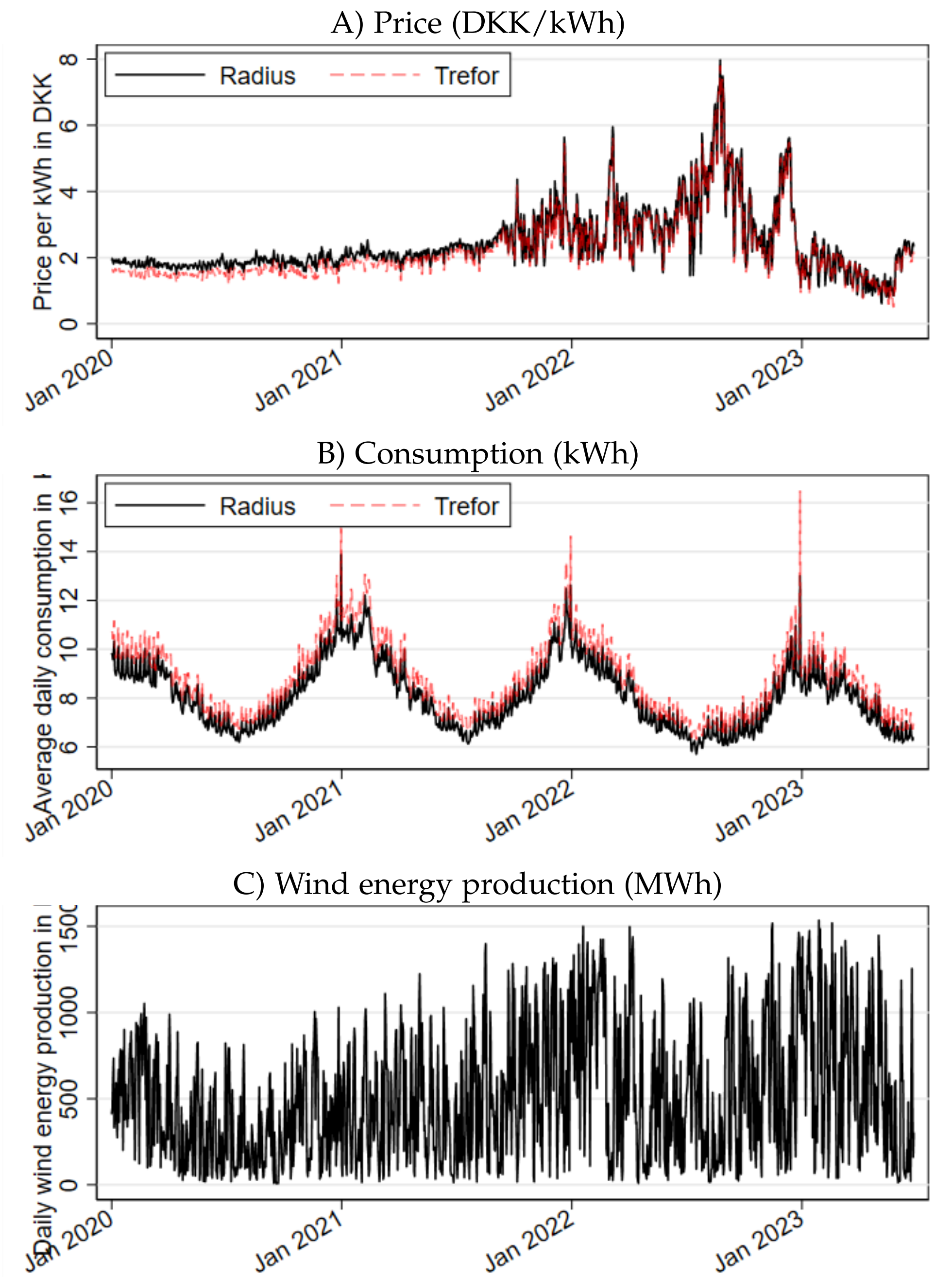
Panel A) of Figure 1 shows the daily average price (arithmetic mean over 24 hours) for both the Radius (black, solid line) and Trefor (red, dashed line) grid areas. We document a strong comovement between prices, although the level of prices seems to be slightly lower in the Trefor grid area. Prices were relatively stable — although with a

[2] See: https://energinet.dk/el/elmarkedet/tariffer/aktuelle-tariffer/

[3] See, for example, Radius: https://radiuselnet.dk/elnetkunder/tariffer-og-netabonnement/

[4] The effects of the PSO (Public Service Obligation) on the total price of electricity are minute and therefore not taken into account. The PSO started being phased out in 2017, and has only a small effect of 1-5 øre/kWh in 2020 and the first quarter of 2021. It only varied quarter to quarter, not throughout the day. From the second quarter of 2021 onwards the PSO was 0 øre/kWh

Figure 1: Price per kWh of electricity, by grid area



Notes: Panel A) of this figure shows the average daily price of electricty, in the Radius and Trefor areas. Panel B) displays the average daily consumption in kWh. Panel C) shows the wind energy production per day.

slight upward trend in 2021 — until the months before the Russian invasion of Ukraine in early 2022. Prices peaked in August 2022, at just below DKK 8 per kWh, more than

4 times the daily average price in 2020. Since 2023 prices have declined again, even dropping below the 2020 level in mid 2023.

2.2 Electricity consumption

Our consumption data are obtained from Danmarks Statistic and include the hourly electricity consumption recorded by smart electricity meters in Denmark. Since the beginning of 2020 every household is required by law to have a smart electricity meter that electronically records and transmits hourly consumption, in order to allow real-time pricing. We therefore rely on data between the start of 2020 until mid 2023. In our data, we use the Danish address registry to uniquely assign electricity meters to households.[5]

Panel B) of Figure 1 shows the average daily consumption across households, in both grid areas. The black line represents average consumption the Radius area and the red line represents average consumption in the Trefor area. We document a strong seasonal consumption pattern, with consumption spiking in the winter months and dropping again during the summer. Likely sources of the seasonal pattern are electricity used as a heating source, the reduced daylight in the winter months, and the typical summer vacation months of June to August (Forsyningstilsynet, 2022). The work by Andersen et al. (2024) and Andersen et al. (2021) discusses intra-day electricity consumption profiles of Danish households in detail.

For computational reasons the analysis is only performed for a subsample of households from the Radius and Trefor grid areas, respectively. Nevertheless, in order to ensure that the analysis results are representative for the entire sample of households a convergence analysis is carried out. This analysis indicates that our sample size is sufficient for the results to converge to a constant value for the estimated elasticity.

2.3 Household characteristics

Using the Danish registry data, we restrict our sample to households that were present in the micro-data between 2020 and 2023. In doing so we avoid comparability issues, for example, through some households only being part for the sample for one year. Furthermore, we only consider unique household address combinations. This step

[5] In the data, we link the electricity meter to an address and can subsequently assign the consumption recorded to the household living at a given point in time at the respective address.

ensures that the electricity consumption can be uniquely attributed to a specific household; we thereby exclude, for example, student accommodation or shared apartments, where recorded consumption cannot be attributed to a specific person or family.

Some addresses that can be linked to a unique household are filtered as they are not deemed relevant for this work. This includes vacation homes or homes that are currently undergoing renovation.[6] Furthermore, some addresses are associated with extremely high or low annual electricity consumption (at the extreme ends either close to 0 kWh or multiple MWh) that are not representative of a household using the address a full time dwelling and furthermore do not host e.g., a small business. We therefore trim the top and bottom 1.5% of households, based on annual consumption.

Finally, we merge household-level estimates for the price elasticity of electricity consumption with socio-demographic characteristics from the registry data. Specifically, we rely on data for the year 2020 and include the age of family members, total income of the family, and the highest educational attainment by any adult family member.

3 Empirical strategy

Price elasticities of demand measure the response of demand for a product in response to changes in the price. For ordinary goods, the microeconomic law of demand assumes a *decrease* if prices increase (e.g., Varian, 2003).[7] Specifically, we define the price elasticity of electricity demand, denoted by σ, as:

$$\sigma = \frac{\Delta C}{C} / \frac{\Delta P}{P} \tag{3.1}$$

where C denotes consumption and P the price of electricity. σ indicates the percentage change in consumption $\frac{\Delta C}{C}$ due to a percentage change in prices $\frac{\Delta P}{P}$. Ultimately, as we do not observe the exact price faced by consumers, we do not compute the relative

[6]We identify these addresses by looking at electricity consumption patterns, and implementing two additional criteria. If an address is associated with an hourly electricity consumption registered as exactly 0 kWh for more hours in a year than there are hours in a week. In other words, if an address is registered to have 0 electricity consumption for a week or more throughout any given year, that address is cut from the sample. Note that an electricity consumption of exactly 0 kWh implies that there are no electrical appliances, such as a fridge or TV connected to the grid.

[7]In contrast to ordinary goods, *Giffen goods* increase in demand, following an increase in prices.

change of prices, but focus on the semi-elasticity of demand,

$$\tilde{\sigma} = \frac{\Delta C}{C} / \Delta P = \sigma P \tag{3.2}$$

The variable $\tilde{\sigma}$ measures the percentage change in demand due to an absolute (DKK 1) change in prices.

When estimating the price elasticity of electricity demand, a significant challenge arises due to the potential endogeneity between electricity consumption and prices. In the Danish retail electricity market, prices vary dynamically in response to expected demand conditions and other external factors. For instance, during predictable periods of high demand—-such as evenings or winter months-—electricity prices tend to rise as part of electricity retailers' demand management strategies and market responses to scarcity. This creates an endogeneity problem: while prices influence electricity demand, electricity demand patterns also influence prices. Consequently, simply observing price and quantity data may reflect this simultaneous relationship rather than the causal effect of price on demand that is described by the price elasticity of demand.

Note that although retail electricity prices in the Danish retail market are set by providers one day ahead, short-term load forecasting still causes the endogeneity problem to persist: Every day, electricity retailers buy energy, to be delivered at a specific time on the next day, on the Nordpool electricity exchange. The amount of electricity purchased depends crucially on the expected demand by consumers for the next day. To asses this demand, retailers employ short-term load forecasting models. Under the assumption that expected demand and realized demand have a positive correlation, the endogeneity problem between prices and demand persists.[8] Indeed, in our dataset, we find a positive unconditional correlation between prices and demand in the data. Hasan et al. (2025) provides an overview of state-of-the-art load forecasting methods and tools used by electricity retailers.

This simultaneity problem introduces a biased estimation of parameters in standard regression approaches, as the price variable is endogenous-—correlated with the error term in the demand equation. Failure to address this endogeneity would lead to incorrect elasticity estimates, potentially underestimating or overestimating the true responsiveness of consumers to price changes.

[8] Electricity retailers have a strong financial inventive to predict future loads accurately. If the energy purchased does not mach the realized demand, short-term capacities must be bought at usually higher prices.

The key to accurately estimating demand elasticities lies in isolating exogenous variations in the supply side of the electricity market that shift prices independently of demand factors. These exogenous shifts provide a quasi-experimental setting, allowing researchers to disentangle the causal effect of price on electricity consumption while holding demand factors constant.

To address the endogeneity problem between electricity prices and demand, we adopt an instrumental variable (IV) approach, following the framework outlined by Angrist and Krueger (2001). The IV method is well-suited for this analysis because it enables the isolation of exogenous variations in prices—variations that are unrelated to demand factors and thus provide a clear path to identifying causal effects.

The success of the IV approach hinges on two key conditions. First, the instrument must be relevant, meaning it is strongly correlated with electricity prices. This ensures that the instrument effectively captures price variation that can be used for identification. Second, the instrument must be exogenous, implying that it is uncorrelated with the unobserved factors in the demand equation. This exogeneity condition ensures that the instrument influences electricity demand only through its impact on prices, not directly or through any omitted variables.

In this paper, we follow the approach by Hirth et al. (2024) and use the production of wind energy as an instrument for prices. To illustrate, panel C) of Figure 1 displays the daily wind energy production, in MWh. The time series of the instrument does not show a trend. Daily wind energy production appears to be random.

Wind energy production impacts electricity prices via the wholesale market. As produced electricity cannot be stored and has to be used at the time of production, an increase in wind energy production in a given hour, due to increased wind speed across wind parks, causes the price of electricity to drop. Indeed, similar to Hirth et al. (2024) we find in Table 1 (first stage regression) that wind energy production has a high explanatory power for retail prices. Thus, it satisfies the relevance condition.

Furthermore, we assume that the exogeneity condition is likely to be fulfilled. As the production of wind energy is predominantly dependent on a stochastic weather condition, wind speed, it is unaffected by electricity prices. Due to the low marginal cost of electricity production using wind turbines, it is unlikely that low prices cause a curtailing of production, due to a partial shutdown of production capacities.

While the price of electricity for consumers is set a day in advance, wind energy production is only observed on the day of electricity production and consumption. We assume that this problem can be overcome by a strong correlation between wind energy production and *expected* wind energy production, that is unobserved, but likely known and relevant to wholesale market participants trading electricity for the next day. These estimates may, for example, be based on weather forecasts. Indeed, electricity retailers have an incentive to take expectations of production into account: If their (pre-purchased) amount of electricity does not meet consumer demand within a specific hour and is too low, they have to settle the difference on a secondary electricity market at likely higher prices and an overall loss.

The second condition for a valid instrument is the exclusion restriction, i.e., the assumption that wind energy production, the instrument, only affects the outcome variable, consumer demand, via the instrumented variable, the retail price. Wind energy production must be uncorrelated with any other omitted variables that may affect electricity consumption.

Hirth et al. (2024) note that this exclusion restriction could potentially be violated through the impact of weather on electricity demand: Certain weather conditions, such as cold temperatures and high wind speeds, might benefit the production of wind energy production, but at the same time cause an increase in consumer demand, due to higher heating requirements or households staying at home. These effects are likely to also feature a strong seasonal pattern. In our specification, we aim to control for these effects by including both time fixed effects (year, month, day of week and hour of day) as well as the average daily temperature measured in Copenhagen, as a proxy for weather conditions. Due to the small geographic size of Denmark, the conditions in Copenhagen are a good proxy for weather conditions in other parts of the country as well.

Formally, we estimate the following instrumental variable setting, described in equations (3.3) and (3.4). In the two stage least squares regression, the first stage regresses the price of electricity P on the wind energy production W_t and a vector of time (hour, day, month, year) fixed effects D_t and the daily average temperature $T_{a,t}$.

$$P_{a,t} = \alpha_0 + \alpha_1 W_t + \alpha_2 D_t + \alpha_3 T_{a,t} + \epsilon_t \tag{3.3}$$

Note that the first stage is identical for all households i in the same grid area a. In the second stage, we regress the log consumption of household i in hour t, $ln(C_{i,a,t})$,[9] on

[9]While consumption cannot be negative, it may be close to zero. We thus add a small constant before taking logs, in order to avoid excluding observations from the data.

the predicted price from the first stage $\hat{P}_{a,t}$, separately for each household:

$$ln(C_{i,a,t}) \;=\; \beta_0 + \beta_{1,i}\hat{P}_{a,t} + \beta_2 D_t + \beta_3 T_{a,t} + v_t \tag{3.4}$$

The regression controls for time fixed effects and the average daily temperature. We estimate the instrumental variable regression described by equations (3.3) and (3.4) separately for each household. The coefficient $\beta_{1,i} = \tilde{\sigma}_i$ indicates the semi-price elasticity for household i. Because the data have strong serial correlation, we estimate heteroskedasticity and autocorrelation (HAC) robust standard errors (e.g., White, 1980). We employ an automatic lag selection for each household, following Newey (1994).

4 Estimated responsiveness of demand to prices

Table 1 presents the first stage results for a typical consumer, both in the Radius and Trefor areas. Note that we estimate this regression separately for each household.[10] The partial F-statistic ($F - stat = 134$ for the Radius area and $F - stat = 188$ for the Trefor area) indicates that the hourly production of wind energy is indeed a strong instrument. We find that a 1 MWh higher production of wind energy correlates with a DKK 0.62 (0.74) lower marginal price per MWh, for consumers. There is a negative correlation between the average daily temperature in Copenhagen and electricity prices, likely reflecting higher demand when temperatures are lower.

Table 2 in turn presents summary statistics for the estimated semi-elasticity of electricity consumption among households, from our second-stage regression. The table presents statistics after trimming the top and bottom 1% of estimation results, to reduce the impact of extreme outliers. We find that on average, a 1 DKK higher price leads to a mean (median) reduction of electricity consumption by 2.6% (2.1%). We document a difference between regions, with consumers in the Trefor area responding slightly stronger, at -2.8%, compared to the Radius area at -2.4%.

Figure 2 shows the distribution of household level estimates by means of a histogram. The blue bars represent the Radius grid area and the white bars represent the Trefor area. Both areas share a similar shape in the distribution. While the mean and median estimate are clearly negative, we document a negative skewness in results,

[10]The first stage regression is identical across all households. However, due to data security limitations, in Table 1 we present results for the average of 5 random households for each area. There might be slight deviations across households in the same area, as we lack some observations for some households.

Table 1: IV Regression: First Stage Results

	(1) Radius Price (in DKK/kWh)	(2) Trefor Price (in DKK/kWh)
Wind Energy Production (MWh)	-0.000615***	-0.000742***
	(-61.66)	(-72.79)
Average Daily Temperature	-0.0252***	-0.0291***
	(-20.00)	(-22.77)
Constant	1.496***	1.802***
	(68.92)	(80.76)
Year	Dummy	Dummy
Month	Dummy	Dummy
Day of Week	Dummy	Dummy
Hour of Day	Dummy	Dummy
N	30644	30644
r2	0.658	0.646
F-stat	134	188

Notes: This table presents the first stage estimation of the 2SLS-IV approach for the semi-price elasticity of aggregate electricity demand in Denmark. Estimation follows equation (3.3). t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

with a long left tail. 69% of households have a negative elasticity. For 29% (22%) the elasticity is significantly below 0, at a 90% (95%) confidence level. In contrast, 31% of households have a positive elasticity of electricity demand, although the elasticity is significantly positive only for 6% (3%). It follows that for 66% of all households, we cannot reject the hypothesis that they do not adjust consumption in response to changes in the marginal price, at a 90% confidence level. Table 6 in the Appendix further analyzes the demographic characteristics of those households with a significantly negative elasticity. We find that older, more educated households with a high relative electricity consumption but lower relative income are significantly more likely to reduce demand if prices are higher.

While the on-average negative semi-elasticity is consistent with economic theory, we interpret the wide distribution of estimates as follows: Firstly, the distribution likely reflects genuine heterogeneity in price responsiveness across households. Differences in income, appliance efficiency, household size, and behavioral factors may all contribute to variations in elasticity. In Section 4, we will investigate if this heterogeneity is sys-

Table 2: IV Regression: Second Stage Results

	Mean	Median	SD	Robust Mean	N	> 0	< 0
All	-0.026	-0.021	0.055	-0.022	24.395	69%	31%
Regional							
Radius	-0.024	-0.020	0.052	-0.020	12.609	69%	31%
Trefor	-0.028	-0.023	0.058	-0.024	11.786	69%	31%

Notes: This table presents 2SLS-IV estimates for the semi-price elasticity of aggregate electricity demand in Denmark. Estimation follows equations (3.3) and (3.4).

tematic rather than purely random, correlating estimates to demographic patterns, to identify which households are more or less responsive to price changes. Secondly, given a true distribution of elasticities in the population, the dataset constitutes a random sample of observations, per household. Therefore, random measurement noise can cause estimates to deviate from true elasticities, causing, for example, a positive estimated elasticity.[11]

How large is the demand response of Danish households to changes in electricity prices, in comparison? To address this question, we convert our estimates into a dimensionless price elasticity, following Hirth et al. (2024). At an average price of around DKK 2.35 per kWh, our estimates imply a mean price elasticity of -0.061, or 6.1%. Our estimate is somewhat larger than the estimates by Hirth et al. (2024), possibly reflecting the use of household-specific data as well as the different retail market structure in Denmark, compared to Germany. Compared to the estimates in Fabra et al. (2021), the mean elasticity of Danish households appears to be slightly larger than for Spanish households (-0.054). Our estimates are within the range reported in Knaut and Paulus (2016).

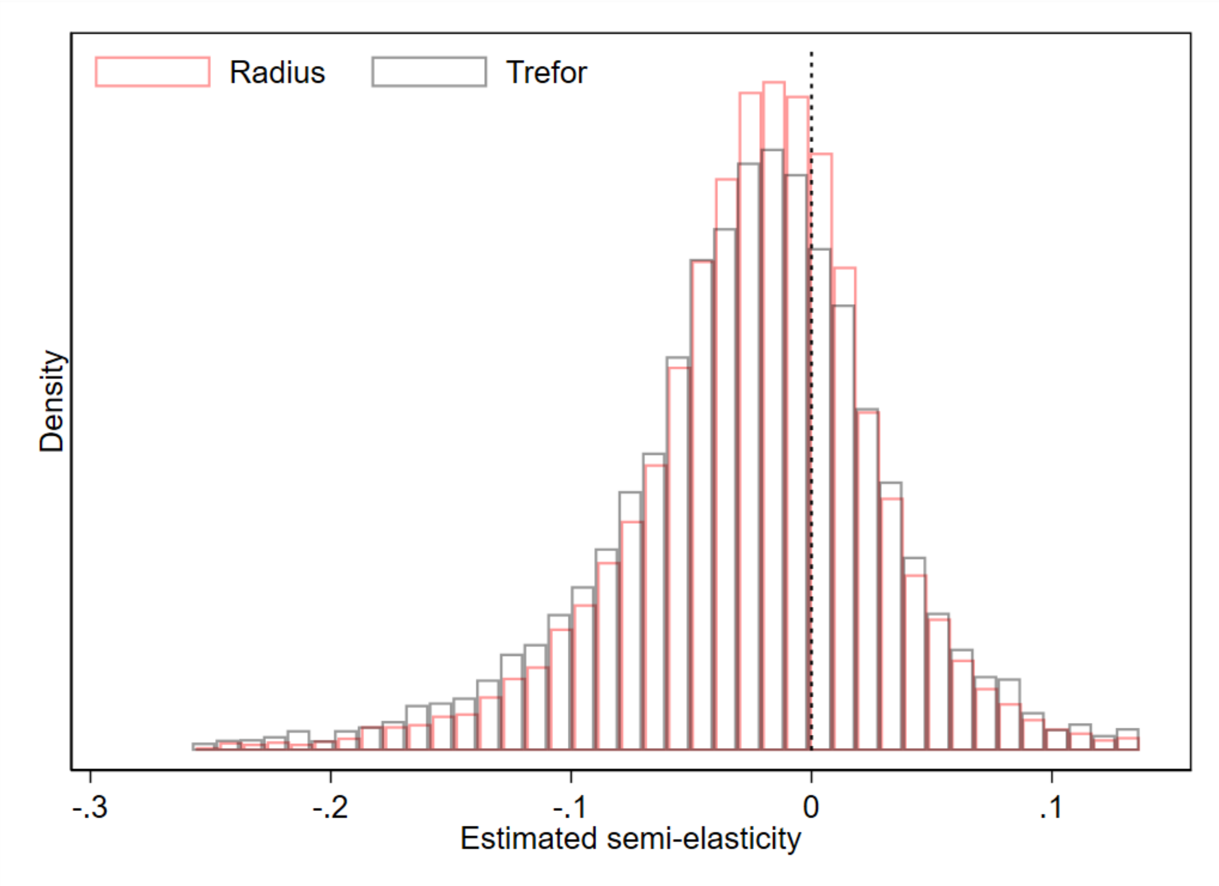
5 Demographic heterogeneity

Finally, we link the estimated semi-elasticity of electricity demand to household specific characteristics, including age, education and income. Specifically, we estimate

$$\tilde{\sigma}_i = \gamma_0 + \gamma_i \mathbb{D}_i + v_t \tag{5.1}$$

[11]Note that only 6% of estimated semi-elasticities are significantly positive at the 10% level. However, assume that the true elasticity for all households would be zero. Then, under that assumption, for 10% we would expect by random chance if the true elasticity were 0.

Figure 2: Semi-Elasticity of Hourly Electricity Consumption



Notes: The figure shows the distribution of the semi-elasticity of hourly electricity consumption at an household level, in the Radius grid area (black) and the Trefor grid area (red). The data is trimmed at the top and bottom 1% of elasticities.

where $\tilde{\sigma}_i$ represents the estimated semi-elasticity of demand from equation 3.4, for household i. The vector $\mathbb{D}_i$ contains demographic characteristics related to household i. Table 3 displays the results.

Firstly, we document that the elasticity is indeed lower in the Trefor area, indicating a stronger response of households to price changes (column 2). However, this effect can be explained when controlling for income and total consumption of electricity. Thus, it likely reflects differences in household characteristics between both areas. Secondly, we find that the elasticity is higher for households with a large total consumption of electricity. Interestingly, income seems not to be a significant driver of the elasticity. Thirdly, households with a higher level of education react more strongly to electricity price changes. This is the case for households with a vocational education and even more so for households with some higher education (university degree); indeed, the unconditional average elasticity for university educated households is at -3.0% per DKK. Fourthly, there seems to be an inverse u-shaped relation between age and the elasticity. Those below 35 years of age seem to react stronger to price signals, compared to those between 35 and 54. However, those above 65 years of age seem to be even more reactive to price signals.

Table 3: Demographic Characteristics and Estimated Elasticities

	(1)	(2)	(3)
	$\tilde{\sigma}$	$\tilde{\sigma}$	$\tilde{\sigma}$
Trefor grid area	-0.00172***	-0.00299***	-0.00181***
	(-3.45)	(-5.92)	(-3.65)
Disposable Income (deciles)	0.000142		-0.0000278
	(1.26)		(-0.20)
Electr. Consumption Income (deciles)	-0.00403***		-0.00410***
	(-34.67)		(-35.04)
Vocational Education		-0.00813***	-0.00262***
		(-12.04)	(-3.81)
Higher Education		-0.0136***	-0.00595***
		(-20.18)	(-7.89)
Age 35-44		-0.00137	0.00343**
		(-1.11)	(2.80)
Age 45-54		-0.000117	0.00357**
		(-0.10)	(3.03)
Age 55-64		-0.00185	-0.00186
		(-1.53)	(-1.57)
Age 65-74		-0.00246*	-0.00433***
		(-2.07)	(-3.68)
Age 75 and older		-0.00122	-0.00579***
		(-1.01)	(-4.80)
Constant	-0.000204	-0.0105***	0.00561***
	(-0.33)	(-8.86)	(4.45)
N	23866	24322	23861
R^2	0.0669	0.0151	0.0750

Notes: The table presents Huber robust regression results, with the estimated semi price elasticity of electricity demand as the dependent variable. Heteroskedasticity robust t-statistics in parasynthesis. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

While we cannot provide causal evidence for the heterogeneity in the semi-elasticity of electricity demand, this section provides several interpretations for the demographic heterogenetic documented, through the lens of economic theory.

Firstly, the higher price sensitivity for highly educated households may be linked to rational inattention, assuming that attention costs decline with higher education. If households are only partially aware of electricity prices due to the costs associated with acquiring this information, the response of consumption to actual prices might be attenuated. Indeed, in a randomized control trial, Jessoe and Rapson (2014) provide evidence for the role of inattention to price information in low electricity demand elasticities. Harding and Sexton (2017) also highlight the role of informational frictions for price elasticities of residential electricity demand.

Secondly, variations in contract types may influence demand elasticities. The availability of fixed-price contracts, although chosen by only a small subset of households, could dampen the observed responsiveness to price changes. Since households on fixed-price contracts are insulated from short-term fluctuations in electricity prices, they have little incentive to adjust their consumption in response to marginal price signals. As a result, the overall distribution of elasticities may reflect a mix of truly price-responsive households and those whose demand remains unaffected due to contractual price stability.

Thirdly, the positive relation between price sensitiveness and overall electricity consumption – while controlling for the level of income – might be an indication of nomothetic preferences, i.e. the role of electricity as a necessity in households' consumption bundles. Intuitively, the adjustment of demand to prices becomes easier for households where electricity is used beyond everyday necessities, such as refrigerators or ovens. Similar insights are documented by Meier et al. (2013) or Baffes et al. (2021) finding income elasticities for electricity demand below 1, highlighting the role of energy as a necessity good.

6 Conclusion

This study investigates the price elasticity of household electricity demand in Denmark using high-resolution smart meter data and an instrumental variables approach. Leveraging hourly electricity consumption records and using wind energy production as an exogenous instrument for price variation, we estimate household-specific semi-elasticities of demand. Our results show that nearly one-third of households significantly reduce their electricity consumption in response to higher prices, while the majority exhibit no statistically significant reaction. On average, households reduce demand by 2.6% following a DKK 1 increase in the hourly electricity price.

We also find substantial heterogeneity in price responsiveness across demographic groups. Households with higher baseline electricity consumption tend to be more price-elastic, consistent with the notion that electricity is a necessity at lower consumption levels but includes more discretionary usage at higher levels. Additionally, households with higher education levels are more responsive to price changes, suggesting a possible role for rational inattention or differences in information processing. Greater price responsiveness is also observed among both younger (< 35) and older (> 65) households, which may reflect variation in flexibility, awareness, or access to enabling technologies.

References

ACER & CEER (2024, September). Market monitoring report 2024: Energy retail and consumer protection. Tech. report MMR2024, Agency for the Cooperation of Energy Regulators Council of European Energy Regulators, Ljubljana / Brussels, EU. Accessed: 2025-06-23.

Andersen, F., P. Gunkel, H. Jacobsen, and L. Kitzing (2021). Residential electricity consumption and household characteristics: An econometric analysis of danish smart-meter data. *Energy Economics 100*, 105341.

Andersen, F. M., P. A. Gunkel, C. Bjerregaard, and H. K. Jacobsen (2024). Changes in hourly electricity consumption profiles and price elasticities in denmark 2019–2022. *Energy 308*, 132798.

Angrist, J. D. and A. B. Krueger (2001, December). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic Perspectives 15*(4), 69–85.

Baffes, J., A. Kabundi, and P. Nagle (2021, 07). The role of income and substitution in commodity demand. *Oxford Economic Papers 74*(2), 498–522.

Blomquist, S., J. B. Bushnell, S. L. Puller, A. Spurlock, and A. Todd (2018). Causal tree estimation of heterogeneous household response to time-of-use electricity pricing schemes.

Branner, V. and M. M. Ingholt (2023). Denmark risks a period of energy price fluctuations, impacting inflation and monetary policy. Danmarks nationalbank economic analysis, no. 10.

Danmarks Statistik (2024). Moduldata for elmålere.

Edenhofer, O., R. Pichs-Madruga, Y. Sokona, K. Seyboth, S. Kadner, T. Zwickel, et al. (2011). *Renewable Energy Sources and Climate Change Mitigation: Special Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Energinet (2024a). Distribution grid tariffs - historical data.

Energinet (2024b). Electricity spot price - historical data.

Energinet (2024c). Transmission grid and system tariffs - historical data.

Enrich, J., R. Li, A. Mizrahi, and M. Reguant (2024). Measuring the impact of time-of-use pricing on electricity consumption: Evidence from spain. *Journal of Environmental Economics and Management 123*, 102901.

European Parliament (2025). Increasing flexibility in the eu energy system. https://www.europarl.europa.eu/RegData/etudes/ATAG/2025/769348/ECTI_ATA(2025)769348_EN.pdf. Accessed: 2025-06-23.

Fabra, N., D. Rapson, M. Reguant, and J. Wang (2021, May). Estimating the elasticity to real-time pricing: Evidence from the spanish electricity market. *AEA Papers and Proceedings 111*, 425–29.

Forsyningstilsynet (2022). Market report 2022 the danish wholesale electricity market. Technical report.

Gabaix, X. (2014). A sparsity-based model of bounded rationality. *The Quarterly Journal of Economics 129*(4), 1661—-1710.

Green Power Denmark (2024). Elkunder flokkes om variable priser.

Harding, M. and S. Sexton (2017). Household response to time-varying electricity prices. *Annual Review of Resource Economics 9*(Volume 9, 2017), 337–359.

Hasan, M., Z. Mifta, S. J. Papiya, P. Roy, P. Dey, N. A. Salsabil, N.-U.-R. Chowdhury, and O. Farrok (2025). A state-of-the-art comparative review of load forecasting methods: Characteristics, perspectives, and applications. *Energy Conversion and Management: X 26*, 100922.

Hirth, L., T. M. Khanna, and O. Ruhnau (2024). How aggregate electricity demand responds to hourly wholesale price fluctuations. *Energy Economics 135*, 107652.

Jessoe, K. and D. Rapson (2014, April). Knowledge is (less) power: Experimental evidence from residential energy use. *American Economic Review 104*(4), 1417–38.

Kahn-Lang, J., Y. Zhu, K. Palmer, and P. Cappers (2025, February). A meta-analysis of time-based electricity rates. Working Paper 25-04, Resources for the Future.

Knaut, A. and S. Paulus (2016). When are consumers responding to electricity prices? an hourly pattern of demand elasticity. Working paper.

Labandeira, X., J. M. Labeaga, and X. López-Otero (2017). A meta-analysis on the price elasticity of energy demand. *Energy Policy 102*, 549–568.

Meier, H., T. Jamasb, and L. Orea (2013). Necessity or luxury good? household energy spending and income in britain 1991-2007. *The Energy Journal 34*(4), 109–128.

Newey, Whitney K.; West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *Review of Economic Studies 61*, 631–654.

Schittekatte, T., D. S. Mallapragada, P. L. Joskow, and R. Schmalensee (2022, October). Electricity retail rate design in a decarbonized economy: An analysis of time-of-use and critical peak pricing. Working Paper 30560, National Bureau of Economic Research, Cambridge, MA.

Simon, D. N. and L. D. Anadon (2025, March). Power price stability and the insurance value of renewable technologies. *Nature Energy 10*(3), 329–341.

SKAT (2024). Electricity fees - historical data.

Statistics Denmark (2022). Household budget survey. Technical report.

Tsiropoulos, I., W. Nijs, D. Tarvydas, and P. Ruiz Castello (2020). Towards net-zero emissions in the eu energy system by 2050 - insights from scenarios in line with the 2030 and 2050 ambitions of the european green deal. Eur 29981 en, publications office of the european union.

Varian, H. (2003). *Intermediate Microeconomics: A Modern Approach*. Norton.

White, H. L. (1980). Heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica 48*, 817–838.

Appendix

A Additional Figures and Tables

Table 4: Data sources

Variable	Description	Source
$E_{i,t}$	Electricity spot price (eltarif)	Energinet (2024b)
G_t	National transmission grid and system tariff	Energinet (2024c)
$G^D_{a,t}$	Local distribution grid tariff	Energinet (2024a)
T_i	Consumption taxes	SKAT (2024)
$C_{i,a,t}$	Hourly consumption of household i	Danmarks Statistik (2024)

Notes: The table describes the data sources for the most relevant variables used.

Table 5: Grid Tariff

Grid Load	Trefor	Radius
Peak Load	58.70 øre	109.34 øre
Low Load	6.52 øre	12.15 øre
High Load	19.57 øre	36.45 øre

Notes: The table describes the historical grid tariffs for the Radius and Trefor areas valid from the 1st of August and 1st of October respectively, and valid until the end of 2023. The different grid load slots are defined as 5 p.m. - 9 p.m. for peak load, 12 p.m. - 6 a.m. for low load, and 6 a.m. - 5 p.m. & 9 p.m. - 12 p.m. for high load. Especially for the Radius area the grid tariff can often make up the largest part of the total electricity price during peak load, providing a strong incentive to move electricity use out of the peak.

Table 6: Demographic characteristics and positive elasticities

	(1) $\mathbb{I}(\tilde{\sigma} < 0, p \leq 0.1)$	(2) $\mathbb{I}(\tilde{\sigma} < 0, p \leq 0.1)$	(3) $\mathbb{I}(\tilde{\sigma} < 0, p \leq 0.1)$
Trefor grid area	-0.0809***	-0.0359*	-0.0809***
	(-4.63)	(-2.10)	(-4.61)
Disposable Income (deciles)	-0.0319***		-0.0141**
	(-8.49)		(-3.05)
Electr. Consumption Income (deciles)	0.102***		0.103***
	(26.69)		(26.77)
Vocational Education		0.169***	0.0586*
		(7.06)	(2.29)
Higher Education		0.229***	0.0924***
		(9.73)	(3.38)
Age 35-44		0.0873*	-0.00741
		(2.18)	(-0.18)
Age 45-54		0.108**	0.0461
		(2.78)	(1.16)
Age 55-64		0.136***	0.151***
		(3.45)	(3.75)
Age 65-74		0.239***	0.280***
		(6.18)	(7.01)
Age 75 and older		0.282***	0.383***
		(7.00)	(9.16)
Constant	-0.924***	-0.861***	-1.253***
	(-40.44)	(-22.14)	(-28.70)
N	23929	24402	23929

Notes: The table presents results from probit regressions. Heteroskedasticity robust t-statistics in parasynthesis. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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