Watt Changes: Households' Response to Hourly Electricity Prices*

Fatima Zahra Filali Adib† Julie Marx ‡
Clara Egehoved Tørsløv§

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Abstract

A successful green transition requires aligning electricity demand with renewable supply, which variable pricing can achieve. We use novel high-frequency data on electricity consumption and an instrumental variable approach to analyze electricity price responsiveness of Danish households. We estimate electricity price elasticities across and within days. We find that higher prices lead households to adjust their consumption, mostly through level decreases rather than shifting use to cheaper off-peak hours. The level cuts persist after prices fall, especially for lower-income households, while within-day shifting is modest and concentrated among higher-income households.

JEL Classification:
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†Copenhagen Business School. Email: fzfa.fi@cbs.dk.
‡Copenhagen Business School. Email: jma.fi@cbs.dk.
§Copenhagen Business School. Email: cet.fi@cbs.dk.

1 Introduction

Electricity and heat together account for 33% of global emissions (Hannah Ritchie and Roser [2024]), with households representing a substantial share of electricity demand. Understanding household consumption behavior is therefore crucial in the context of renewable energy transition. Renewable sources such as wind, solar, or hydropower provide environmentally friendly alternatives to fossil fuels, but suffer from limited storage possibilities. This makes household adaptability to fluctuations in renewable energy supply a key for a successful energy transition. One policy tool to motivate households to adjust their consumption is through pigouvian taxes that would align with the marginal cost of non-renewable electricity (Pigou, 1920). In practice, this translates to setting variable electricity prices. This raises two central questions: to what extend do prices drive households to lower and/or smooth their consumption, both across and within days, and do all households respond to prices in the same way?

Evidence on households' response to electricity prices remains limited for several reasons. First, granular data on hourly electricity consumption, especially at a country-level, is often difficult to obtain. Second, electricity prices are typically set by grid operators in ways that correlate with demand, with higher prices prevailing during high demand periods. As a result, a simple analysis of intraday consumption relative to prices can be misleading, since hours of high demand are inherently associated with higher prices. Third, isolating exogenous shocks to electricity prices to study potential shifts in medium to long term consumption patterns is challenging.[1]

In this study, we examine how households adjust both the level and timing of their electricity consumption in response to price fluctuations, using novel

[1]Studies using household-level hourly electricity consumption include but are not limited to Jessoe and Rapson [2014], Wolak [2011], Di Cosmo et al. [2014], Ida et al. [2015], Lanot and Vesterberg [2021], Guo [2023], Fabra et al. [2021], (2021, 2024). These are typically focused on small-scale pilots, aggregate measures, specific regions or cities, or short time periods, underscoring the scarcity of nationally representative, long-run datasets.

high frequency electricity consumption data from Denmark. Our dataset covers hourly electricity consumption of all Danish households from 2021 to 2023, which we link to electricity price data as well as households background characteristics using the rich administrative register data. Denmark is also an ideal candidate for our analysis as its electricity supply relies predominantly on wind power. In 2023, wind generated 65.5% of domestic electricity supply (Energistyrelsen, 2023). This allows us to exploit wind forecasts as an instrumental variable for electricity price variation that is exogenous to household demand. Furthermore, we investigate household responses to the sharp increase in electricity prices following the Ukraine 2022 invasion, treating this as a shock to energy costs. Finally, we extend the analysis to 2023 to explore potential evidence of habit formation in household electricity consumption behavior.

We start by documenting some insightful patterns in monthly as well as hourly electricity consumption for the entire population. Overall, it corroborates the idea that households have been decreasing their consumption as electricity prices have been soaring. It also shows heterogeneity in households' response, especially by household income. Given the high frequency of our data, our analysis focuses on 10.344 households, which provides a reasonable sample for conducting the study.

Next, we formally examine how households' electricity bills are reacting to price changes. We aim to quantify the bills' reactions to price fluctuations. If households are indeed attentive and responsive to prices, we would expect their bills to vary less than one-for-one with prices. Indeed, our analysis shows that a 1% increase in electricity prices corresponds to only a 0.94% increase in daily bills. This suggests that households respond to higher prices by reducing or re-allocating their electricity consumption.

We further investigate how this readjustment of electricity consumption translates into price elasticities at different horizons. To obtain consistent estimates, we employ forward-looking wind forecasts as an instrumental vari-

able for electricity prices. Our results indicate elasticities of -0.8 at the monthly level, -0.05 at the daily level, and -0.017 at the hourly level.[2]These findings reinforce the earlier evidence from household bills, further demonstrating that households are responsive to fluctuations in electricity prices. These estimates are also consistent with prior evidence showing elasticities generally small in magnitude. [3] Some evidence help explain why estimated elasticities are generally small - households react to average rather than marginal prices [Ito, 2014]; load shifting is driven more by relative within-day price differences than by absolute hourly spikes [Schittekatte et al., 2022]; providing real-time information strengthens responses to temporary price changes [Jessoe and Rapson, 2014]; the duration of the price signal has little effect on the size of the response [Wolak, 2011]; and short-term elasticities increase during periods of high prices and volatility (Andersen et al. [2024]; Andersen and Dietrich [2025]).

Elasticity estimates alone cannot disentangle the mechanisms through which households reduce their electricity bills. Broadly, there are two adjustment channels. First, households may lower the overall level of consumption during periods of high prices - for example, by foregoing certain uses such as cooking with an oven or by substituting toward more energy-efficient appliances. Second, households may adjust the timing of their consumption. Electricity pricing typically follows two regimes: peak hours (5–8 a.m. and 4–10 p.m.), when both household and industrial demand is elevated and providers increase tariffs and spot prices, and off-peak hours, when demand, and thus price, is lower. Thus, a second channel to keep electricity bills unchanged would be that, in response to higher prices, households may shift

[2]We account for endogeneity and autocorrelation in electricity demand estimation by using nuisance IV regression as proposed by Thams et al. [2022].

[3]For example, in the meta-analysis of Labandeira et al. [2017] the authors find an average short-run elasticity of -0.24, based on 966 elasticity estimates (with short-run being defined as up to one year). Shorter-run responses are generally small - in Spain Fabra et al. [2021] finds hourly elasticities in the range -0.054 to -0.014 and not significantly different from zero, with similar results found in Sweden Lanot and Vesterberg [2021])

part of their electricity use from peak to off-peak hours in order to mitigate increases in their total bills.

First, to measure adjustments in electricity consumption levels during exogenous surges in energy prices, as well as to assess potential long-term habit formation, we divide our sample into three distinct periods. The *during* window which starts in March 2022, immediately following the Ukraine invasion, and spans the following 12 months. The event was accompanied by a sudden escalation in electricity prices that lingered over the following year. The *pre* window covers the preceding year while the *post* window corresponds to the subsequent year. Using 2023 as a longer term horizon (*post* window) is revealing, as Denmark removed its electricity tax during this period, lowering prices to levels even below those observed in the during window as documented in Figure 1. We then estimate changes in electricity consumption across these periods by regressing household consumption on period indicators. Our results show that in the *during* period—when prices were at their peak—households reduced their daily electricity use by 3.5% relative to the *pre* window. Strikingly, this reduction persisted into the post period, even after prices declined, suggesting that households not only curtail consumption in response to sudden price increases but also form longer-lasting consumption habits.

We then test whether households adjust to electricity prices by reallocating consumption within the day: shifting usage from costly peak hours to cheaper off-peak hours along two different dimensions. First, we compare intra-day reallocation across the *pre*, *during*, and *post* periods to capture responses to overall price levels. We find that households shift about 0.5% of daily consumption to off-peak hours in high-price periods, and this shift persists after prices decline. Second, we examine responses to daily price variation by estimating the share of consumption occurring during peak hours as a function of average peak to total daily prices. Consistent with the hypothesis of intra-day adjustment, we find that households reduce peak-hour

consumption when peak prices increase. This response was exacerbated in the *during* period and persisted into the *post* period when electricity prices went down. These tests provide evidence that households reallocate some of their electricity consumption to time of days when prices are lower.

We subsequently assess the relative importance of changes in consumption levels versus changes in timing in driving households' electricity bill responses. To this end, we decompose the bill change into change in overall consumption and change in the timing. Our estimates show that nearly all of the reduction in household electricity bills —approximately 98%— is attributable to lower overall consumption rather than intra-day reallocation.

Lastly, we conduct a set of heterogeneity analyses to identify the main drivers of household adjustments to fluctuating electricity prices. First, we document that income levels play an important role for how households react to price surges. While households belonging to a higher income bracket are more likely to adjust their intra-day consumption, they are also the ones for which the levels of consumption revert back in the *post* period. This could either be a result of individuals with higher income being more flexible or more aware of price changes. We then use having at least one unemployed or retired household member as a proxy for flexibility. We find that households with retired or unemployed members do not adjust their consumption intra-day when peak prices are higher. This suggests that higher income households are more likely to be attentive to prices and adjust their consumption as well as build habits on the long term, that they keep even after prices are down.

Our findings supplement the findings of a large and fast growing literature on the role of households in the green transition. Adib et al. [2024] and Riedl and Smeets [2017], among others, study how retail investors are shifting their preferences towards more responsible financial assets. Liao et al. [2017] provide a literature review of all the studies on consumers' preferences for electric vehicles and other responsible consumption in general (Ferreira et al.

[2024]). Another way that households participate in reducing their carbon footprint is through their energy consumption. Households are significant consumers of electricity, and the patterns of their energy use directly influence carbon emissions (IEA (2020, 2021), Davis and Gertler [2015]). In this study, we illustrate how households can have a role in the green transition through their electricity consumption.

A long standing debate however is on the requirements needed for a successful transition to lower carbon emissions. Renewable energies are less damaging to the planet but the main challenge is their transient nature. Renewable energies are hard to store and in order for economies to fully rely on green electricity, society needs to be able to adjust its consumptions. Pigouvian taxes and other externalities have been studied in the context of developing the right incentives for firms and countries to adopt more environmentally conscious behavior (Döttling and RolaJanicka [2025], Bovenberg and de Mooij [1994], Calel and Dechezleprêtre [2016]). Our paper sheds the light on the effect of variable electricity pricing on the retail sector.

Additionally, our study contributes to a limited literature on the effects of real-time varying electricity prices on household behavior (Faruqui and Sergici [2010], Metcalf [2025], Fabra et al. [2021]). Reiss and White [2005] develop a theoretical model that they test using California's tariff changes to highlight the difficulty in anticipating price changes response. Ito [2014] on the other hand finds that households are not receptive to nonlinear prices but rather marginal ones. We find that people react to overall levels of electricity prices and the more attentive groups even follow daily price changes. Lastly, while several studies have examined the elasticity of electricity (Hirth et al. [2024], and Deryugina et al. [2020]), a major research gap is how and which households respond to intra-day variations. We contribute to both and measure the relative effect of level versus timing consumption adjustment.

The paper proceeds as follows: Section 2 presents the institutional details of the Danish electricity market, and Section 3 describes the data and pro-

vides summary statistics of both monthly and hourly electricity consumption. Section 4 estimates electricity bills' price reaction and elasticities. In Section 5 we discuss the different ways households react to electricity prices. Section 6 presents results split by different household characteristics and section 7 concludes.

2 The Danish Electricity Market

Electricity prices are shaped by unique market structures that reflect the physical realities of power generation and delivery. The following sections explain the mechanisms that determine household electricity costs in Denmark.

Electricity differs from most commodities. It is fungible - 1 kWh is identical regardless of source - and it cannot be stored at scale, so supply and demand must balance in real time. The market is structured in three layers to accommodate these unique features: day-ahead, intraday, and balancing. In the day-ahead market, prices are set hourly through an auction based on supply and demand forecasts. These are the prices that households observe. Producers submit offers ranked by cost (the merit order). Cheapest sources - mainly renewable ones - are dispatched first, with progressively costlier units (e.g., coal or gas) added until expected demand is met. If only renewable energy suffices, the price is low; as more expensive sources enter, the price rises stepwise. The intraday market allows trading closer to real time when forecasts change. Balancing markets, run by transmission system operators (TSOs), correct residual mismatches between forecast and actual consumption/production. Transmission costs are separate from energy prices. TSOs operate the high-voltage grid, while distribution system operators (DSOs) handle local delivery. The distinction is analogous to highways versus local roads.

2.1 Electricity Sources

Denmark has two bidding zones: DK1 (west, linked to Germany/Continental Europe) and DK2 (east, linked to the Nordic market). Denmark is a leader in wind power. In 2022, 81.4% of electricity came from renewable sources, with wind alone providing 53.6% Danish Energy Agency [2022]. During demand peaks, gas turbines provide backup. The government aims to achieve a 100% renewable energy system by 2050 Danish Ministry of Energy, Utilities and Climate [2011].

2.2 Household Electricity Bills

Household electricity bills in Denmark comprise three main components: the energy component (spot price plus any supplier margin), grid payments (covering TSO and DSO tariffs), and taxes. In 2022, households paid approximately 48% for the energy component, 11% for grid tariffs, and 41% for taxes. Grid payments are monitored and regulated by the Danish Utility Regulator, and set in advance, typically announced for the coming year. Taxes are set for extended periods (e.g., six months), designed partly to discourage use, and announced in advance. About 70% of households choose floating-price contracts (Hinrichsen [2024]). Electricity suppliers recommend flexible pricing to all customers due to its potential cost advantages; however acknowledge that households with electric heating or living in apartments may derive fewer benefits from such a scheme.

2.3 Smart Meters

Smart meters located in each household record hourly household consumption and transmit data automatically to the provider. They enable consumers to benefit from dynamic pricing and allow suppliers and operators to manage demand more efficiently. In Denmark, a nationwide rollout of smart meters was completed by 2020.

3 Data and summary statistics

This section introduces our data and provides key summary statistics on electricity use and prices in Denmark. We combine register data with detailed electricity meter records covering monthly and hourly consumption. The data allows us to track how households adjust their usage over time and across income groups, laying the groundwork for the analyses that follow.

3.1 Data Sources

We rely on monthly and hourly electricity consumption data covering all Danish meters from 2021 to 2024. We link the data to electricity price data as well as administrative data covering the entire Danish population.

Electricity consumption data is collected by Energinet and made available to us through Statistics Denmark.[4] We obtain price data directly from Energinet's public website. It includes hourly spot prices, taxes and tariffs, along with hourly forecasts of wind and solar power and the total production and consumption of electricity in Denmark. We compute local electricity prices by adding the national electricity tax and the local grid area tariffs to the spot price, as described in Section 2.2.

Household characteristics come from Danish administrative data. A key advantage of the administrative registers (Det centrale personregister, CPR) is that they contain personal identification numbers (CPR), analogous to Social Security numbers in the United States, which enable us to link to various demographic data such as gender, age, location, and household composition. Income and wealth data is collected by the Danish tax authorities and car holdings are from the Danish motor registry. Housing characteristics are from the Danish housing registry (Bygnings- og boligregistret, BBR). Everything is made available to us by Statistics Denmark. When using data at

[4]Energinet is an independent public enterprise owned by the Danish Ministry of Climate, Energy and Utilities. Energinet owns, operates and develops the transmission systems for electricity and gas in Denmark.

the monthly frequency, we include the entire Danish population. However, since daily electricity consumption data are considerably larger and computationally demanding, we restrict the analysis to a subsample of households residing in houses. We restrict our sample to houses for two main reasons. First, households living in houses are less likely to opt for fixed-price electricity contracts (Hinrichsen [2024]). Second, residents in houses face fewer constraints on the timing of appliance use. For instance, running a washing machine late at night is typically less disruptive in a house than in an apartment building, where noise may affect neighboring units.

To ensure a high-quality sample, we begin by identifying the households from which we draw our data. We first restrict the sample to adult, single-family households with a valid tax record. Because most of the variation in electricity prices occurs in 2022, we require that households are present in both 2021 and 2022 and that their family composition and residential address remain unchanged throughout 2022. We exclude households for which a unique meter address cannot be identified, as well as those with irregular or ambiguous housing types. To enable consistent matching with electricity data, we further exclude households lacking a unique electricity meter. Lastly, we require households to have electricity consumption data for all months of 2022. From the filtered pool of single-meter households living in houses, we randomly select 12,500 addresses observed in 2022, retaining their complete address histories data from 2021 through 2024. We remove duplicate records and observations deemed unreasonable.[5]

The final dataset comprises 8,871 addresses corresponding to 10,334 households observed between 2021 and 2024, yielding a total of 10,515,864 household-day observations. Appendix Table A-1 provides an overview of the data filtering process.

Table 1 presents summary statistics of our sample. Panel A shows in-

[5]We define unreasonable consumption as usage below the minimum required to power an efficient refrigerator continuously. We also exclude households whose annual electricity bill exceeds their annual income.

formation on electricity consumption and prices. The average daily household electricity consumption is 8.81 KWh and the average electricity price amounts to 1.92 DKK per KWh. This price consists of three components: the wholesale spot price (0.97 DKK), the national tax (0.69 DKK), and the local distribution tariff (0.26 DKK). The average day-ahead wind forecast for the relevant price area (zones 1 or 2) is 1.09 GWh. This forecast serves as our instrumental variable for total electricity prices, as discussed in Section 4.1.

Table 1, Panel B reports household characteristics for our sample. On average, households consist of 1.6 adults and 0.57 children, with an average age of 58 years. The relatively high average age reflects that our sample includes households across all age groups, not only those of working age. The mean annual household income is 667,473 DKK (approximately 90,000 EUR). In terms of technology adoption, about 2 percent of households use electric heating, and 1 percent own an electric vehicle.

3.2 Electricity prices and overall consumption

In this section, we describe patterns of electricity consumption within the Danish population. Figure 1, Panel A, illustrates the evolution of average electricity prices over time. At the beginning of the sample period, prices were around 1.5 DKK per kWh and began to rise toward the end of 2021. Prices spiked sharply in March 2022 following the Russian invasion of Ukraine, peaking at over 4 DKK per kWh in August 2022. Beginning in January 2023, the Danish government temporarily removed the electricity tax for the entire year, an intervention that substantially reduced the consumer price of electricity.

We divide the sample into three periods based on price dynamics and the February 2022 Russian invasion, which serves as an exogenous shock to electricity prices: *pre* (March 2021–February 2022), *during* (March 2022–February 2023), and *post* (March 2023–February 2024). Figure 2 Panel A displays

average monthly household electricity consumption across all Danish households, using this time split. Consumption follows a clear U-shaped seasonal pattern, with higher levels during the colder months.[6] Relative to the *pre* period, households substantially reduce electricity consumption during the *during* period, when prices rise sharply, and continue to exhibit somewhat lower consumption levels in the *post* period, even after prices fall.

Figure A-1, Panel A, presents electricity consumption patterns by income quartile. As expected, electricity consumption rises with income, and seasonal variation is more pronounced among higher-income households. This pattern likely reflects that wealthier households tend to live in larger homes, own more electrical appliances, or engage in activities that are more energy-intensive, thereby amplifying seasonal fluctuations. Across periods, households in the lowest income quartile exhibit only modest adjustments to price fluctuations during the *during* period, suggesting limited scope for further reductions. In contrast, households in the second and third quartiles reduce their consumption noticeably and sustain part of this reduction even after prices decline in 2023. The highest income quartile decreases electricity use primarily during the colder months of the *during* period but rapidly returns to *pre*-period consumption levels in the *post* period.

After examining monthly consumption patterns, we turn to how Danish households allocate electricity use across the day. Whereas the previous figures analyzes the entire population, , this section focuses on a random sample of households residing in single-family houses. Figure 1 Panel B reports average hourly electricity prices. Prices generally exhibit two daily peaks: one in the morning and another in the evening. The spread between peak and off-peak prices is most pronounced during the *during* period, when overall price levels were highest (approximately 2.2 DKK versus 3.1 DKK

[6]Since the vast majority (approximately 96 percent) of Danish homes do not rely on electric heating, this pattern likely reflects increased time spent indoors during winter and reduced electricity use during summer months when individuals spend more time outdoors or traveling.

per kWh).[7] In the subsequent analysis, we define peak hours as 5–8 a.m. and 4–10 p.m.

Reflecting household routines and the interaction of electricity demand and supply, both consumption and prices vary throughout the day, with prices peaking around 6 p.m.. Figure 2 Panel B reports average consumption by hour. Unlike prices, electricity use displays a single prominent peak in the evening, a plateau during daytime hours, and a low point at night. Relative to the *pre* period, overall consumption declines across the day in the *during* period. In the *post* period, consumption partly reverts back and households shift some of their use from daytime to nighttime hours, implying greater off-peak consumption.

When splitting households by income quartiles (Figure A-1 Panel B, we find that the gap between peak and off-peak consumption widens with income. This suggests that differences in overall monthly consumption across income groups are largely driven by variation in peak-time use. Moreover, the shift toward greater nighttime consumption in the *post* period is more pronounced among higher-income households, possibly reflecting the use of electric vehicles or other appliances that can be more easily scheduled outside peak hours.

Overall, the data show clear differences in how households use electricity across time, income, and hours of the day. We now turn to the electricity bill and households' price elasticity, which set the stage for our main results.

[7]Within-day variation in prices arises primarily from fluctuations in the spot price, which reflects both supply and demand conditions. A smaller share of the variation stems from local electricity providers applying Pigouvian-like tariffs to incentivize households to shift consumption away from peak hours. For a decomposition of hourly prices, see Figure A-2.

4 Electricity bill and price elasticity

4.1 Regression specification

In this section and the next, we examine how electricity bills, consumption levels, and consumption timing respond to price changes. We begin by outlining the regression specification in general terms.

Naturally, since the spot price is determined by both supply and demand, and that some local tariffs are higher in times of peak consumption, a naïve OLS regression of electricity consumption on price would suffer from simultaneity bias and yield positive price elasticities. As Danish electricity prices are heavily affected by the supply of wind energy, we instrument the electricity price with the day-ahead wind forecast and capture the supply driven variations in the price. To instrument prices we estimate the first-stage regression:

$$\log(p_{gt}) = \beta \log(w_{dt}) + \omega_a + \omega_m + e_t \tag{1}$$

where w_{dt} is the day-ahead forecast of time t and price area d wind, and ω_a and ω_m are address and time fixed effects.

The main analyses then applies a second stage regression of the following form, with y_{at} being either bill b_{at}, consumption q_{at}, or peak-share of consumption π_{at}.

$$\log(y_{at}) = \varepsilon \widehat{\log(p_{gt})} + \log(y_{at-1}) + \log(y_{at-7}) + \alpha_a + \alpha_m + \epsilon_{at} \tag{2}$$

where p_{gt} is the average price of electricity in grid area g at time t. We control for any house specific characteristics using address fixed effects α_a and for any aggregate consumption trends using time fixed effects α_m.

We include lagged values of the dependent variable in our regressions. This follows the insight from Thams et al. [2022], who demonstrate that instrumental variable (IV) estimates of high-frequency electricity demand

elasticities can be biased when using wind as an instrument. The bias arises because both wind generation and electricity consumption exhibit temporal persistence, violating the exclusion restriction across time. This issue, commonly referred to as Thams' bias, leads to upward-biased elasticity estimates if unaddressed. To correct for this, Thams et al. [2022] propose two approaches: the nuisance IV and the conditional IV estimators. Tiedemann et al. [2023] empirically evaluate these methods and find that standard IV estimation inflates elasticity estimates, while the nuisance IV approach performs best and effectively mitigates the bias. In our analysis, we adopt the nuisance IV estimator, incorporating lagged dependent variables to control for serial correlation. Specifically, we include lags of 1 and 7 days in the daily regression specification, lags of 1 and 24 hours in the hourly specification, and a lag of 1 month in the monthly specification. [8]

4.2 Daily electricity bill

Households observe their electricity consumption mainly through their electricity bills. We begin by examining how daily electricity expenditures respond to daily electricity prices. Consistent with the rest of the study, we rely on wind forecast as an instrumental variable to explain exogenous variation in electricity prices, orthogonal to household demand. Specifically, we estimate the following two-stage instrumental variable (IV) regression:[9]

$$\log(b_{at}) = \gamma \widehat{log(p_{gt})} + \log(b_{at-1}) + \log(b_{at-7}) + \alpha_a + \alpha_m + \epsilon_{at} \tag{3}$$

The first dependent variable is the logarithm of the daily electricity bill (in DKK) of address a in day t, $(log(b_{at}))$.

[8] PACF can be seen in the appendix, where we can see that lags 1 and 7 need to be accounted for.

[9] The first stage regression is described in Equation 1

Table 2 presents the results of the second-stage regression.[10] As expected, daily electricity bills increase with daily electricity prices. However, households adjust their consumption in response to higher prices: a 1% increase in electricity price is associated with only a 0.94% increase in the electricity bill (and significantly different from 1%). In other words, household bills increase by about 6% less than they would have if consumption had remained unchanged. This finding motivates our subsequent analysis of price elasticities and the mechanisms through which households adjust their electricity use during periods of high prices.

4.3 Price elasticities

To analyze how household consumption levels responds to price changes, we now turn to estimating households electricity price elasticities over different horizons. In section 5 we examine the other dimension of adjustment, namely the intraday timing of consumption.

We first estimate the following regression:

$$\log(q_{at}) = \varepsilon \widehat{log(p_{gt})} + \log(q_{at-1}) + \log(q_{at-7}) + \alpha_a + \alpha_m + \epsilon_{at} \qquad (4)$$

where q_{at} is the address-specific amount of kWh consumed in time period t, ε is the elasticity that we want to estimate. We vary the time horizon from monthly over daily to hourly prices.

Table 3 reports the second stage estimates of household electricity price elasticities, showing how consumption responds to changes in the day-ahead electricity price.[11]. Across all time aggregations, consumption is negatively related to price, with statistically significant effects at the 1 percent level. The sensitivity towards prices however decreases with the frequency of observation. At the monthly level, elasticities are large: a 1 percent increase

[10] First-stage results can be seen in Table A-2

[11] First-stage results are in Table A-2

in price reduces consumption by about 0.81 percent when controlling for address-specific fixed effects. At higher-frequencies, the elasticities remain negative and highly significant, but magnitudes are smaller: daily elasticities are -0.05, while hourly elasticities are around –0.01 to -0.02.

Our estimates are consistent with previous estimates of price elasticities of electricity demand. The meta-study of Labandeira et al. [2017] finds average elasticities for horizons of less than a year of about -0.24, and evidence from Spain and Sweden reports hourly elasticities close to zero (Fabra et al. [2021], Lanot and Vesterberg [2021]). An Australian meta-study further indicates that long-run elasticities range from -0.75 to -0.3, while short-run elasticities - defined as a month or less - fall between -0.47 and -0.026.

This pattern suggests that households adjust to prices by lowering consumption, but also that they react more to average prices than to marginal (in accordance with [Ito, 2014]) - potentially because electricity consumption adjustments are more driven by investments (replacing old appliances with more energy efficient ones) and habit change (always doing laundry in off-peak hours) than attention to hourly prices. This distinction is the subject of Section 5

5 Levels vs Timing

In section 4, we show that households do respond to electricity prices. We now examine the adjustment channels and potential habit formation by splitting the sample period and comparing behavior across price regimes. Households can respond by (i) lowering overall electricity use when average prices are high, (ii) shifting the timing of daily peak consumption across periods, and (iii) further modifying peak demand as the peak–off-peak price differential changes.

5.1 Consumption levels

When faced with high electricity prices, households may reduce overall consumption to contain their bills. Households may adopt persistent changes—for example, upgrading to more efficient appliances or routinely switching off lights in unoccupied rooms. To quantify this response, we estimate the following regression, evaluating the effects of the *during* and *post* periods, as identified in section 3, on households electricity consumption:

$$\log(q_{at}) = \beta_1 \, 1_{during} + \beta_2 \, 1_{post} + \log(q_{at-1}) + + \log(q_{at-7}) + \alpha_i + \alpha_{\mathrm{m}} + \epsilon_{at} \quad (5)$$

where q_{at} is address-specific electricity consumption in kWh on day t. 1_{during} and 1_{post} are indicators for days in the high-price period (*during*) and the subsequent low-price period (*post*), respectively. We control for address and specific month fixed effects, α_d and α_m, as well as lagged consumption to account for autocorrelation (Thams et al. [2022]). Our first coefficient of interest, β_1, measures the change in daily consumption between the *during* and *pre* periods. This will measure the overall decrease in consumption when electricity prices increase. Our second coefficient of interest, β_2, captures the change between *post* and *pre* periods, providing evidence on any habit formation; behaviors that persist even after prices revert to lower levels.

Results are reported in table 4. Households decrease their daily consumption by 3.5% in the *during* period relative to the *pre* suggesting that when prices go up, they adjust the overall level of electricity consumption. What is even more interesting is that this effect persists even into the *post* period where prices are back to lower levels. Therefore any habits households started adopting, regarding their overall consumption, when prices went up did not subside after the spike.

5.2 Static daily readjustments

Alternatively, households may limit bill increases by shifting usage from peak to off-peak times (as defined in Section 3.2) during periods with high electricity prices. To test this, we re-estimate equation 5 with the share of address a's daily consumption occurring during peak hours, $\pi_{at} \in [0, 1]$, as the dependent variable:

$$\pi_{at} = \beta_1 \, 1_{during} + \beta_2 \, 1_{post} + \pi_{at-1} + \pi_{at-7} + \alpha_a + \alpha_{\mathrm{m}} + \epsilon_{at} \tag{6}$$

The last two columns of table 4 report the results of this analysis. As expected, households shift toward intra-day reallocation during high electricity price periods (*during*). Specifically, they move about 0.5% of their daily consumption to off-peak hours when prices are overall high. Importantly, these adjustments persist. Even after prices fall, in the *post* period, off-peak consumption remains elevated relative to the *pre* period, consistent with habit formation.

5.3 Dynamic daily readjustments

The second way households can adjust their daily consumption can be by following daily prices. They can be attentive to daily prices fluctuation and dynamically adjust their consumption during days where peak electricity prices vary more than average daily prices. Even though households may not always be attentive to short-term price fluctuations, attention to prices generally increase in the *during* period, as illustrated by Figure A-3 which shows the surge in electricity price app downloads that peak in the second half of 2022.

To estimate household response to peak vs off-peak prices, we run a specification similar to regression (6), but including time period interactions with day t average peak and off-peak prices, $p_{gt,peak}$ and $p_{gt,offpeak}$, in grid area g. Time period specific variation is accounted for through month–event fixed

effects, α_m.

$$\begin{aligned}\pi_{at} =&\beta_1 \, 1_{during} p_{gt,peak} + \beta_2 \, 1_{post} p_{gt,peak} + \beta_3 \, 1_{during} p_{gt,offpeak} + \\ &\beta_4 \, 1_{post} p_{gt,offpeak} + \pi_{at-1} + \pi_{at-7} + \alpha_i + \alpha_{\mathrm{m}} + \epsilon_{at}\end{aligned} \tag{7}$$

Table 5 reports the results. Overall, households respond to higher peak prices by reducing the share of daily electricity consumption during peak hours by approximately 0.7 percentage points for each one-DKK increase. Conversely, households on average increase the peak share by about 0.8 percentage points when off-peak prices rise by one DKK. These effects, however, are observed only after the price hike. The coefficients are statistically insignificant and close to zero in the *pre* period, but they become larger in magnitude and statistically significant during the high-price period (0.4 percentage point increase per DKK) and even more pronounced in the subsequent period when prices fell again (0.23 percentage point increase per DKK).

Although these effects are statistically significant, they remain economically small, suggesting that households pay limited attention to hourly price variation. [12]

5.4 Contribution of level vs. timing adjustments

One question that is still pending is to what extent the timing and level participate to the overall bill adjustments across periods. Comparing standalone regressions coefficients does not help and we need a way to disentangle the importance of the two effects simultaneously.

To examine this we construct counterfactual bills. We treat the house-

[12] A 0.7 percentage-point reduction in the peak share equals roughly 0.07 kWh of electricity shifted to off-peak hours for a typical 10 kWh household - about 0.1 kWh is required to boil one liter of water in an electric kettle Durand et al. [2022]

hold bill, $\mathcal{B}_i$, as a function of total consumption, C, and the share of peak consumption, s, at times $t \in \{\text{pre}, \text{during}\}$.

$$\mathcal{B}_i(C_t, s_t) = C_t \left(s_t \cdot p^{\text{peak}} + (1 - s_t) \cdot p^{\text{off-peak}} \right)$$

To assess the effect of changing either the timing or level of consumption we calculate the Shapley contributions. Shapley values [Shapley, 1953] provide a way to attribute a total change in outcomes to different underlying drivers. They are defined as the average marginal contribution of each factor across all possible orders in which the factors could be adjusted. In terms of electricity consumption, it could for example be that households would not have adjusted the level of their consumption had they not already adjusted the split. This way to calculate the contribution of each driver ensures an additive, path-independent decomposition, since the parts sum exactly to the total change, and each driver is credited only for what it contributes on average.[13]

In our setting, we hold prices fixed at the average *during* level, and for ease of notation let pre-period values be (C_0, s_0) and during-period values be (C_1, s_1). The Shapley contribution of for example timing is the average of the marginal effects when timing is changed first and when it is changed

[13]Examples of other papers applying Shapley values are Tarashev et al. [2016], who use them to decompose systemic financial risk across banks; Graham et al. [1990], who show that side-payments in collusive bidding correspond to Shapley allocations; Moulin [1992], who demonstrates that Shapley values satisfy equity axioms in fair division with money; and Stole and Zwiebel [1996], who derive wages in intra-firm bargaining that coincide with Shapley payoffs.

second:

$$\Delta_i^{\text{timing}} = \tfrac{1}{2} \underbrace{\mathcal{B}_i(C_0, s_1) - \mathcal{B}_i(C_0, s_0)}_{\text{effect of timing given no change in level}} + \tfrac{1}{2} \underbrace{\mathcal{B}_i(C_1, s_1) - \mathcal{B}_i(C_1, s_0)}_{\text{effect of timing given change in level}}$$

$$\Delta_i^{\text{level}} = \tfrac{1}{2} \underbrace{\mathcal{B}_i(C_1, s_0) - \mathcal{B}_i(C_0, s_0)}_{\text{effect of level given no change in timing}} + \tfrac{1}{2} \underbrace{\mathcal{B}_i(C_1, s_1) - \mathcal{B}_i(C_0, s_1)}_{\text{effect of level given change in timing}}$$

$$\Delta_i^{\text{total}} = \Delta_i^{\text{timing}} + \Delta_i^{\text{level}} = \mathcal{B}_i(C_1, s_1) - \mathcal{B}_i(C_0, s_0).$$

Applying this decomposition to our data shows that for the average household, almost the entire reduction in electricity bills stems from a lower overall level of consumption, while changes in the timing of use play only a very minor role. Quantitatively, about 98% of the behavioral change is attributable to reduced consumption, and only about 2% to shifts in the timing of use. Formally, we compute

$$\frac{\Delta^{\text{level}}}{\Delta^{\text{level}} + \Delta^{\text{timing}}} = \frac{1}{N} \sum_{i=1}^{N} \frac{\Delta_i^{\text{level}}}{\Delta_i^{\text{level}} + \Delta_i^{\text{timing}}} \approx 0.98$$

where Δ_i^{level} and Δ_i^{timing} denote the Shapley contributions of level and timing for household i.

6 Heterogeneity and discussion

On average, we have documented that households react to electricity prices through both a decrease in their overall consumption and a readjustment of daily usage towards off-peak hours. In this section, we make use of the richness of our data to identify any heterogeneity in responses across households.

6.1 Income split

Households with different income can have varying incentives of adjusting their electricity consumption. On the one hand, households facing tighter budget constraints may already be close to their consumption optimum before prices rise, leaving limited scope for further reductions and thus a muted response. On the other hand, lower-income households may react more strongly if liquidity constraints make higher bills particularly salient. Ex ante, the net effect is ambiguous.

We separately estimate level and intra-day adjustments by income quartile in Table 6. Panel A shows that all quartiles reduce their levels of electricity use by similar magnitudes in the *during* period. By contrast, in the *post* period, lower-income households sustain larger reductions relative to higher-income households. Panel B examines intra-day reallocation as a function of prices across income groups. The bottom two quartiles show little evidence of shifting consumption toward off-peak hours when peak prices rise in the *during* period. Intra-day adjustment is concentrated among the highest-income households and persists into the *post* period. Taken together, while lower-income households maintain reduced total usage after prices fall, higher-income households are most responsive in adjusting the timing of their consumption.

6.2 Flexibility

We proxy household flexibility using working status. First, we classify households by working arrangements: (i) *not working*, defined as having at least one unemployed or retired member; (ii) *retired*, where at least one member is retired; (iii) *working*, where at least one member is employed; and (iv) *working remote*, where at least one member is employed in an industry with

the highest incidence of remote work. [14]

Table 7 reports results for level adjustments (Panel A) and intra-day adjustments (Panel B). In terms of levels, all household types reduce consumption by similar magnitudes in the *during* period. In the *post* period, most households sustain these reductions, whereas households with at least one remote worker revert more substantially toward pre-treatment consumption. Regarding intra-day adjustments, most shifting occurs among households with at least one employed member, with little distinction between those able to work remotely and those who are not. A caveat is that industries with higher remote-work prevalence are also associated with higher income and potentially greater familiarity with the electricity market. Since we already control for address fixed effects, incorporating additional quasi-time-invariant characteristics would not improve identification. Overall, we find that households with members more often at home do not systematically readjust their electricity consumption.

7 Conclusion

This study documents how households respond to electricity price fluctuations in Denmark. We start by measuring households' bills and consumptions' sensitivities to electricity prices. We later show that when prices rise, households adjust along two dimensions: by reducing their overall level of electricity use and by shifting consumption across the day. Our evidence demonstrates that the dominant channel is the former: nearly all of the reduction in electricity bills (98%) stems from lower total consumption, while intra-day reallocations play only a minor role. Strikingly, these level adjustments persist even after prices fall back, consistent with households investing in more energy-efficient appliances or adopting new routines and habits that

[14] Specifically, the top three industries identified by Statistics Denmark in 2024 as having the largest shares of remote workers: finance and research (79%), information and communication (76.9%), and public administration and teaching (63.4%) (Danmarks Statistik).

reduce their electricity demand in the long run. These findings underscore the importance of price signals not only as short-term incentives but also as mechanisms for lasting behavioral change.

Heterogeneity analysis highlights how households with higher income are more likely to adopt daily readjustment of consumption towards off-peak hours while not necessarily because of more flexibility in their schedules. On the other hand, lower income households decrease their overall consumption and maintain low levels even when prices revert.

For policymakers, the results suggest that maintaining consistent peak-to–off-peak price differences can effectively smooth household electricity demand across the day, while hour-by-hour prices that mirror short-run supply fluctuations are far less effective in shifting consumption within the day and can further create inequalities across households with different income.

References

Fatima Zahra Filali Adib, Steffen Andersen, Dmitry Chebotarev, and Kasper Meisner Nielsen. Rich and responsible: Is esg a luxury good? *Working Paper*, 2024.

Per Andersen and Alexander M. Dietrich. Price response in residential electricity demand: Evidence from danish smart meter data. Working Paper Working Paper No. 214, Danmarks Nationalbank, Copenhagen, August 2025.

Thomas Møller Andersen, Philipp A. Gunkel, Henrik J. Jacobsen, and Lena Kitzing. Household characteristics and electricity consumption: Evidence from danish smart-meter data. *Energy Economics*, 100:105371, 2021.

Thomas Møller Andersen, Philipp A. Gunkel, Jonas Bjerregaard, and Henrik J. Jacobsen. Electricity consumption patterns and price responsiveness during the european energy crisis. *Energy*, 290:130441, 2024.

A. Lans Bovenberg and Ruud A. de Mooij. Environmental levies and distortionary taxation. *The American Economic Review*, 84(4):1085–1089, 1994.

Raphael Calel and Antoine Dechezleprêtre. Environmental policy and directed technological change: Evidence from the european carbon market. *The Review of Economics and Statistics*, 98(1):173–191, 2016. doi: 10.1162/REST_a_00470.

Danish Energy Agency. Energy statistics 2022. Technical report, Danish Ministry of Climate, Energy and Utilities, 2022. URL `https://ens.dk/sites/ens.dk/files/Statistik/energy_statistic_2022.pdf`.

Danish Ministry of Energy, Utilities and Climate. Denmark: Energy strategy for 2050 – from coal, oil and gas to green energy. Technical report, Danish Government, Copenhagen, Denmark, 2011.

Danmarks Statistik. Hjemmearbejde er på sit højeste siden covid-19. URL `https://www.dst.dk/da/Statistik/nyheder-analyser-publ/nyt/NytHtml?cid=49082`. Nyt fra Danmarks Statistik, nr. 239.

Lucas W. Davis and Paul J. Gertler. Contribution of air conditioning adoption to future energy use under global warming. *Proceedings of the National Academy of Sciences*, 112(19):5962–5967, 2015. doi: 10.1073/pnas.1423558112.

Tatyana Deryugina, Alexander MacKay, and James Reif. The long-run dynamics of electricity demand: Evidence from municipal aggregation. *American Economic Journal: Applied Economics*, 12(1):86–114, 2020. doi: 10.1257/app.20180136.

Valeria Di Cosmo, Seán Lyons, and Anne Nolan. Demand response with smart meters: Evidence from irish households. *The Energy Journal*, 35(4): 117–134, 2014.

Robin Döttling and Magdalena RolaJanicka. Too levered for pigou: Carbon pricing, financial constraints, and leverage regulation. *Journal of Financial Economics*, 172:104105, 2025. doi: 10.1016/j.jfineco.2025.104105.

A. Durand et al. Electric kettles: An assessment of energy-saving potential. *Sustainability*, 14(20), 2022. doi: 10.3390/su142012963.

Energistyrelsen. Data, tables, statistics and maps energy statistics 2023. 2023.

Natalia Fabra, David Rapson, Mar Reguant, and Jingjing Wang. Real-time pricing and electricity consumption: Evidence from spain. *American Economic Review: Papers & Proceedings*, 111:315–319, 2021.

Ahmad Faruqui and Sanem Sergici. Household response to dynamic pricing of electricity: a survey of 15 experiments. *Journal of Regulatory Economic*, 38:193–225, 2010.

Miguel A. Ferreira, Pedro A. Pires, Margarida Soares, and Andre Trindade. Income shocks and demand for sustainable products. *Working Paper*, 2024.

Daniel A Graham, Robert C Marshall, and Jean-Francois Richard. Differential payments within a bidder coalition and the shapley value. *American Economic Review*, 80(3):493–510, 1990.

Tianqi Guo. Peak pricing and spillovers in residential electricity demand. *Journal of Environmental Economics and Management*, 121:102812, 2023.

Pablo Rosado Hannah Ritchie and Max Roser. Breakdown of carbon dioxide, methane and nitrous oxide emissions by sector, 2024. URL https://ourworldindata.org/emissions-by-sector/.

Michael Bilde Hinrichsen. Elkunder flokkes om variable priser, November 2024. URL https://greenpowerdenmark.dk/nyheder/elkunder-flokkes-om-variable-priser. Accessed online.

Lion Hirth, Tarun M. Khanna, and Oliver Ruhnau. How aggregate electricity demand responds to hourly wholesale price fluctuations. *Energy Economics*, 135:107652, 2024. doi: 10.1016/j.eneco.2024.107652.

Takanori Ida, Koichiro Murakami, and Makoto Tanaka. Can information provision affect electricity consumption? evidence from japanese field experiments. *Economics of Energy & Environmental Policy*, 4(1):113–130, 2015.

International Energy Agency. *End-Use Energy Efficiency*. IEA, Paris, 2020. URL https://www.iea.org/reports/end-use-energy-efficiency.

International Energy Agency. *Net Zero by 2050: A Roadmap for the Global Energy Sector*. IEA, Paris, 2021. URL https://www.iea.org/reports/net-zero-by-2050.

Koichiro Ito. Do consumers respond to marginal or average price? evidence from nonlinear electricity pricing. *American Economic Review*, 104(2): 537–563, February 2014. doi: 10.1257/aer.104.2.537. URL https://www.aeaweb.org/articles?id=10.1257/aer.104.2.537.

Katrina Jessoe and David Rapson. Knowledge is (less) power: Experimental evidence from residential energy use. *American Economic Review*, 104(4): 1417–1438, 2014.

Xavier Labandeira, José M. Labeaga, and Xiral López-Otero. A meta-analysis on the price elasticity of energy demand. *Energy Policy*, 102: 549–568, 2017.

Gauthier Lanot and Mattias Vesterberg. The effects of demand charges on household electricity use: Evidence from sweden. *Energy Economics*, 95: 105004, 2021.

Fanchao Liao, Erik Molin, and Bert van Wee. Consumer preferences for electric vehicles: a literature review. *Transport Reviews*, 37(3):252–275, 2017. doi: 10.1080/01441647.2016.1230794. URL https://doi.org/10.1080/01441647.2016.1230794.

Gilbert E. Metcalf. An informational nudge to shave peak demand. Technical Report Working Paper No. 34089, National Bureau of Economic Research, August 2025. URL https://www.nber.org/papers/w34089.

Hervé Moulin. An application of the shapley value to fair division with money. *Econometrica*, 60(6):1331–1349, 1992.

Cecil Arthur Pigou. *The Economics of Welfare*. MacMillan and Co., 1920.

Peter C. Reiss and Matthew W. White. Household electricity demand, revisited. *The Review of Economic Studies*, 72(3):853–883, 2005. doi: 10.1093/restud/1557538. URL https://academic.oup.com/restud/article/72/3/853/1557538.

Arno M. Riedl and Paul Smeets. Why do investors hold socially responsible mutual funds? *Journal of Finance*, 72(6):2505–2550, 2017. doi: 10.1111/jofi.12547. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12547.

Tim Schittekatte, Deepak Mallapragada, Paul L. Joskow, and Richard Schmalensee. Electricity retail rate design in a decarbonized economy: An analysis of time-of-use and critical peak pricing. NBER Working Paper 30560, National Bureau of Economic Research, 2022. URL https://www.nber.org/papers/w30560.

Lloyd S Shapley. A value for n-person games. *Contributions to the Theory of Games*, 2(28):307–317, 1953.

Lars A Stole and Jeffrey Zwiebel. Intra-firm bargaining under non-binding contracts. *Review of Economic Studies*, 63(3):375–410, 1996.

Nikola A Tarashev, Kostas Tsatsaronis, and Claudio Borio. Risk attribution using the shapley value: Methodology and policy applications. *Review of Finance*, 20(3):1189–1213, 2016.

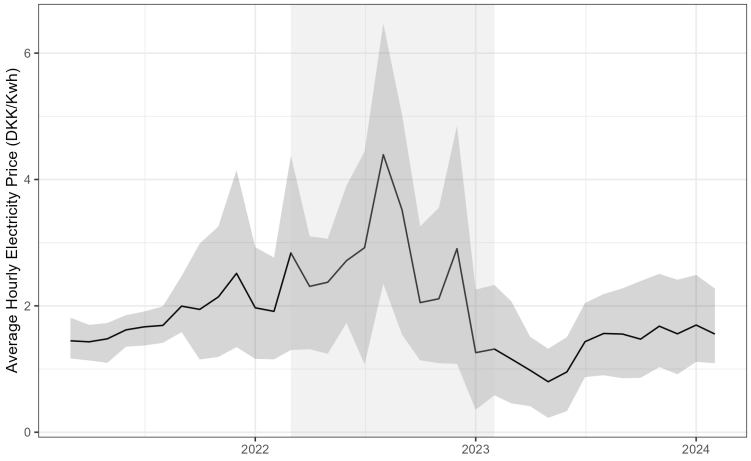
Nikolaj Thams, Rikke Søndergaard, Sebastian Weichwald, and Jonas Peters. Identifying causal effects using instrumental time series: Nuisance iv and correcting for the past, 2022. URL https://arxiv.org/abs/2203.06056. v3 (2024-07-19).

Silvana Tiedemann, Raffaele Sgarlato, and Lion Hirth. Price elasticity of electricity demand: Using instrumental variable regressions to address endogeneity and autocorrelation of high-frequency time series, 2023. URL https://arxiv.org/abs/2306.12863.

Frank A. Wolak. Do residential customers respond to hourly prices? evidence from a dynamic pricing experiment. *American Economic Review: Papers & Proceedings*, 101(3):83–87, 2011.

Figure 1: **Electricity prices**
The figures show average monthly (panel a) and hourly (panel b) electricity prices in DKK/KWh

(a) **Average monthly electricity price**



(b) **Average hourly electricity price**

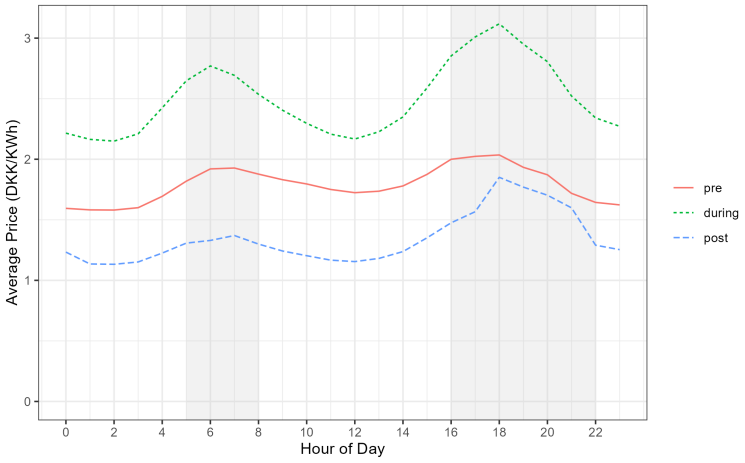
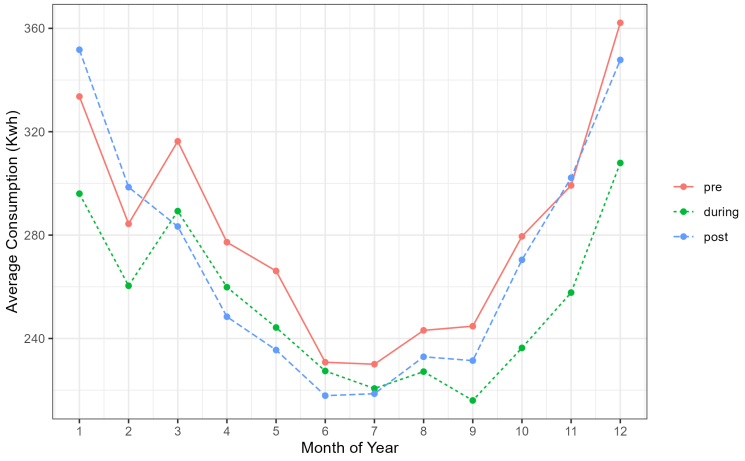


Figure 2: **Household electricity consumption**
The figures show average monthly (panel a) and hourly (panel b) electricity consumption by Danish households

(a) **Average monthly electricity consumption**



(b) **Average hourly electricity consumption**

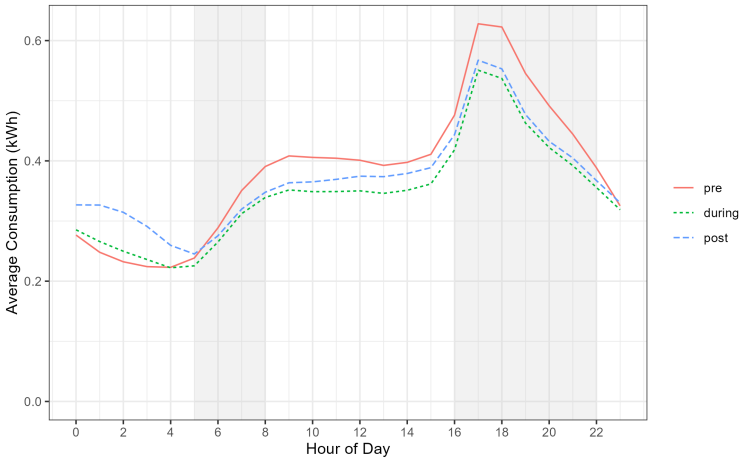


Table 1: Summary Statistics

This table shows mean and standard deviations of household and address data. Panel A shows daily peak and off-peak electricity price and consumption, as well as wind forecast for our random sample of meters in houses. Units of observations is household-day. Panel B contains household characteristics for our random sample. Unit of observations is household-year.

Panel A: Electricity Consumption

	(1)
Sample	
Consumption (kWh)	8.81
	(8.01)
Wind forecast day-ahead (kWh)	1,096,225.10
	(938,637.78)
Total price per kWh (DKK)	1.92
	(0.87)
Spot price (DKK)	0.97
	(0.79)
Tax (DKK)	0.69
	(0.31)
Tariff (DKK)	0.26
	(0.12)
Observations	10,515,864

Panel B: Household Characteristics

Sample	(1)
Adults	1.61
	(0.49)
Nb kids	0.57
	(0.94)
Have kids	0.32
	(0.46)
Age	59.11
	(16.38)
Female	0.55
	(0.31)
Income	667,472.88
	(467,639.26)
Electric Heating	0.02
	(0.14)
Electric Car	0.01
	(0.08)
Retired	0.43
	(0.49)
Unemployed	0.09
	(0.28)
Self-employed	0.04
	(0.20)
Working remote	0.28
	(0.45)
Observations	28,874

Table 2: Household daily electricity bill response to price

This table reports IV estimates from a 2SLS regression of the log of household daily electricity bill on the log of electricity price, using the day-ahead wind forecast as an instrument for price. Regression is shown in Equation (3). The daily bill, bill_{it}, is constructed by aggregating hourly consumption of household i multiplied by the corresponding hourly price. Prices and wind forecasts are averaged to the daily level within grid area g. The null hypothesis $\beta = 1$ is rejected at conventional levels ($t = -51.22$ and $t = -49.49$ for columns (1) and (2)). Standard errors clustered at the household level are shown in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)
$\log(\widehat{Price})$	0.946***	0.940***
	(0.001)	(0.001)
Municipality	X	
Month-Event	X	X
Address ID		X
Lagged Consumption	X	X
Observations	10,447,212	10,447,212
R^2	0.80845	0.82251
F-test (1st stage), log(Price)	3,730,177.7	3,793,240.9

Table 3: Price elasticities

This table reports IV estimates from 2SLS regressions of log household electricity consumption on log electricity price, using the day-ahead wind forecast as an instrument for price. Regression is shown in Equation (2). Dependent variable consumption$_{it}$ is aggregated at the monthly, daily, or hourly level. Prices and wind forecasts are averaged at the corresponding time scale within grid area g. Standard errors clustered at the address level are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Monthly		Daily		Hourly	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\widehat{Price})$	-0.238***	-0.805***	-0.046***	-0.052***	-0.010***	-0.017***
	(0.014)	(0.020)	(0.001)	(0.001)	(0.0004)	(0.0005)
Municipality	X		X		X	
Event	X	X				
Address ID		X		X		X
Month-Event			X	X	X	X
Lagged Consumption	X	X	X	X	X	X
Observations	335,971	335,971	10,447,964	10,447,964	250,394,622	250,394,622
R^2	0.86283	0.75413	0.74964	0.76789	0.64716	0.65752
F-test (1st stage), log(Price)	4,149.4	3,894.5	3,726,302.4	3,789,442.5	45,707,872.3	46,536,717.1

Table 4: Level adjustment

This table reports estimates from regressions of log household daily electricity consumption on indicators for the price shock period. Regression for columns 1 and 2 is shown in Equation (5) and for columns 3 and 4 in Equation (6). The first coefficient captures the consumption change during the price event relative to the pre-period, and the second captures the change in the post-period. Standard errors are clustered at the household level. Standard errors clustered at the address level are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Log(Consumption)		$\frac{\text{Peak Consumption}}{\text{Total Consumption}}$	
	(1)	(2)	(3)	(4)
1_{during}	-0.010***	-0.035***	-0.003***	-0.005***
	(0.0002)	(0.0007)	(0.0002)	(0.0002)
1_{post}	-0.007***	-0.030***	-0.006***	-0.008***
	(0.0003)	(0.0009)	(0.0002)	(0.0003)
Municipality	X		X	
Month	X	X	X	X
Address ID		X		X
Lagged Consumption	X	X	X	X
Observations	10,447,964	10,447,964	10,380,444	10,380,444
R^2	0.74946	0.76751	0.13771	0.19334

Table 5: Intra-day allocation of electricity consumption

This table reports IV estimates from 2SLS regressions of the household share of daily electricity consumption in peak hours on electricity prices, as shown in Equation (7). The dependent variable is the fraction of household i's electricity consumption that occurs during peak hours (peak consumption divided by total daily consumption). $\widehat{Price}^{Peak}$ is the daily average hourly electricity price during peak hours in grid area g, and $\widehat{Price}^{Offpeak}$ is during off-peak hours. Both price measures are instrumented using the day-ahead wind forecast. 1_{during} is an indicator for the price shock period, and 1_{post} is an indicator for the post-period, both relative to the pre-period baseline. Standard errors clustered at the household level are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)
$\widehat{Price}$ (Peak)	-0.006***	-0.007***	-0.001	-0.0002
	(0.0006)	(0.0006)	(0.001)	(0.001)
$\widehat{Price}$(Peak) $\times$ 1_{during}			-0.004***	-0.005***
			(0.001)	(0.001)
$\widehat{Price}$(Peak) $\times$ 1_{post}			-0.010***	-0.013***
			(0.002)	(0.002)
$\widehat{Price}$(Off-Peak) $\times$ 1_{during}			0.010***	0.012***
			(0.002)	(0.002)
$\widehat{Price}$(Off-Peak) $\times$ 1_{post}			0.019***	0.023***
			(0.003)	(0.003)
$\widehat{Price}$ (Off-peak)	0.008***	0.008***	-0.002	-0.004**
	(0.0007)	(0.0007)	(0.002)	(0.002)
Municipality	X		X	
Month-Event	X	X	X	X
Address ID		X		X
Lagged Consumption	X	X	X	X
Observations	10,380,444	10,380,444	10,380,444	10,380,444
R^2	0.13786	0.19352	0.13780	0.19343
F-test (1st stage), $\widehat{Price}$ (Off-peak)	1,292,582.9	1,303,962.9	467,074.7	471,243.5
F-test (1st stage), $\widehat{Price}$ (Peak)	1,345,809.6	1,359,424.7	480,378.5	485,285.7
F-test (1st stage), $\widehat{Price}$(Peak) $\times$ 1_{during}			349,767.9	351,035.9
F-test (1st stage), $\widehat{Price}$(Peak) $\times$ 1_{post}			957,217.4	970,608.6
F-test (1st stage), $\widehat{Price}$(Off-Peak) $\times$ 1_{during}			310,574.0	311,557.9
F-test (1st stage), $\widehat{Price}$(Off-Peak) $\times$ 1_{post}			689,753.4	698,998.8

Table 6: Heterogeneous consumption responses by income quartile

Panel A reports estimates from regressions of log daily household electricity consumption on indicators for the price shock period, as shown in Equation (6). The dependent variable is log(consumption) of household i at the daily frequency. The coefficient captures the consumption change relative to the pre-period. The row labeled *during – post (t-stat)* reports the test statistic for the null hypothesis that the consumption response during the price event differs significantly from the response in the post-period. Panel B reports IV estimates from 2SLS regressions of the household share of daily consumption in peak hours on electricity prices, following Equation (7). In both panels, column (1) uses all households, while columns (2)–(5) restrict the sample to households in the 0–25%, 25–50%, 50–75%, and 75–100% income quartiles, respectively. Standard errors are clustered at the household level. Standard errors clustered at the address level are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

(a) Panel A: Level

	All (1)	$0-25\%$ (2)	$25-50\%$ (3)	$50-75\%$ (4)	$75-100\%$ (5)
1_{during}	-0.035***	-0.030***	-0.040***	-0.038***	-0.035***
	(0.0007)	(0.001)	(0.001)	(0.002)	(0.002)
1_{post}	-0.030***	-0.035***	-0.039***	-0.028***	-0.012***
	(0.0009)	(0.002)	(0.002)	(0.002)	(0.002)
during - post (t-stat)	-7.7	4.102	-0.718	-7.466	-14.398
Address ID	X	X	X	X	X
Month	X	X	X	X	X
Lagged Consumption	X	X	X	X	X
Observations	10,447,964	2,637,767	2,626,836	2,614,745	2,568,616
R^2	0.76751	0.78593	0.73003	0.69101	0.64609

(b) Panel B: Intra-day adjustment

	All (1)	$0-25\%$ (2)	$25-50\%$ (3)	$50-75\%$ (4)	$75-100\%$ (5)
$\widehat{Price}$ (Peak)	-0.0002	-0.008***	-0.001	0.004*	0.007***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$\widehat{Price}$(Peak) $\times 1_{during}$	-0.005***	0.001	-0.002	-0.011***	-0.012***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
$\widehat{Price}$(Peak) $\times 1_{post}$	-0.013***	0.003	-0.007**	-0.025***	-0.028***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
$\widehat{Price}$(Off-Peak) $\times 1_{during}$	0.012***	0.001	0.008**	0.020***	0.028***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)
$\widehat{Price}$(Off-Peak) $\times 1_{post}$	0.023***	0.002	0.014***	0.039***	0.052***
	(0.003)	(0.005)	(0.005)	(0.006)	(0.007)
$\widehat{Price}$ (Off-peak)	-0.004**	0.007**	-0.002	-0.012***	-0.019***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Address ID	X	X	X	X	X
Month-Event	X	X	X	X	X
Lagged Consumption	X	X	X	X	X
Observations	10,380,444	2,619,370	2,610,036	2,598,724	2,552,314
R^2	0.19343	0.18325	0.18183	0.19943	0.20416
F-test (1st stage), $\widehat{Price}$ (Off-peak)	471,243.5	127,001.2	124,811.5	121,392.7	104,265.6
F-test (1st stage), $\widehat{Price}$ (Peak)	485,285.7	130,768.1	128,756.7	125,558.9	108,398.3
F-test (1st stage), $\widehat{Price}$(Peak) $\times 1_{during}$	351,035.9	98,075.6	96,317.9	91,658.0	75,436.9
F-test (1st stage), $\widehat{Price}$(Peak) $\times 1_{post}$	970,608.6	247,024.4	247,631.0	245,834.7	232,187.7
F-test (1st stage), $\widehat{Price}$(Off-Peak) $\times 1_{during}$	311,557.9	87,682.7	86,016.5	81,636.7	65,802.5
F-test (1st stage), $\widehat{Price}$(Off-Peak) $\times 1_{post}$	698,998.8	187,148.4	190,023.3	185,475.1	168,020.7

Table 7: Heterogeneous consumption responses by flexibility

Panel A reports estimates from regressions of log daily household electricity consumption on indicators for the price shock period, as shown in Equation (6). The dependent variable is log(consumption) of household i at the daily frequency. The coefficient captures the consumption change relative to the pre-period. The row labeled *during – post (t-stat)* reports the test statistic for the null hypothesis that the consumption response during the price event differs significantly from the response in the post-period. Panel B reports IV estimates from 2SLS regressions of the household share of daily consumption in peak hours on electricity prices, following Equation (7). In both panels, column (1) uses all households, while columns (2)–(5) restrict the sample to households where at least one member is not working, retired, working, or working in a sector where remote work is very likely, respectively. Standard errors are clustered at the household level. Standard errors clustered at the address level are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

(a) Panel A: Level

	All (1)	Not working (2)	Retired (3)	Working (4)	Working remote (5)
1_{during}	-0.035***	-0.038***	-0.035***	-0.035***	-0.033***
	(0.0007)	(0.003)	(0.001)	(0.001)	(0.002)
1_{post}	-0.030***	-0.030***	-0.038***	-0.023***	-0.014***
	(0.0009)	(0.004)	(0.001)	(0.002)	(0.003)
during - post (t-stat)	-7.7	-3.142	4.154	-10.235	-9.713
Address ID	X	X	X	X	X
Month	X	X	X	X	X
Lagged Consumption	X	X	X	X	X
Observations	10,447,964	688,486	4,462,927	3,621,374	1,640,961
R^2	0.76751	0.75125	0.79387	0.73879	0.68970

(b) Panel B: Intra-day adjustment

	All (1)	Not working (2)	Retired (3)	Working (4)	Working remote (5)
$\widehat{Price}$ (Peak)	-0.0002	-0.005	-0.008***	0.008***	0.007**
	(0.001)	(0.004)	(0.002)	(0.002)	(0.003)
$\widehat{Price}$(Peak) × 1_{during}	-0.005***	0.003	0.003*	-0.015***	-0.012***
	(0.001)	(0.005)	(0.002)	(0.002)	(0.004)
$\widehat{Price}$(Peak) × 1_{post}	-0.013***	-0.012*	0.003	-0.025***	-0.027***
	(0.002)	(0.007)	(0.002)	(0.003)	(0.005)
$\widehat{Price}$(Off-Peak) × 1_{during}	0.012***	-0.0008	-0.003	0.027***	0.024***
	(0.002)	(0.007)	(0.003)	(0.004)	(0.006)
$\widehat{Price}$(Off-Peak) × 1_{post}	0.023***	0.016	0.0004	0.042***	0.045***
	(0.003)	(0.010)	(0.004)	(0.005)	(0.008)
$\widehat{Price}$ (Off-peak)	-0.004**	0.005	0.010***	-0.018***	-0.017***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.005)
Address ID	X	X	X	X	X
Month-Event	X	X	X	X	X
Lagged Consumption	X	X	X	X	X
Observations	10,380,444	683,908	4,435,920	3,596,202	1,630,540
R^2	0.19343	0.15919	0.17251	0.20201	0.19449
F-test (1st stage), $\widehat{Price}$ (Off-peak)	471,243.5	33,383.5	200,876.6	169,757.8	68,585.3
F-test (1st stage), $\widehat{Price}$ (Peak)	485,285.7	34,288.0	206,596.9	174,825.2	71,010.0
F-test (1st stage), $\widehat{Price}$(Peak) × 1_{during}	351,035.9	25,625.8	151,612.9	127,023.8	49,501.0
F-test (1st stage), $\widehat{Price}$(Peak) × 1_{post}	970,608.6	66,096.5	415,076.9	336,988.1	150,563.2
F-test (1st stage), $\widehat{Price}$(Off-Peak) × 1_{during}	311,557.9	23,107.0	134,748.3	113,109.3	43,514.2
F-test (1st stage), $\widehat{Price}$(Off-Peak) × 1_{post}	698,998.8	50,871.0	298,876.7	251,558.3	108,926.1

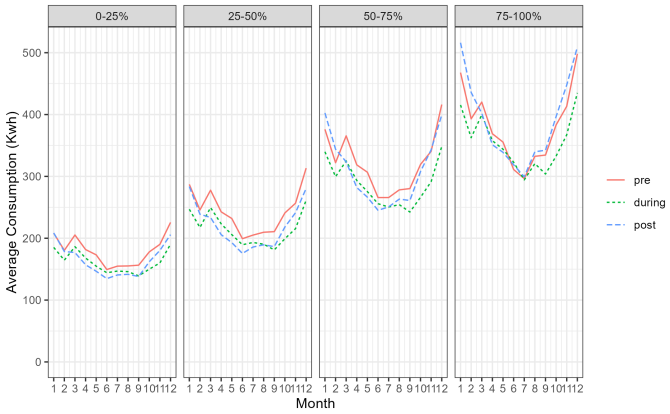
Appendix

A-1 Additional tables and figures

Figure A-1: **Household electricity consumption by income**

These figures plot the evolution of monthly (panel a) and hourly (panel b) household electricity consumption, by income quartiles and time period

(a) **Average monthly electricity**



(b) **Average hourly electricity**

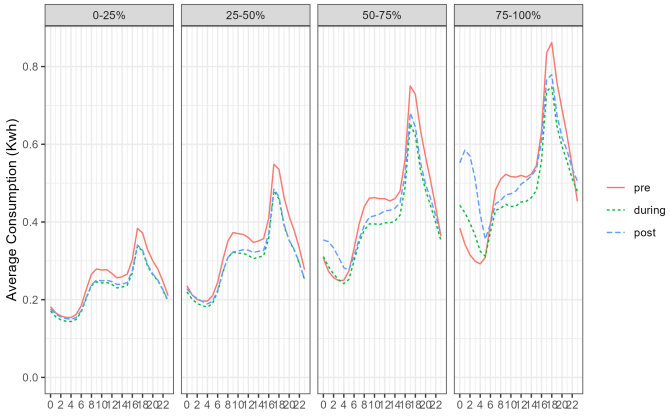


Figure A-2: **Decomposed Hourly Price**

The figure plots the components of the total electricity price: national tax, local tariff, and the spot price.

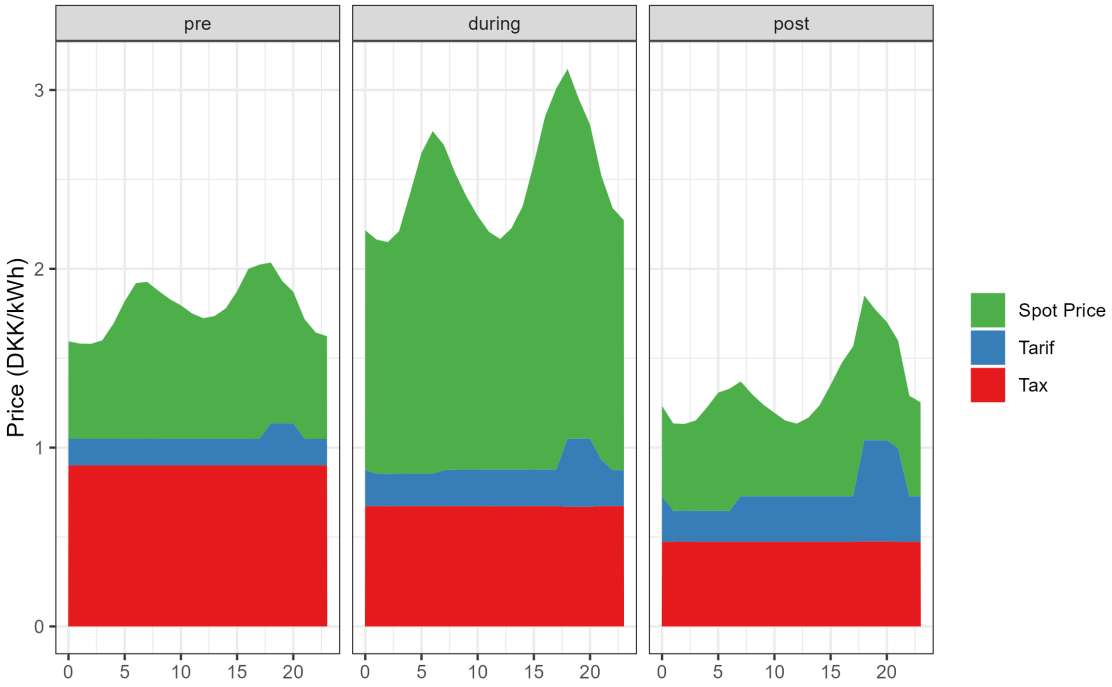


Figure A-3: Price app downloads

This figure shows monthly downloads of the app Watts®, indexed by January 2018. Watts® is a Danish company that provide sustainable energy solutions to Danish households (and firms). A core product is the Watts® Homegrid Controller, an intelligent system that automatically manages energy flows between solar panels, batteries, and the grid, optimizing for maximum savings and efficiency, but the company also provides a free app, which provides 24-hour advance electricity price forecasts as well as detailed insights into energy consumption and production. We are gratefull to Watts® for providing the data.

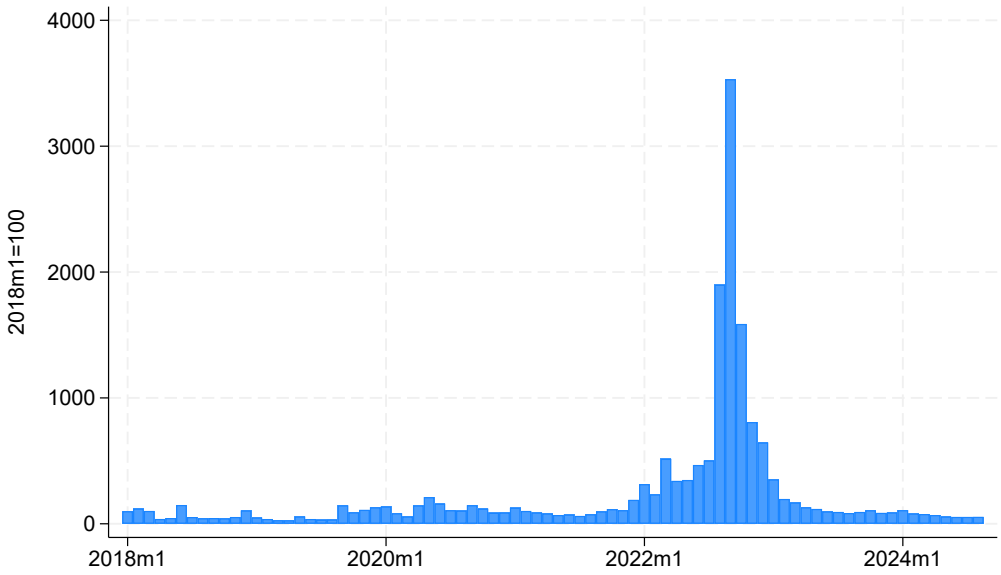


Table A-1: Data Filtering - Houses

	Household-years	*Households*	*Addresses*
All households	5,636,626	2,259,362	
- Non-standard households[a]	963,558	467,785	
- Household do not exists 2022	255,781	201,389	
- Changed family composition 2022	226,992	74,626	
- Moved 2022	198,999	76,598	
- Unclear meter address	30	11	
- Not regular housing[b]	564,878	230,987	
- Income filter[c]	66,350	11,183	
Filtered households	4,420,024	1,224,308	
- No detected meter	71,883	20,529	
- More than two meters	279,446	74,267	
- Inconsistent reporting 2022	11,008	3,489	
Filtered data	4,057,687	1,126,023	
Sample[d]			12,500
	Household-year / Household-day	*Households*	*Addresses*
Sample linked to electricy data[e]	38,390 / 10,515,864	10,334	8,871

a) Children under 18 or multi-family homes
b) Home is not house (detaached or attached) or apartment
c) No income information, top and bottom 1 percent, income below 100K DKK
d) 12.500 meters in the the filtered data in 2022

Table A-2: First stage regression - wind forecast

This table reports first-stage regressions of log(Price) on log(Wind). Second stage results are shown in Table (3). Columns (1)–(2) use monthly data, (3)–(4) use daily data, and (5)–(6) use hourly data. Standards errors are clustered on address level. Parentheses contain p-values and stars show significance level. *** is 1%, ** 5%, and * 10% significance level.

	log(Price)					
	Monthly		Daily		Hourly	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Wind)	-0.087***	-0.085***	-0.145***	-0.145***	-0.128***	-0.129***
	(0.0004)	(0.0006)	(6.86×10^{-5})	(6.83×10^{-5})	(7.17×10^{-5})	(7.2×10^{-5})
Observations	335,971	335,971	10,447,964	10,447,964	250,394,622	250,394,622
R^2	0.46908	0.47328	0.79859	0.80192	0.64168	0.64687
F-test (1st stage)	4,149.4	3,894.5	3,726,302.4	3,789,442.5	45,707,872.3	46,536,717.1
Municipality	X		X		X	
Event	X	X				
Address ID		X		X		X
Month-Event			X	X	X	X

Table A-3: First stage regression - wind forecast

This table reports first-stage regressions corresponding to the 2SLS estimates in Table 5. The dependent variables are the daily average peak and off-peak electricity prices, instrumented using the day-ahead wind forecast interacted with indicators for the *during* and *post* periods. All regressions include grid-area and month-event fixed effects. Standard errors are clustered at the meter level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	$\widehat{Price}$ (Off-peak) (1)	$\widehat{Price}$ (Peak) (2)	$\widehat{Price}$ (Off-peak) (3)	$\widehat{Price}$ (Peak) (4)	$\widehat{Price}$ (Off-peak) (5)	$\widehat{Price}$ (Peak) (6)	$\widehat{Price}$(Peak) × 1_{during} (7)	$\widehat{Price}$(Peak) × 1_{post} (8)	$\widehat{Price}$(Off-Peak) × 1_{during} (9)	$\widehat{Price}$(Off-Peak) × 1_{post} (10)	$\widehat{Price}$ (Off-peak) (11)	$\widehat{Price}$ (Peak) (12)	$\widehat{Price}$(Peak) × 1_{during} (13)	$\widehat{Price}$(Peak) × 1_{post} (14)	$\widehat{Price}$(Off-Peak) × 1_{during} (15)	$\widehat{Price}$(Off-Peak) × 1_{post} (16)
wind_offpeak	$-2.18 \times 10^{-7***}$	$-2.25 \times 10^{-8***}$	$-2.18 \times 10^{-7***}$	$-2.25 \times 10^{-8***}$	$-1.45 \times 10^{-7***}$	$5.99 \times 10^{-8***}$	$-4.1 \times 10^{-8***}$	$-7.89 \times 10^{-9***}$	$-4.19 \times 10^{-8***}$	$-1.82 \times 10^{-8***}$	$-1.45 \times 10^{-7***}$	$5.96 \times 10^{-8***}$	$-4.11 \times 10^{-8***}$	$-7.87 \times 10^{-9***}$	$-4.2 \times 10^{-8***}$	$-1.81 \times 10^{-8***}$
	(2.75 × 10^-11)	(2.15 × 10^-9)	(2.75 × 10^-10)	(2.17 × 10^-10)	(3.76 × 10^-9)	(2.53 × 10^-10)	(3.95 × 10^-9)	(1.77 × 10^-10)	(3.84 × 10^-10)	(2.22 × 10^-10)	(3.79 × 10^-9)	(2.57 × 10^-10)	(3.97 × 10^-9)	(1.77 × 10^-10)	(3.87 × 10^-10)	(2.22 × 10^-10)
wind_peak	$-5.78 \times 10^{-8***}$	$-2.98 \times 10^{-7***}$	$-5.79 \times 10^{-8***}$	$-2.98 \times 10^{-7***}$	$-9.2 \times 10^{-8***}$	$-3.22 \times 10^{-7***}$	$-1.18 \times 10^{-8***}$	$-2.23 \times 10^{-9***}$	$-1.22 \times 10^{-8***}$	$-5.32 \times 10^{-9***}$	$-9.19 \times 10^{-8***}$	$-3.22 \times 10^{-7***}$	$-1.18 \times 10^{-8***}$	$-2.21 \times 10^{-9***}$	$-1.21 \times 10^{-8***}$	$-5.28 \times 10^{-9***}$
	(2.47 × 10^-11)	(7.75 × 10^-9)	(2.48 × 10^-10)	(7.77 × 10^-10)	(2 × 10^-10)	(6.58 × 10^-10)	(8.95 × 10^-11)	(4.79 × 10^-11)	(7.58 × 10^-11)	(4.86 × 10^-11)	(2.04 × 10^-10)	(6.6 × 10^-10)	(8.56 × 10^-11)	(4.85 × 10^-11)	(9.07 × 10^-11)	(4.94 × 10^-11)
wind_peak × 1_{during}					$6.18 \times 10^{-9***}$	$-2.96 \times 10^{-8***}$	$-3.3 \times 10^{-7***}$	$-7.49 \times 10^{-10***}$	$-4.58 \times 10^{-9***}$	$-1.59 \times 10^{-9***}$	$6.16 \times 10^{-9***}$	$-2.98 \times 10^{-8***}$	$-3.3 \times 10^{-7***}$	$-7.71 \times 10^{-10***}$	$-4.69 \times 10^{-9***}$	$-1.61 \times 10^{-9***}$
					(4.28 × 10^-10)	(8.65 × 10^-10)	(1.33 × 10^-7)	(2.35 × 10^-11)	(4.31 × 10^-10)	(3.54 × 10^-11)	(4.45 × 10^-10)	(8.66 × 10^-10)	(1.33 × 10^-7)	(2.57 × 10^-11)	(4.32 × 10^-10)	(3.65 × 10^-11)
wind_peak × 1_{post}					$4.9 \times 10^{-8***}$	$8.6 \times 10^{-8***}$	$1.36 \times 10^{-6***}$	$-2.37 \times 10^{-7***}$	$1.39 \times 10^{-8***}$	$-4.02 \times 10^{-8***}$	$4.86 \times 10^{-8***}$	$8.57 \times 10^{-8***}$	$1.34 \times 10^{-6***}$	$-2.37 \times 10^{-7***}$	$1.37 \times 10^{-8***}$	$-4.03 \times 10^{-8***}$
					(1.47 × 10^-10)	(1.9 × 10^-10)	(1.22 × 10^-10)	(6.99 × 10^-10)	(1.18 × 10^-10)	(1.12 × 10^-10)	(1.58 × 10^-10)	(2 × 10^-10)	(1.28 × 10^-10)	(6.99 × 10^-10)	(1.24 × 10^-10)	(1.12 × 10^-10)
wind_offpeak × 1_{during}					$-1.74 \times 10^{-7***}$	$-1.07 \times 10^{-7***}$	$1.76 \times 10^{-6***}$	$7.52 \times 10^{-9***}$	$-2.45 \times 10^{-7***}$	$1.57 \times 10^{-8***}$	$-1.74 \times 10^{-7***}$	$-1.07 \times 10^{-7***}$	$1.77 \times 10^{-6***}$	$7.44 \times 10^{-9***}$	$-2.45 \times 10^{-7***}$	$1.5 \times 10^{-8***}$
					(7.71 × 10^-10)	(1.13 × 10^-9)	(1.88 × 10^-9)	(2.35 × 10^-11)	(1.09 × 10^-9)	(3.27 × 10^-11)	(7.73 × 10^-10)	(1.13 × 10^-9)	(1.88 × 10^-9)	(2.64 × 10^-11)	(1.09 × 10^-9)	(3.53 × 10^-11)
wind_offpeak × 1_{post}					$-4.49 \times 10^{-8***}$	$-1.17 \times 10^{-7***}$	$-8.19 \times 10^{-8***}$	$2.16 \times 10^{-8***}$	$-8.42 \times 10^{-8***}$	$-1.01 \times 10^{-7***}$	$-4.46 \times 10^{-8***}$	$-1.16 \times 10^{-7***}$	$-7.82 \times 10^{-9***}$	$2.15 \times 10^{-8***}$	$-8.14 \times 10^{-8***}$	$-1.01 \times 10^{-7***}$
					(4.6 × 10^-10)	(6.89 × 10^-10)	(1.4 × 10^-9)	(5.94 × 10^-10)	(1.39 × 10^-9)	(3.3 × 10^-10)	(4.68 × 10^-10)	(6.93 × 10^-10)	(1.53 × 10^-9)	(5.93 × 10^-10)	(1.51 × 10^-9)	(3.28 × 10^-10)
Observations	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444	10,380,444
R^2	0.77022	0.78569	0.77213	0.78772	0.77401	0.78877	0.93700	0.97162	0.92563	0.96442	0.77591	0.79080	0.93720	0.97202	0.92384	0.96485
F-test (1st stage)	1,294,562.9	1,345,809.6	1,303,962.9	1,359,424.7	467,074.7	486,378.5	349,787.9	957,217.4	310,574.0	689,753.4	471,243.5	485,285.7	351,685.9	970,698.6	311,557.9	698,998.8
Municipality	X	X			X	X	X	X	X	X						
Month-Event	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Address ID			X	X							X	X	X	X	X	X

Table A-4: Price elasticities by time of week

This table shows the the IV regression of household electricity consumption (log) on electricity price (log), similar to column 3 and 6 in Table 3, but separate for weekdays (column 1 and 2) and weekends (column 3 and 4). Column 1 and 3 have average hourly price elasticities and column 2 and 4 shows price elasticities separately for peak, off-peak day and off-peak night. Standards errors are clustered on meter level. Parentheses contain p-values and stars show significance level. *** is 1%, ** 5%, and * 10% significance level.

	log(consumption)			
log(price)	-0.3642***		-0.4164***	
	(0.0073)		(0.0095)	
	(0.0027)	(0.0064)	(0.0024)	(0.0052)
log(price)×Off-Peak Day		-0.4137***		-0.5015***
		(0.0110)		(0.0133)
log(price)×Off-Peak Night		-0.1905***		-0.2056***
		(0.0091)		(0.0107)
log(price)×Peak		-0.5322***		-0.6143***
		(0.0099)		(0.0114)
Off-Peak Day	-0.2052***	-0.2781***	-0.0481***	-0.1160***
	(0.0020)	(0.0055)	(0.0023)	(0.0035)
Off-Peak Night	-0.5222***	-0.6818***	-0.4430***	-0.6001***
Observations	303,336,418	303,336,418	121,539,832	121,539,832
Meter ID FE				
Date FE				

Table A-5: Background controls

This table shows estimates of the IV regression of household electricity consumption (log) on electricity price (log), using the day-ahead wind forecast to instrument electricity price, and controlling for household background characteristics. Fixed effects correspond to column 2 in Table 3. Parentheses contain p-values and stars show significance level. *** is 1%, ** 5%, and * 10% significance level.

	log(consumption)	
	(1)	(2)
log(price)	-0.3689***	
	(0.0903)	
log(price)×Off-Peak Day		-0.4217***
		(0.0878)
log(price)×Off-Peak Night		-0.1819**
		(0.0869)
log(price)×Peak		-0.5537***
		(0.1071)
Off-Peak Night	-0.3416***	-0.4293***
	(0.0046)	(0.0124)
Peak	0.1588***	0.2369***
	(0.0128)	(0.0266)
No electric heating/pump	-0.7992***	-0.7992***
	(0.0095)	(0.0095)
No electric car	-0.0855***	-0.0855***
	(0.0020)	(0.0020)
Above 2 household members	0.2539***	0.2539***
	(0.0010)	(0.0010)
Employed	0.0706***	0.0706***
	(0.0011)	(0.0011)
No school-age child	-0.0234***	-0.0234***
	(0.0008)	(0.0008)
Income 25–50%	0.2261***	0.2261***
	(0.0011)	(0.0011)
Income 50–75%	0.4427***	0.4427***
	(0.0019)	(0.0019)
Income 75–100%	0.6119***	0.6119***
	(0.0025)	(0.0025)
Age (years)	0.0234***	0.0234***
	(0.0001)	(0.0001)
Age^2	-0.0002***	-0.0002***
	(9.72e-07)	(9.72e-07)
Below 65	-0.0464***	-0.0464***
	(0.0008)	(0.0008)
Observations	424,635,754	424,635,754
R^2	0.16671	0.16013
Within R^2	0.14374	0.13698