Watt Changes: Households' Response to Hourly Electricity Prices*

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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. Electric car usage explains some, but not all, of the income gradient.

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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 extent 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 first half of 2024, 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 unbiased estimates, we employ forward-looking wind forecasts as an instrumental variable

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 series of heterogeneity analyses to identify the main drivers of household adjustments to fluctuating electricity prices. We start by documenting 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 likely to own an electric vehicle, more flexible or more aware of price changes which we test separately.

We divide the sample into households that own at least one electric vehicle (EV) and those that do not own any. As expected, EV-owning households, who are disproportionately concentrated in higher income groups, exhibit stronger shifts in electricity consumption away from high, price peak hours. This pattern largely reflects the mechanical response of EV chargers that automatically schedule charging during lower-price periods. Nevertheless, we continue to observe meaningful intra-day adjustments among higher-income households without EVs. Thus, while automated charging contributes to the reallocation of consumption across hours, higher-income households remain more responsive to intra-day price variation even in the absence of EVs.

We conclude by testing whether flexibility drives intra-day electricity ad-

justments. We 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 carry several implications for the broader energy transition. First, automated technologies appear particularly effective at facilitating intra-day load shifting. The sharp contrast between EV-owning and non–EV-owning households suggests that technologies that can schedule consumption automatically—analogous to smart EV charging—can deliver meaningful efficiency gains by moving demand into low-price hours. Second, the benefits of variable electricity pricing are unevenly distributed: higher-income households shift more in response to within-day price variation, even when controlling for EV ownership. This may reflect differences in attention or greater flexibility in shifting consumption. Third, temporary price shocks appear to generate persistent reductions in electricity use; even after prices revert, households maintain lower consumption levels. This persistence could stem from investments in more energy-efficient appliances or from the adoption of longer-term electricity-saving behaviors.

Our results supplement a large and fast growing literature on the role of households in the green transition. A first strand studies households as financial decision-makers and find that retail investors are increasingly reallocating portfolios toward socially responsible assets (e.g., Adib et al. [2024], Riedl and Smeets [2017]). A second strand examines households as consumers, documenting preferences for electric vehicles and other forms of responsible consumption (Liao et al. [2017], Ferreira et al. [2024]). A third concerns households as energy users. Because households account for a substantial share of electricity demand, their consumption patterns directly affect carbon emissions, particularly when generation is still partly fossil-based (IEA

2020, 2021; Davis and Gertler [2015]). We contribute to this literature by showing how households can support the green transition through adjustments in electricity use in response to variable prices.

A long-standing debate concerns the conditions required for a successful shift to low-carbon electricity systems. Renewable energies reduces emissions but the main challenge is their transient nature. Renewable energies are hard to store and in order for economies benefit from green electricity when consumption can adjust to the availability. A large literature studies policy instruments, such as Pigouvian taxes and other mechanisms aimed at internalizing externalities, to encourage cleaner production and consumption choices (Bovenberg and de Mooij [1994], Calel and Dechezleprêtre [2016], Döttling and RolaJanicka [2025]). Our work complements this literature by focusing on variable electricity pricing for retail customers and by quantifying how households adjust both how much they consume and when they consume it as a reaction to price changes.

More closely related, our study contributes to the still limited literature on how real-time or high-frequency electricity prices affect household behavior (Faruqui and Sergici [2010], Fabra et al. [2021], Metcalf [2025]). Reiss and White [2005] develop and test a model using California tariff changes, emphasizing the difficulty households face in anticipating and responding to price variation. Ito [2014] similarly shows that households often respond weakly to nonlinear price schedules and instead react more to marginal prices. In contrast, we find that households respond to overall price levels, and that more attentive groups additionally track and respond to intra-day price movements.

Finally, while a broad literature estimates electricity demand elasticities (e.g., Deryugina et al. [2020], Hirth et al. [2024]), less is known about heterogeneity in responses to within-day price variation and about the margins through which adjustment occurs. We help fill this gap by (i) identifying which households shift consumption in response to intra-day price changes

and (ii) separating responses along the intensive margin (reducing total consumption) versus the timing margin (reallocating use across hours).

The paper proceeds as follows: Section 2 presents the institutional details of the Danish electricity market, and Section 3 describes the data and provides 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 determined within market structures that reflect the physical constraints of power generation and transmission. In this section, we describe the institutional features of the Danish electricity market that shape household electricity prices and underpin our empirical strategy.

Electricity differs from most commodities in two fundamental ways. First, it is fungible: one kilowatt-hour is identical regardless of the source of generation. Second, electricity cannot be stored at scale, implying that supply and demand must be balanced continuously in real time. To accommodate these features, electricity trading is organized across three interconnected markets: the day-ahead market, the intraday market, and the balancing market.

The day-ahead market is the primary venue for price formation. Prices are set hourly through a price auction based on forecasts of supply and demand for the following day. These day-ahead prices constitute the core price signal faced by households. Electricity producers submit supply bids ranked by marginal production cost, the so-called merit order. Low-cost sources, primarily renewable sources such as wind and solar, are dispatched first. As demand increases, progressively more expensive technologies, such as coal- or gas-fired plants, are added until expected demand is met. Consequently,

prices remain low when renewable generation is sufficient to meet demand but rise when higher-cost fossil fuel generation is required. The market price is determined by the price of the highest-cost source that is needed to meet demand.

The intraday market allows participants to trade electricity closer to real time, adjusting positions in response to updated information about demand or renewable generation. Finally, balancing markets are operated by the transmission system operators (TSOs) to correct any remaining discrepancies between realized supply and demand.

Electricity transmission and distribution are regulated separately from energy trading. TSOs manage the high-voltage transmission network, while distribution system operators (DSOs) are responsible for delivering electricity to end users through local grids. This division is analogous to highways and local roads, with grid tariffs reflecting the cost of maintaining and operating these networks.

2.1 Electricity Sources

Denmark is divided into two electricity bidding zones: DK1, covering western Denmark and connected to Germany and the Continental European market, and DK2, covering eastern Denmark and connected to the Nordic market. Denmark is a global leader in renewable electricity generation, particularly wind power. In 2022, renewable sources accounted for 81.4% of total electricity production, with wind alone contributing 53.6% Danish Energy Agency [2022]. During periods of high demand or low wind generation, gas-fired power plants provide backup capacity. In line with its long-term climate objectives, Denmark aims to transition to a fully renewable electricity system by 2050 Danish Ministry of Energy, Utilities and Climate [2011].

2.2 Household Electricity Bills

Household electricity bills in Denmark consist of three main components: the energy component, grid payments, and taxes. The energy component includes the spot market price and any margin charged by the electricity supplier. Grid payments cover tariffs set by TSOs and DSOs to finance transmission and distribution infrastructure. Taxes are imposed by the government and are designed in part to discourage excessive electricity use.

In 2022, approximately 48% of the average household electricity bill was attributable to the energy component, 11% to grid tariffs, and 41% to taxes. Grid tariffs are regulated by the Danish Utility Regulator and are typically set and announced in advance for the coming year. Electricity taxes are also announced ahead of time and are usually fixed for extended periods, such as six months.

A majority of Danish households (around 70%) are enrolled in contracts with floating electricity prices Hinrichsen [2024]. Electricity suppliers generally recommend such contracts, as they allow households to benefit from periods of low spot prices. At the same time, suppliers note that households with electric heating or those living in apartments may experience smaller gains from variable pricing, due to more limited flexibility in adjusting consumption.

2.3 Smart Meters

Smart meters installed in households record electricity consumption at an hourly frequency and automatically transmit this information to electricity providers. These meters enable the implementation of dynamic pricing schemes and facilitate more efficient demand management by suppliers and grid operators. In Denmark, the nationwide rollout of smart meters was completed by 2020, ensuring comprehensive coverage of hourly household electricity consumption. This infrastructure is central to our analysis, as it

allows us to observe high-frequency consumption responses to price variation at the household level.

3 Data and Summary Statistics

This section describes the data sources used in the analysis and presents key summary statistics on electricity prices and consumption in Denmark. We combine high-frequency electricity meter data with rich administrative registers, allowing us to track household electricity use over time, across income groups, and within the day. Descriptive patterns motivate the empirical analysis that follows.

3.1 Data Sources

Our study relies on monthly and hourly electricity consumption data covering all electricity meters in Denmark from 2021 to first half of 2024. We link the data to detailed electricity price information as well as administrative registers that cover the entire Danish population.

Electricity consumption data are collected by Energinet and made available through Statistics Denmark.[4] Electricity price data are obtained directly from Energinet's public website and include hourly spot prices, taxes, and grid tariffs, as well as hourly forecasts of wind and solar power generation and aggregate electricity production and consumption. We compute local electricity prices by adding the national electricity tax and local grid tariffs to the spot price, following the institutional setup described in Section 2.2.

Household characteristics are drawn from Danish administrative registers. A key advantage of these data is the presence of unique personal identification numbers (CPR), which allow us to link individuals across multiple reg-

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

isters. We observe demographic characteristics such as age, gender, location, and household composition from the population register, as well as income and wealth from tax records, vehicle ownership from the Danish motor registry, and housing characteristics from the building and dwelling register (Bygnings- og boligregistret, BBR). All data are accessed through Statistics Denmark.

At the monthly frequency, we include the full population of Danish households. However, daily and hourly electricity data are substantially larger and computationally more demanding. For analyses at these higher frequencies, we restrict attention to a subsample of households residing in single-family houses. This restriction is motivated by two considerations. First, households living in houses are less likely to hold fixed-price electricity contracts Hinrichsen [2024]. Second, residents of single-family homes generally face fewer constraints on the timing of appliance use—for example, running a washing machine late at night is less disruptive than in apartment buildings, where noise may affect neighbors.

To construct a high-quality sample, we apply several restrictions. We begin by selecting adult single-family households with valid tax records. Because most variation in electricity prices occurs in 2022, we require households to be present in both 2021 and 2022 and to have stable household composition and residential address throughout 2022. We exclude households for which a unique meter address cannot be identified, as well as those with ambiguous housing classifications. We further restrict the sample to households with complete electricity consumption data for all months of 2022. From the resulting pool of eligible households living in houses, we randomly select 12,500 addresses observed in 2022 and retain their full address electricity histories from 2021 through 2024. We then remove duplicate observations and exclude implausible records.[5]

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

The final dataset consists of 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 summarizes the data construction and filtering process.

Table 1 reports summary statistics for the estimation sample. Panel A presents electricity consumption and price measures. Average daily household electricity consumption is 8.81 kWh, and the average electricity price is 1.92 DKK per kWh. This price comprises three components: a wholesale spot price of 0.97 DKK, a national electricity tax of 0.69 DKK, and a local distribution tariff of 0.26 DKK. The average day-ahead wind forecast in the relevant price area (DK1 or DK2) is 1.09 GWh. As discussed in Section 4.1, this forecast serves as our instrumental variable for electricity prices.

Panel B of Table 1 reports household characteristics. On average, households consist of 1.6 adults and 0.57 children, with a mean age of 58 years. The relatively high average age reflects that the sample includes households across the entire age distribution, not only those of working age. 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 roughly 1 percent own an electric vehicle.

3.2 Electricity Prices and Overall Consumption

We begin by describing aggregate patterns in electricity prices and consumption. Figure 1, Panel A, shows the evolution of average electricity prices over time. Prices were around 1.5 DKK per kWh at the beginning of the sample period but began rising toward the end of 2021. Following the Russian invasion of Ukraine in February 2022, electricity prices increased sharply, peaking at over 4 DKK per kWh in August 2022. In January 2023, the Danish government temporarily removed the electricity tax for the entire year, leading to a substantial decline in consumer electricity prices.

Motivated by these developments, we divide the sample into three peri-

ods: *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 for the full population using this time split. Consumption exhibits a pronounced U-shaped seasonal pattern, with higher usage during colder months.[6] Relative to the *pre* period, households substantially reduce electricity consumption during the *during* period, when prices are highest. Consumption remains somewhat lower in the *post* period, even after prices decline.

Figure A-1, Panel A, plots monthly electricity consumption by income quartile. As expected, consumption increases with income, and seasonal variation is more pronounced among higher-income households. This likely reflects differences in housing size, appliance ownership, and energy-intensive activities. Across periods, households in the lowest income quartile exhibit only modest adjustments during the *during* period, suggesting limited scope for further reductions. In contrast, households in the middle income quartiles reduce consumption noticeably and maintain part of this reduction in the *post* period. Households in the highest income quartile primarily reduce electricity use during colder months of the *during* period but rapidly revert to *pre*-period consumption levels once prices fall.

We next examine how households allocate electricity consumption within the day. While the preceding figures cover the full population at the monthly level, the remainder of this section focuses on the subsample of households residing in single-family houses. Figure 1, Panel B, reports average hourly electricity prices. Prices exhibit two daily peaks—one in the morning and one in the evening—with the largest spread between peak and off-peak prices occurring during the *during* period, when overall price levels are highest

[6]Because approximately 96 percent of Danish households do not rely on electric heating, this pattern likely reflects increased time spent indoors during winter and lower electricity use during summer months.

(approximately 2.2 DKK versus 3.1 DKK per kWh).[7] In the analysis that follows, we define peak hours as 5–8 a.m. and 4–10 p.m.

Figure 2, Panel B, shows average hourly electricity consumption. In contrast to prices, consumption exhibits a single pronounced peak in the evening, a relatively flat profile during daytime hours, and a trough overnight. Relative to the *pre* period, consumption declines throughout the day during the *during* period. In the *post* period, consumption partially rebounds, with households shifting some usage from daytime to nighttime hours, indicating greater off-peak consumption.

Finally, Figure A-1, Panel B, presents hourly consumption patterns by income quartile. The gap between peak and off-peak consumption increases with income, suggesting that differences in monthly consumption across income groups are largely driven by variation in peak-time usage. Moreover, the shift toward greater nighttime consumption in the *post* period is more pronounced among higher-income households, consistent with greater adoption of technologies, such as electric vehicles, or appliances that can be more easily scheduled outside peak hours.

Taken together, these descriptive patterns reveal substantial heterogeneity in electricity use across time, income, and hours of the day. We next turn to the response of household electricity bills and estimate price elasticities, which form the basis of our main empirical results.

[7] Within-day price variation is driven primarily by fluctuations in the spot price, reflecting changes in supply and demand conditions. A smaller share is attributable to local tariffs designed to incentivize consumption away from peak hours. Figure A-3 decomposes hourly price components.

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 p_{gt} is the grid g specific price in time t and w_{dt} is the day-ahead forecast of time t and price area d wind. 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 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 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-4 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.

We further apply a Shapley decomposition of changes in households' electricity bills to separate the contributions of intra-day load shifting and changes in overall consumption. Figure 3 reports the decomposition for the *during* and *post* periods by income quartile. Consistent with the regression results, bill reductions attributable to intra-day adjustment are concentrated among higher-income households. On average, however, most of the bill change reflects lower electricity consumption levels. Also consistent with the regression analysis, lower-income households partially sustain their lower consumption in the *post* period, whereas higher-income households sustain primarily their intra-day adjustments and increase consumption, reverting

to roughly (or slightly above) *pre*-period levels. Overall, the decomposition highlights heterogeneity in responses to higher electricity prices across the income distribution.

6.2 Electric cars

One possible mechanism underlying the stronger intra-day load adjustments and the reversal in overall electricity consumption among higher-income households in the *Post* period is differential adoption of electric vehicles (EVs). Modern EV chargers allow owners to shift charging to hours with lower electricity prices, potentially generating mechanically timed consumption patterns that could be confounded with behavioral responses. To separate these effects, we exploit administrative data on vehicle ownership to distinguish households with EVs from those without.

Using the Danish Motor Vehicle Register, we classify a household as an EV owner if at least one adult is listed as the registered owner of an electric or hybrid vehicle that year.

We begin by plotting average electricity consumption for households without EVs, by income quartile, in Figure A-2. Whereas Panel B of Figure A-1 shows that higher-income households exhibit increased electricity use during nighttime hours, this pattern largely disappears once EV-owning households are excluded. This attenuation is consistent with EV charging predominantly occurring at night.

We next replicate the analysis of electricity consumption across periods separately for households with and without EVs, as reported in Table A-6. The reversal in electricity use observed in the *Post* period is concentrated almost entirely among EV-owning households. This pattern is consistent with the continued expansion of EV ownership throughout the sample periods.

Table 7 examines intra-day consumption responses among EV-owning households and non-EV-owning households. While the price sensitivity of higher-income households is markedly stronger within the subgroup of EV

owners, higher-income households without EVs also exhibit greater intra-day load adjustments than their lower-income counterparts. This pattern suggests that EV charging behavior does not fully account for the income gradient in the ability to respond to time-varying electricity prices.

6.3 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 8 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.

[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).

6.4 Policy discussion

Our findings yield several policy implications for the transition toward greater reliance on renewable energy and the containment of overall pollution stemming from traditional sources of energy. First, temporary shocks to energy prices can induce households to reduce consumption and form more persistent consumption habits. This reduction appears to be driven both by deliberate efforts to optimize usage and potentially due to replacement with more energy-efficient appliances. Second, variable pricing predominantly benefits higher-income households, who are more likely to reallocate their intra-day consumption toward off-peak periods. Third, and perhaps most importantly, automated technologies, as we have documented with our results on electric cars, are the primary drivers of adjustments toward periods with excess renewable supply/cheaper electricity prices. Automatic charging that responds directly to high-supply periods is more effective than expecting households to track and react to real-time price signals. Consequently, relying solely on variable pricing to achieve a green transition is unlikely to be sufficient. A more effective strategy is to prioritize the development and diffusion of automated appliances that do not require active household intervention.

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 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. Electric car ownership explain some of the difference, but not all.

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.

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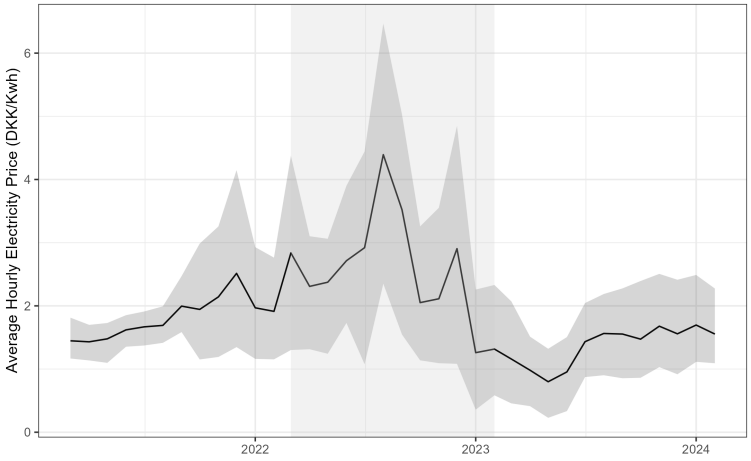
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Figure 1: **Electricity prices**
The figures show average monthly (panel a) and hourly (panel b) electricity prices in DKK/KWh

(a) **Average monthly electricity price**



(b) **Average hourly electricity price**

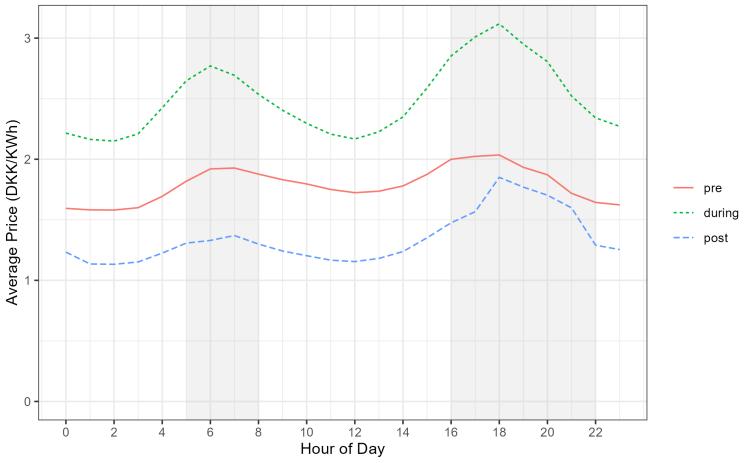
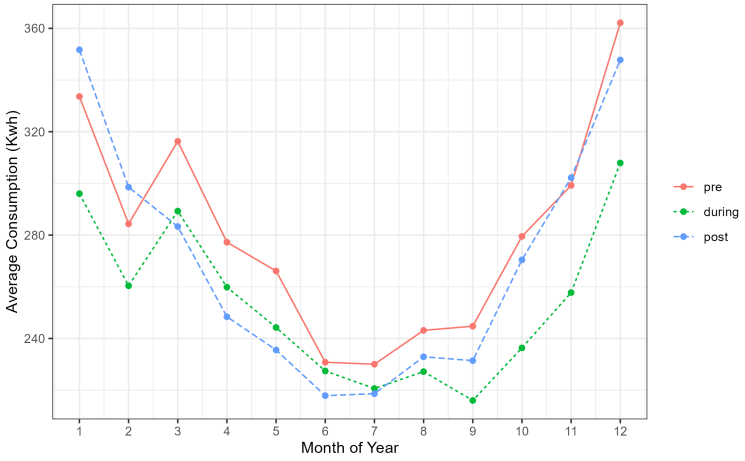


Figure 2: **Household electricity consumption**
The figures show average monthly (panel a) and hourly (panel b) electricity consumption by Danish households.

(a) **Average monthly electricity consumption**



(b) **Average hourly electricity consumption**

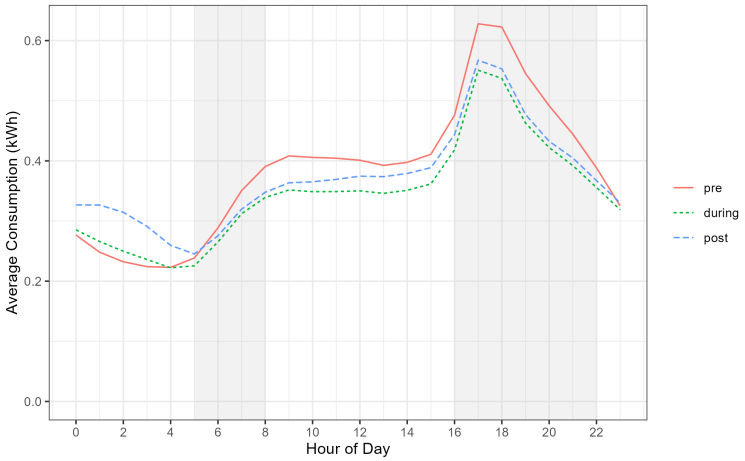


Figure 3: **Shapley decomposition of bill changes**
The figure shows the Shapley decomposition of electricity bills changes for the during and post periods for different income quartiles. The decomposition is on intra-day adjustment (Timing) effects versus consumption changes (Level).

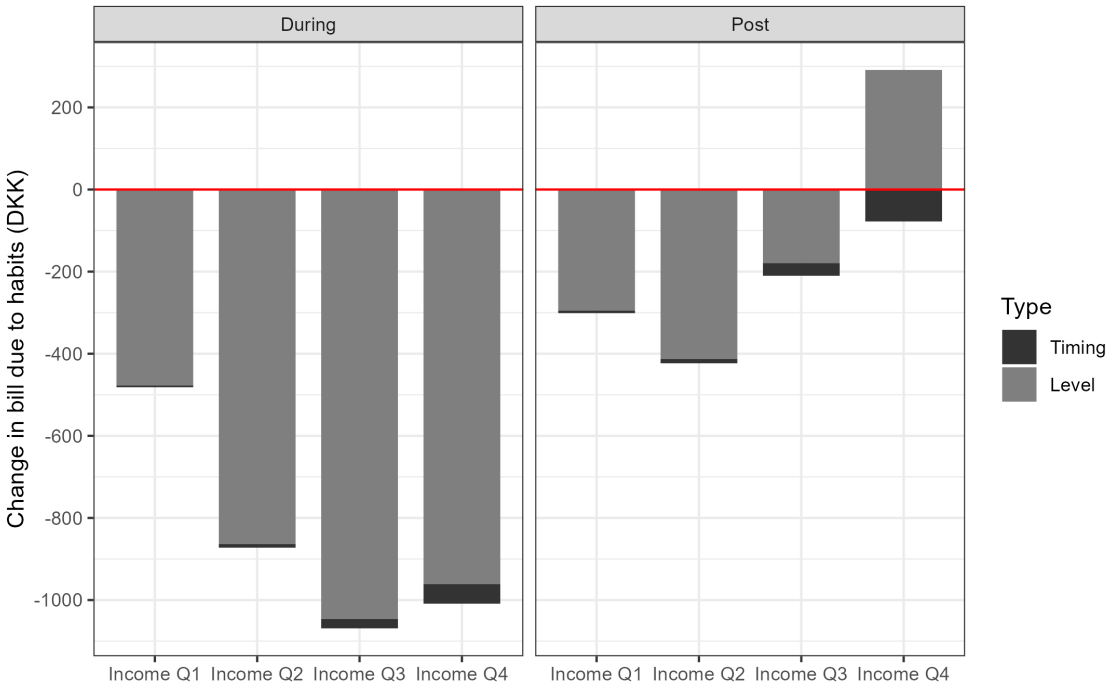


Table 1: Summary Statistics

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: Intra-day allocation, income bracket and EVs

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), by electric car ownership and income bracket. 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

(a) Panel A: Electric Car Owners

	All	$0-25\%$	$25-50\%$	$50-75\%$	$75-100\%$
	(1)	(2)	(3)	(4)	(5)
$\widehat{Price}$ (Peak)	0.005	0.003	-0.022	0.003	0.013
	(0.006)	(0.024)	(0.015)	(0.012)	(0.008)
$\widehat{Price}$(Peak) $\times 1_{during}$	-0.016**	-0.042	0.002	-0.011	-0.020**
	(0.007)	(0.030)	(0.018)	(0.015)	(0.010)
$\widehat{Price}$(Peak) $\times 1_{post}$	-0.040***	-0.008	0.002	-0.031**	-0.058***
	(0.008)	(0.040)	(0.020)	(0.015)	(0.011)
$\widehat{Price}$(Off-Peak) $\times 1_{during}$	0.049***	0.062	0.043	0.035	0.061***
	(0.012)	(0.042)	(0.028)	(0.022)	(0.016)
$\widehat{Price}$(Off-Peak) $\times 1_{post}$	0.090***	0.038	0.057*	0.062**	0.119***
	(0.014)	(0.056)	(0.031)	(0.025)	(0.019)
$\widehat{Price}$ (Off-peak)	-0.035***	-0.019	-0.015	-0.023	-0.051***
	(0.010)	(0.035)	(0.026)	(0.018)	(0.014)
Address ID	X	X	X	X	X
Month-Event	X	X	X	X	X
Lagged Consumption	X	X	X	X	X
Observations	871,302	36,228	91,055	250,345	493,674
R^2	0.19084	0.21732	0.17719	0.20209	0.18850

(b) Panel B: No Electric Car Owners

	All	$0-25\%$	$25-50\%$	$50-75\%$	$75-100\%$
	(1)	(2)	(3)	(4)	(5)
$\widehat{Price}$ (Peak)	-0.0003	-0.008***	-0.001	0.004*	0.005**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$\widehat{Price}$(Peak) $\times 1_{during}$	-0.005***	0.002	-0.002	-0.010***	-0.011***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
$\widehat{Price}$(Peak) $\times 1_{post}$	-0.010***	0.004	-0.006*	-0.023***	-0.019***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
$\widehat{Price}$(Off-Peak) $\times 1_{during}$	0.010***	0.0007	0.007*	0.018***	0.020***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
$\widehat{Price}$(Off-Peak) $\times 1_{post}$	0.018***	0.002	0.010**	0.034***	0.032***
	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)
$\widehat{Price}$ (Off-peak)	-0.003**	0.007**	-0.001	-0.010***	-0.013***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Address ID	X	X	X	X	X
Month-Event	X	X	X	X	X
Lagged Consumption	X	X	X	X	X
Observations	9,509,142	2,583,142	2,518,981	2,348,379	2,058,640
R^2	0.19134	0.18239	0.17942	0.19375	0.19146

Table 8: 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

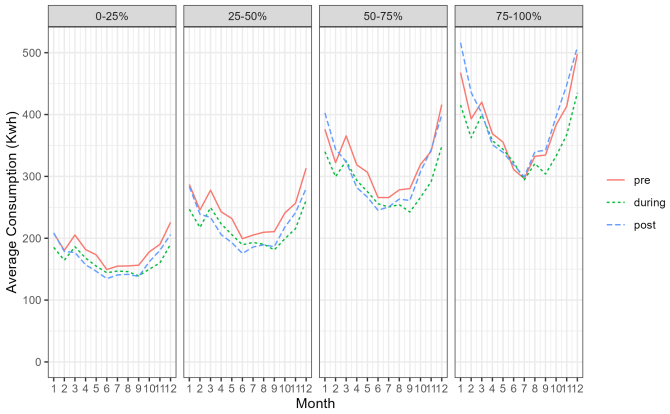
Appendix

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**

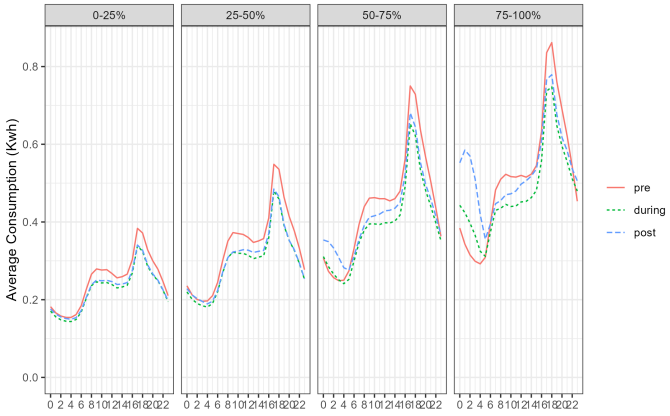


Figure A-2: **Household hourly electricity consumption by income, excluding EVs**

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

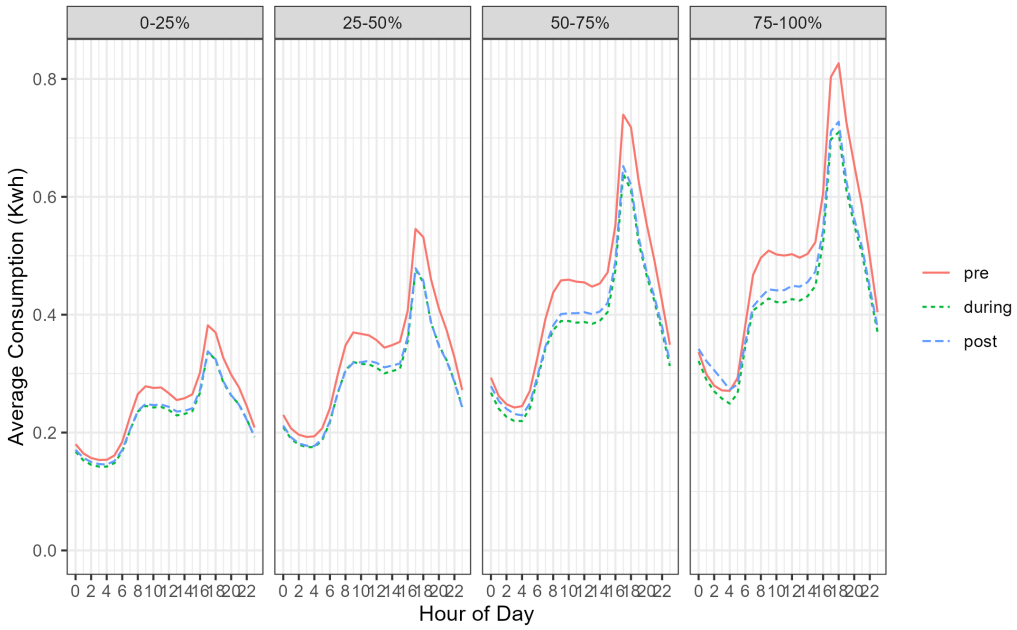


Figure A-3: **Decomposed Hourly Price**

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

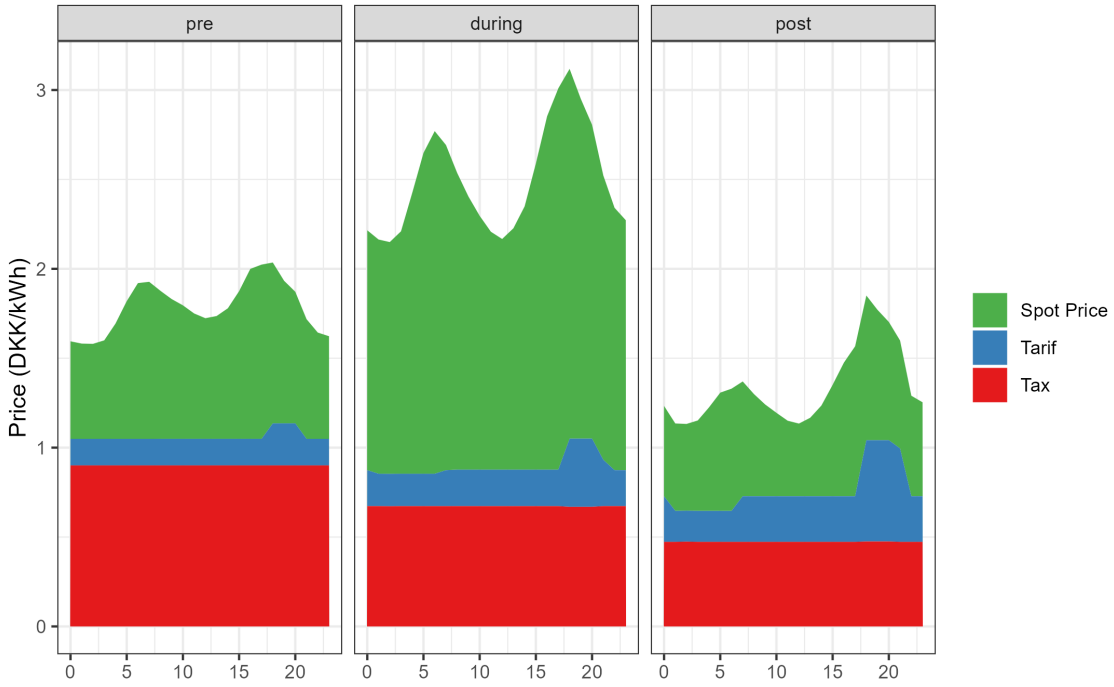


Figure A-4: Attention to Electricity Prices

This figure shows three indices of attention on electricity prices: Google searches, Infomedia articles, and monthly downloads of the app Watts®. 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 their data. All three measures are indexed with the peak = 100.

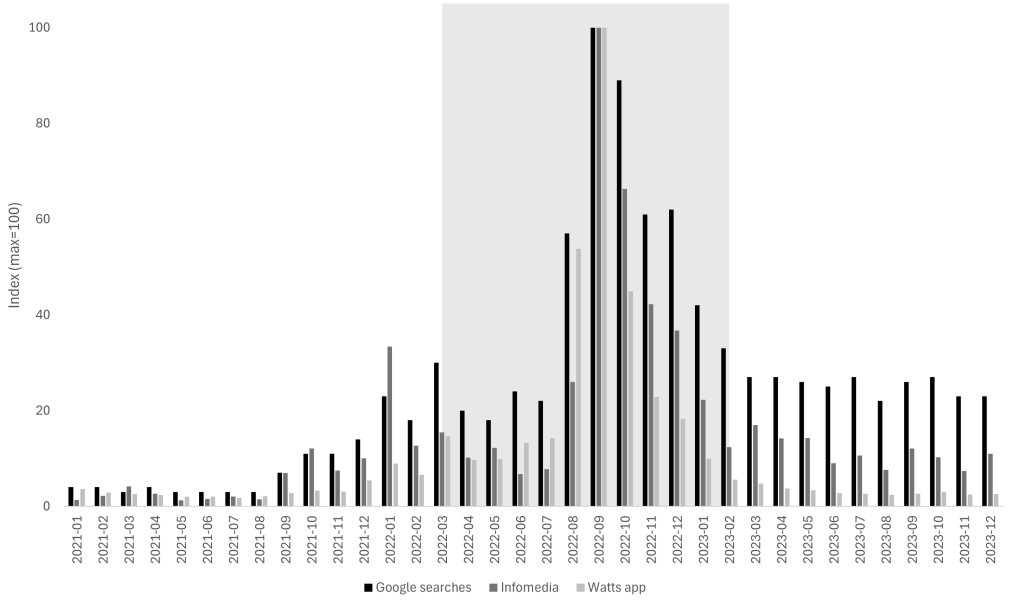


Table A-1: Data Filtering - Houses

	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^{-12})	(2.15×10^{-09})	(2.75×10^{-12})	(2.17×10^{-10})	(3.76×10^{-10})	(2.53×10^{-10})	(3.95×10^{-10})	(1.77×10^{-10})	(3.84×10^{-10})	(2.22×10^{-10})	(3.79×10^{-10})	(2.57×10^{-10})	(3.97×10^{-10})	(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^{-12})	(7.75×10^{-09})	(2.48×10^{-09})	(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^{-09})	(6.6×10^{-10})	(8.56×10^{-11})	(4.85×10^{-11})	(9.07×10^{-11})	(4.94×10^{-11})
$wind_peak \times 1_{during}$					$6.18 \times 10^{-9***}$	$-2.96 \times 10^{-8***}$	$-3.3 \times 10^{-7***}$	$-7.49 \times 10^{-10***}$	$-4.58 \times 10^{-8***}$	$-1.59 \times 10^{-8***}$	$6.16 \times 10^{-9***}$	$-2.98 \times 10^{-8***}$	$-3.3 \times 10^{-7***}$	$-7.71 \times 10^{-10***}$	$-4.69 \times 10^{-8***}$	$-1.61 \times 10^{-8***}$
					(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})
$wind_peak \times 1_{post}$					$4.9 \times 10^{-8***}$	$8.6 \times 10^{-8***}$	$1.36 \times 10^{-8***}$	$-2.37 \times 10^{-7***}$	$1.39 \times 10^{-8***}$	$-4.02 \times 10^{-8***}$	$4.86 \times 10^{-8***}$	$8.57 \times 10^{-8***}$	$1.34 \times 10^{-8***}$	$-2.37 \times 10^{-7***}$	$1.37 \times 10^{-8***}$	$-4.03 \times 10^{-8***}$
					(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})
$wind_offpeak \times 1_{during}$					$-1.74 \times 10^{-7***}$	$-1.07 \times 10^{-7***}$	$1.76 \times 10^{-8***}$	$7.52 \times 10^{-10***}$	$-2.45 \times 10^{-7***}$	$1.57 \times 10^{-8***}$	$-1.74 \times 10^{-7***}$	$-1.07 \times 10^{-7***}$	$1.77 \times 10^{-8***}$	$7.44 \times 10^{-10***}$	$-2.45 \times 10^{-7***}$	$1.5 \times 10^{-8***}$
					(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})	(1.98×10^{-9})	(2.64×10^{-11})	(1.09×10^{-9})	(3.53×10^{-11})
$wind_offpeak \times 1_{post}$					$-4.49 \times 10^{-8***}$	$-1.17 \times 10^{-7***}$	$-8.19 \times 10^{-9***}$	$2.16 \times 10^{-8***}$	$-8.42 \times 10^{-8***}$	$-1.01 \times 10^{-7***}$	$-4.46 \times 10^{-8***}$	$-1.16 \times 10^{-7***}$	$-7.82 \times 10^{-9***}$	$2.15 \times 10^{-8***}$	$-8.14 \times 10^{-8***}$	$-1.01 \times 10^{-7***}$
					(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	10,380,446	10,380,444	10,380,446	10,380,444
R^2	0.77022	0.78569	0.77213	0.78772	0.77401	0.78877	0.93700	0.97462	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	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

Table A-6: Consumption responses by income quartile and EVs

This Table reports estimates from regressions of log daily household electricity consumption on indicators for the price shock period, as shown in Equation (6), by electric car ownership. 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. Columns (1) includes 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: Electric Car Owners

	All	$0-25\%$	$25-50\%$	$50-75\%$	$75-100\%$
	(1)	(2)	(3)	(4)	(5)
1_{during}	-0.012**	-0.041**	0.002	-0.013	-0.010
	(0.006)	(0.017)	(0.015)	(0.011)	(0.008)
1_{post}	0.042***	-0.004	0.038**	0.042***	0.053***
	(0.007)	(0.017)	(0.018)	(0.014)	(0.009)
during - post (t-stat)	-14.613	-2.447	-3.77	-7.085	-11.888
Address ID	X	X	X	X	X
Month	X	X	X	X	X
Lagged Consumption	X	X	X	X	X
Observations	877,494	36,430	91,620	252,088	497,356
R^2	0.52464	0.63637	0.58232	0.49286	0.46852

(b) Panel B: No Electric Car Owners

	All	$0-25\%$	$25-50\%$	$50-75\%$	$75-100\%$
	(1)	(2)	(3)	(4)	(5)
1_{during}	-0.037***	-0.030***	-0.040***	-0.041***	-0.042***
	(0.0007)	(0.001)	(0.001)	(0.001)	(0.002)
1_{post}	-0.037***	-0.035***	-0.041***	-0.037***	-0.035***
	(0.0009)	(0.002)	(0.002)	(0.002)	(0.002)
during - post (t-stat)	0.826	4.572	0.573	-2.948	-6.075
Address ID	X	X	X	X	X
Month	X	X	X	X	X
Lagged Consumption	X	X	X	X	X
Observations	9,570,470	2,601,337	2,535,216	2,362,657	2,071,260
R^2	0.78315	0.78766	0.73547	0.71413	0.69685