WORKING PAPER

MIND THE PEAK: THE ROLE OF PEAK DEMAND CHARGES AND REAL-TIME PRICING IN RESIDENTIAL ELECTRICITY FLEXIBILITY

Marten Ovaere
Mark Vergouwen

June 2025
2025/1115

GHENT UNIVERSITY

Department of Economics

Faculty of Economics and Business Administration
Campus Tweekerken, St.-Pietersplein 5, 9000 Ghent - BELGIUM

Mind the Peak: The Role of Peak Demand Charges and Real-Time Pricing in Residential Electricity Flexibility

Marten Ovaere, Mark Vergouwen

Abstract

We use high-frequency electricity consumption data from a natural experiment in Flanders to study the interacting effects of real-time electricity pricing, which encourages consumption during periods of low generation cost, and peak demand charges, which discourage simultaneous demand that stresses local grids. Our matched difference-in-differences estimates show that real-time pricing increases household peak demand, while peak demand charges reduce it by 1–3% on average. Reductions are largest among electric vehicle owners, who shift up to 0.75 kWh per day to nighttime hours. These household-level responses result in lower coincident grid-level demand peaks, reducing the need for costly grid reinforcement.

JEL: C23, D12, Q48, L94, D91, Q41

Ovaere: Department of Economics, Ghent University (marten.ovaere@ugent.be); Vergouwen: Department of Economics, Ghent University (mark.vergouwen@ugent.be). We are deeply grateful to the partnering distribution system operator Fluvius and to Ruben Peene and Raf Smet, in particular, for securing data access and for their technical assistance in preparing the dataset. We thank Nicolas Astier, James Bushnell, Paul Joskow, and conference and seminar participants at Paris School of Economics, Technische Universität München, Groningen University, the 13th Mannheim Conference on Energy and the Environment, and IAEE Paris for valuable comments.

1. Introduction

The shift toward a zero-carbon energy system is transforming how electricity is priced and consumed. To manage rising infrastructure and generation costs, many regions are moving beyond static tariffs toward pricing schemes that better reflect the underlying cost structure of supply. For energy production, real-time electricity prices are being introduced. By varying prices over time based on actual energy market conditions, consumers are incentivized to align their demand with times of low cost of supply (Burkhardt et al., 2023; Harding and Sexton, 2017; Jessoe and Rapson, 2014; Borenstein, 2005). However, distribution grids face an additional constraint: the need to limit coincident peak demand. Increasing electrification and electric vehicle (EV) ownership creates higher consumption peaks than traditional appliances. In Europe, the expected number of EVs is expected to grow from 3.2 million in 2023 to 30 million by 2030, (ACER, 2024; Eurelectric, 2024). This increases the risk of overloading transformers, feeders, and distribution substations, and accelerates the need for costly grid investments (Bailey et al., 2025b; Becker et al., 2025; Powell et al., 2022). Real-time pricing (RTP) and time-of-use tariffs may further inadvertently increase peaks on local grids by encouraging consumption to be concentrated in low-cost hours (Bailey et al., 2025b).

Because of these developments, annual investments in grid infrastructure are projected to reach $300 billion (US) and €100 billion (Europe) by 2050 (ACER, 2024; US Energy Information Administration, 2023), with two-thirds expected to go to local distribution networks. In Europe, for instance, the number of required transformer stations is expected to double and the distribution lines are required to grow with 70% between 2021 and 2050 (Eurelectric, 2024). Given the scale of these economically significant investments, identifying ways to mitigate future costs is essential, requiring charges that are increasingly forward-looking (signalling future investment costs), rather than backward looking (recovering historical costs) (Schittekatte et al., 2023). The literature explores several solutions, including time-of-use pricing (Bernard et al., 2024; Bailey et al., 2025a; Blonz et al., 2025), critical peak pricing (Garnache et al., 2025), and managed charging (Bailey et al., 2025b). In this context, we focus on peak demand charges as a tariff designed to encourage consumers to reduce their demand during peak times and distribute their consumption more evenly across the day.

In this study, we examine the combined effects of the introduction of peak demand charges and real-time electricity pricing on residential customers. While peak demand charges and real-time pricing coexist within the retail electricity bill, they have distinct effects on the consumption profile of electricity consumers. Particularly, real-time electricity prices follow the marginal cost of producing electricity and incentivize consumers to shift their demand to the lowest-price hour. In contrast, peak demand charges do the exact opposite, effectively reducing the marginal cost of electricity consumption to zero in all but the highest-demand hour, thus encouraging consumers to flatten their demand profile entirely. This study considers both components: real-time prices for the electricity production cost component and peak demand charges to alleviate local distribution network capacity constraints. The possible effects of both real-time prices and peak demand charges are expected to increase (Borenstein and Holland, 2005; Borenstein, 2005), as the increasing expansion of heat pumps (Blonz et al., 2025; Bernard et al., 2024) and EVs (Bailey et al., 2025a), whose demand is increasingly automated (Bollinger and Hartmann, 2020; Harding and Lamarche, 2016), contribute to the growing elasticity of demand.

With these insights, this paper evaluates the impact of both peak demand charges and RTP on electricity consumption in the region of Flanders (Belgium), using a unique high-frequency panel of 15-minute level consumption data of over 42,000 residential low-voltage consumers between 2022 and 2024. Both the peak demand charge and the RTP were introduced in this period. Firstly, as of January 2022, every consumer had the option to switch from a flat energy price contract to a RTP one. Secondly, as of January 2023, the volumetric tariff for network costs was partially replaced by a peak demand charge that is based on a consumer's monthly 15-minute peak demand, with a minimum of 2.5 kW. Consumers pay between €35.18/kW-year and €50.05/kW-year in 2023 and from €35.12/kW-year to €53.39/kW-year in 2024. As these energy and network prices collectively contribute to the total retail price, they each affect the consumers' electricity load profiles, albeit in distinctive ways, as previously discussed.

We provide empirical evidence on the causal impacts of peak demand charges and RTP on household electricity consumption behavior, focusing on monthly peak demand at the individual and grid level. Exploiting a natural experiment in which a subset of households, protected consumers, were exempt from the newly introduced peak demand tariff, we identify the causal effect of peak pricing using a difference-in-differences (DID) strategy. To account for differences in pre-treatment load profiles and observable characteristics between treated and control groups, we estimate a two-way fixed effects DID model with covariates, an inverse probability weighted DID estimator Abadie (2005), and a doubly robust estimator DID Sant'Anna and Zhao (2020). Across specifications, we find that the introduction of peak demand charges reduces household monthly peak demand by 50 to 120 watts, equivalent to approximately 1–3 percent of the average pre-treatment peak of 4,000 watts. This effect corresponds to switching off roughly ten 10 watt LED light bulbs during peak load hours.

To estimate the effect of real-time pricing, we exploit the staggered rollout of RTP contracts across households. Using a similar DID framework adjusted for variation in treatment timing, we find that RTP increases monthly peak demand by 30 to 120 watts per household. These increases are concentrated in periods when real-time prices are low, suggesting households respond by shifting or adding consumption to take advantage of lower marginal prices.

Event-study estimates reveal heterogeneous and time-varying treatment effects. The effect of RTP is most pronounced during summer months, when households respond to low real-time prices by increasing usage during low-cost periods. In contrast, the effect of peak demand charges shows little seasonal variation but is strongly moderated by low-carbon technology adoption. Households with EVs exhibit a sustained reduction in peak demand by shifting charging to nighttime or hours of high solar production. By contrast, households without low-carbon technologies relying solely on manual demand response display diminishing responsiveness over time, with peak load gradually reverting to pre-treatment levels five months post-introduction.

To assess how household-level price responses scale to the level of the electricity distribution grid, we construct synthetic distribution circuit-level data by aggregating smart meter readings to randomly assigned circuits of 10 or 25 households, simulating local distribution feeders and cables, following an approach inspired by Bailey et al. (2025b). We simulate varying levels of EV adoption across these circuits to capture different stages of transport electrification. Our findings reveal that peak demand charges significantly reduce coincident peak load at the grid level, particularly in highly electrified circuits. In circuits with 100% EV adoption, we estimate that monthly distribution circuit-level peak demand declines by up to 6.8% for 10-household groups (1.8 kW) and 6.0% for 25-household groups (3.1 kW) following the introduction of peak demand charges. This grid-level effect arises because EV charging tends to occur simultaneously across households, often in the early evening, so reductions in individual peaks aggregate into meaningful declines in coincident circuit-level peak demand. Our findings suggest that peak demand charges can be an effective tool to reduce local grid congestion, supporting recent calls in the literature for tariff structures that address rising peak loads from electrification and help avoid costly grid reinforcement (Bailey et al., 2025b; Becker et al., 2025; Powell et al., 2022).

Related literature and contributions Our paper contributes to several strands of the literature. First, we contribute to the literature on household electricity demand response by analyzing how multiple pricing schemes, specifically real-time pricing and capacity-based peak demand charges, jointly affect household behavior. While earlier observational studies have estimated household price elasticities under RTP (Fabra et al., 2021) and time-of-use (TOU) tariffs (Enrich et al., 2024), others have relied on experimental designs to evaluate TOU (Bollinger and Hartmann, 2020; Blonz et al., 2025), critical-peak pricing (CPP) (Jessoe and Rapson, 2014; Garnache et al., 2025), and RTP interventions (Allcott, 2011; Hofmann and Lindberg, 2024). We extend this literature in four key ways.

First, our study is among the first to examine the interaction between pricing schemes with distinct incentive structures. We show that combining RTP and peak demand charges can either amplify or attenuate their individual effects, depending on household characteristics and prevailing market prices. Second, we present one of the first large-scale empirical evaluations of peak demand charges in a European context. On average, we find that the introduction of a capacity-based tariff leads to a monthly peak reduction of between 50-120 watts per household, equivalent to a 1–3% decline relative to pre-treatment levels. This complements earlier, smaller-scale work such as Stokke et al. (2010), who found peak reductions of up to 12% in a sample of Norwegian households exposed to seasonal peak charges based on winter weekday consumption. Third, we provide an extensive heterogeneity analysis of household responses to the compulsory peak demand charge. While prior work has examined the effects of solar PV adoption (Astier et al., 2023; Gillingham et al., 2025; Qiu et al., 2019), in-home EV charging and EV-specific TOU tariffs (Qiu et al., 2022; La Nauze et al., 2024), and smart heating incentives (Blonz et al., 2025), as well as the joint adoption of EVs and solar panels (Liang et al., 2022), our results document substantial heterogeneity in responsiveness to peak pricing. In particular, households owning EVs exhibit peak reductions up to six times larger than the average. Finally, a related branch of the literature examines if households respond to average or marginal price incentives (Ito, 2014; Shaffer, 2020; Ito and Zhang, 2025). Peak demand charges introduce a non-linear and cost structure, with marginal cost equal to zero in all but the highest-demand hour. Marginal price incentives are prevalent under real-time pricing as well, where the marginal prices vary daily. Our analysis briefly contributes to this literature by showing that households can respond to marginal pricing schemes: in response to real-time prices, households increase consumption during low-price summer afternoon hours and winter night hours. Our findings do not provide a conclusive answer to the debate around marginal and average pricing. We complement, rather than contradict, this existing literature by highlighting some conditions under which marginal pricing may elicit a demand response.

Secondly, we link our results to an underexplored challenge for demand-side flexibility and electrification: capacity constraints in local distribution networks. As indicated by Bailey et al. (2025b), existing literature primarily focuses on the electricity production cost component of the overall electricity bill (e.g. Allcott (2011); Fabra et al. (2021); Burkhardt et al. (2023)). Although important, these largely neglect the role of electricity distribution. Electricity distribution and local distribution circuits, however, are likely to be the earliest constraint on residential electrification and demand response (Bailey et al., 2025b). The needs to expand local distribution networks are particularly acute in circuits with high EV penetration, where simultaneous fast charging causes sharper consumption peaks than traditional appliances, thereby accelerating the need for upgrades (Becker et al., 2025; Powell et al., 2022). Moreover, well-intended time-of-use tariffs can even exacerbate the problem by inducing new and larger "shadow peaks", particularly in highly electrified neighborhoods (Bailey et al., 2025a,b; Turk et al., 2025). A similar argument could hold for real-time electricity pricing, as these incentivize a coincident shift of electricity consumption towards periods with low cost of generation. Our findings indicate the introduction of the peak demand charge scheme can alleviate these concerns and lead to a statistically and economically significant reduction in the coincident monthly peak in distribution circuits. This result holds, and is even stronger, in distribution circuits with high EV penetration, for which the introduction of peak demand charges can create reductions of up to 6% of pre-treatment circuit level peaks.

Thirdly, we provide an extensive discussion of the behavioral mechanisms underlying demand response. The literature identifies several factors that either hinder or enhance residential electricity flexibility. Mechanisms that impede behavioral responses include lack of awareness of the tariff, information and adaptation costs (Fabra et al., 2021), and response fatigue (Hofmann and Lindberg, 2024). By examining the dynamics of demand response over time, our analysis uncovers response fatigue, with the effects of peak demand charges gradually decaying away over time, especially for households without low-carbon technologies. Conversely, the literature also discusses two factors that enhance demand response to pricing: the availability of information (Jessoe and Rapson, 2014) and the role of automation (Bollinger and Hartmann, 2020; Blonz et al., 2025). We complement this work by linking the mechanisms underlying the demand response to the incentives provided by peak demand charges and RTP. We show that the largest overall reduction of monthly peak electricity demand is obtained by households adopting low-carbon technologies and emphasize EV charging as a largely automated process driving demand flexibility.

The remainder of this paper is structured as follows. Section 2 provides a stylized microeconomic model of electricity consumption, aiming to clarify the incentives behind peak demand charges and real-time pricing. Section 3 introduces our institutional setting and data. In Section 4 we introduce our research design and empirical strategy. Section 5 presents the main results and extensions. Finally, Section 6 concludes.

2. Theoretical Predictions

We develop a stylized microeconomic model of electricity consumption over two periods to illustrate the effects of peak-demand charges (PDC) and real-time pricing (RTP), extending the model of Berg and Savvides (1983). The two periods, kWh_1 and kWh_2, can, for instance, represent electricity consumption of an individual consumer during peak and off-peak hours, respectively. We start from a baseline scenario with static pricing. In this baseline, the consumer faces a budget constraint determined by a uniform electricity price p_o for both periods, consisting of an energy component, volumetric network tariffs, levies and taxes, and total income I. This is represented as BC1:

$$\text{BC1} : p_o \times kWh_1 + p_o \times kWh_2 = I \tag{1}$$

We assume the consumer maximizes a standard CES utility function and has a preference for kWh_1, i.e., peak-period consumption. At the initial optimum, depicted in Figure 1, peak electricity consumption kWh_1^* exceeds off-peak consumption kWh_2^*. Now, consider the introduction of a peak-demand charge scheme, fully or partly replacing a volumetric distribution network tariff. This scheme has two key features. First, a surcharge p_p is applied to the period with the highest electricity consumption. Second, the per-unit electricity price in both periods is reduced from p_o to the rate p_n, as we impose the introduction of a peak demand charge to be budget-neutral. The new budget constraint BC2 is:

$$\text{BC2} : p_n \times kWh_1 + p_n \times kWh_2 + \underbrace{p_p\{\mathbb{1}(kWh_1 \geq kWh_2)kWh_1 + \mathbb{1}(kWh_1 < kWh_2)kWh_2\}}_{\text{PDC}} = I \tag{2}$$

Figure 1 illustrates the new kinked budget curve BC2 and the corresponding shift in the consumer's optimum from (kWh_1^*, kWh_2^*) to (kWh_1^{**}, kWh_2^{**}) following the introduction of the peak demand charge. In our stylized model, the effects of the policy are twofold. First, as shown in the left panel, the PDC incentivizes the consumer to reduce peak consumption (kWh_1) by shifting load to the off-peak period (kWh_2). Second, as represented in the right panel, the impact of the PDC is stronger when the consumer's CES utility function has a higher elasticity of substitution. This reflects greater residential flexibility: more elastic consumers are more responsive to changes in relative prices and can more easily substitute between time periods.

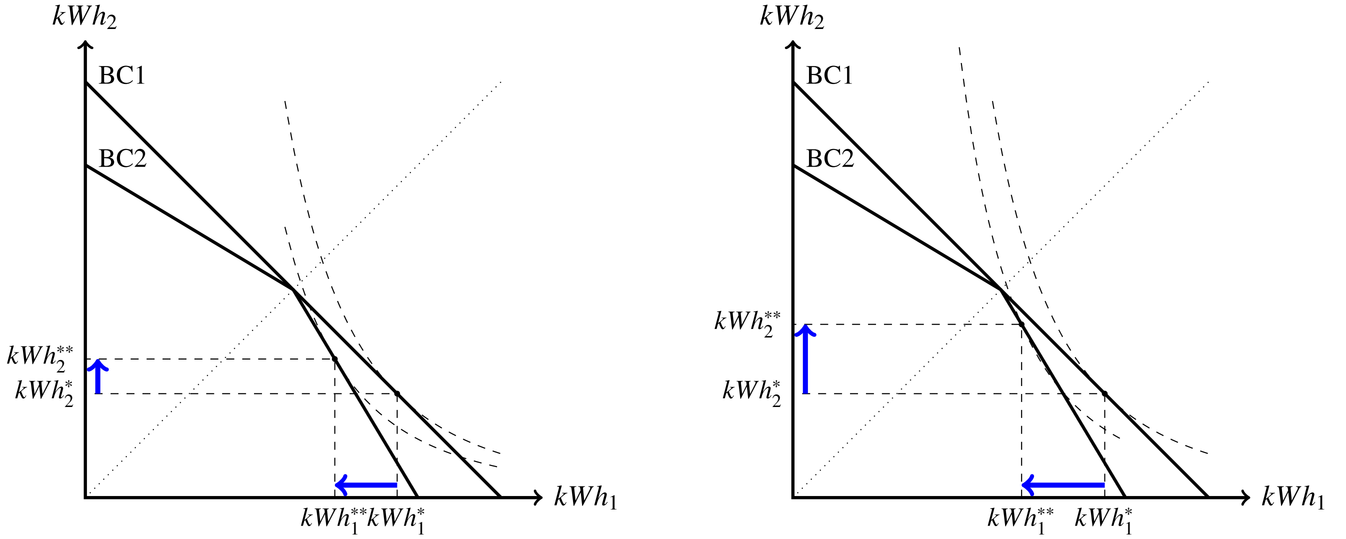
If, in addition to the peak-demand charge, real-time prices are introduced to reflect variation in the marginal cost of generating electricity, the per-unit electricity price in both periods p_n becomes period-dependent, changing the budget constraint to BC3 :

$$\text{BC3} : \underbrace{p_1}_{\text{RTP}} \times kWh_1 + \underbrace{p_2}_{\text{RTP}} \times kWh_2 + \underbrace{p_p\{\mathbb{1}(kWh_1 \geq kWh_2)kWh_1 + \mathbb{1}(kWh_1 < kWh_2)kWh_2\}}_{\text{PDC}} = I \tag{3}$$

Here, p_1 and p_2 represent the real-time price for the peak and off-peak periods, respectively. Figure 2 illustrates the possible effects the introduction of real-time pricing can have on peak and off-peak electricity demand. On the one hand, as represented in the left panel, real-time prices can reinforce the incentive given by peak demand charges. This is the case if real-time electricity prices are high in periods of peak electricity demand, or, in our model, if p_1 is high [1]. In the extreme case, though, an offsetting very low value of p_2, the off-peak real-time electricity price could theoretically generate shadow peaks (Bailey et al., 2025b), with electricity demand peaking in period 2. On the other hand, as represented in the right panel, real-time prices can also counteract peak demand charges. This is the case if electricity prices are low in periods where the individual household has its peak electricity demand, or, in our model, if p_1 is low.

In summary, our model provides several key insights. First, peak demand charges reduce peak electricity consumption without incentivizing shadow peaks. Second, the magnitude of the demand response is influenced by the elasticity of substitution in the CES utility function, which serves as a proxy for household flexibility. Finally, the introduction of real-time pricing in conjunction with peak demand charges can either reinforce or counteract the effects of peak-demand charges, depending on the correlation between system level energy prices (represented by p_1 and p_2) and local distribution network tariffs (represented by p_p).

[1] At the transmission system level, real-time electricity prices typically used to be high in periods of peak electricity demand. However, renewables generation has an increasingly important impact on prices. As shown in Figure A.3 in Appendix A.1, prices tend to fall when solar and wind generation is high: the correlation between the hourly day-ahead price (€/MWh) and hourly total renewables generation (MWh) equalled -0.53 in 2023 and -0.56 in 2024. At the household or distribution level, peak electricity demand can occur in periods with high renewable generation, and low real-time electricity prices. This decoupling implies that real-time price signals may no longer align with local demand stress.

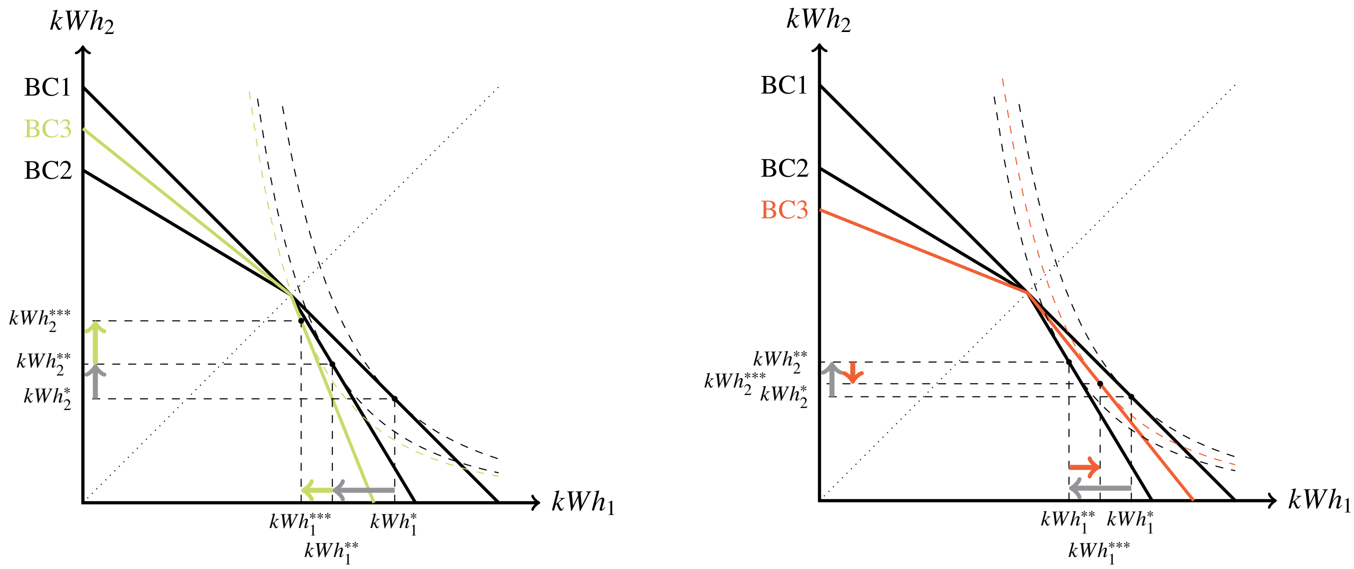


(a) Introduction of peak demand charges reduces peak consumption and increases off-peak consumption

(b) Consumption changes are larger when the elasticity of substitution increases

Figure 1: Conceptual Framework: Household electricity consumption under peak demand charges

Notes: Assume household can consume electricity in two periods 1, 2: kWh_1 and kWh_2. These periods can refer to system peak versus off-peak hours. Budget constraint BC1 applies under a static flat-rate tariff. BC2 reduces overall static flat-rate tariff and introduces a peak-demand charge that applies to all consumption in the most-used period. The left panel illustrates a household with lower substitution flexibility; the right panel illustrates a household that adjusts more to the price structure because of higher substitution flexibility.



(a) Reinforcing effect of RTP on peak demand

(b) Counteracting effect of RTP on peak demand

Figure 2: Conceptual Framework: Household electricity consumption under peak demand charges and real-time pricing

Notes: Assume household can consume electricity in two periods 1, 2: kWh_1 and kWh_2. These periods can refer to system peak versus off-peak hours. Budget constraint BC1 applies under a static flat-rate tariff. BC2 reduces overall static flat-rate tariff and introduces a peak-demand charge that applies to all consumption in the most-used period. BC3 introduces, on top of the peak-demand charge, real-time price variation. The left panel illustrates a setup in which real-time pricing reinforces the effect of peak demand charges; the right panel illustrates a setup in which real-time pricing counteracts the effect of peak demand charges

3. Data

As described in the model in previous section, the joint introduction of peak demand charges and real-time pricing affects peak electricity demand. The model also emphasizes heterogeneous effects, and the combination of incentives leads to an overall effect on peak electricity demand that is difficult to pin down ex ante. This paper, therefore, aims to evaluate the empirical impact of both peak demand charges and real-time pricing on electricity consumption, using as a case study the region of Flanders and a high-frequency panel of 15-minute level consumption data of 42,000 residential low-voltage consumers between 2022 and 2024. This section introduces in more detail our institutional setting and data.

3.1. Institutional Setting

As of January 2022, all residential consumers in Flanders were given the voluntary option to switch from a flat-rate electricity contract, where the electricity price remains constant throughout the day, to a real-time pricing contract. Under real-time pricing, the electricity price changes every hour and is directly linked to the Belgian day-ahead wholesale electricity market. These prices can vary substantially: in 2023, the month-by-hour average ranged from below €20/MWh during periods of high solar generation to over €180/MWh during winter evening peak hours or tight supply conditions, as described in Appendix Figure A.1. Secondly, as of January 2023, the grid charge design changed. The volumetric kWh-based tariff for network costs was replaced by a tariff for network costs based on a combination of a volumetric kWh-based tariff, representing 20% of overall grid charges, and a kW-based peak demand charge, representing the other 80% of overall grid charges. The volumetric kWh-based tariff was reduced, such that the total grid charge reform was budget-neutral. The kW-based peak demand charge is based on a consumer's monthly 15-minute peak demand, which is computed based on the 15-minute interval with the highest electricity consumption and takes a minimum value of 2.5 kW. The yearly average of the twelve 15-minute monthly peak demands is multiplied by the per kW-price, ranging from €35.18/kW-year to €50.05/kW-year in 2023 and from €35.12/kW-year to €53.39/kW-year in 2024. As these energy and network prices collectively contribute to the total retail price, they each affect the consumers' electricity load profiles and monthly peaks, albeit in distinctive ways.

3.2. Data sources and sample construction

We use high-frequency smart meter data on household electricity consumption as our primary data source. The dataset comprises 15-minute interval electricity usage records for over 50,000 households before pre-processing. Data comes from Flanders, Belgium, spanning the period from January 2022 to December 2024. The data were provided by Fluvius, the Flemish distribution system operator (DSO).

Prior to analysis, we applied a series of preprocessing steps. For the main analysis, we restricted the sample to households with at least one full year of data preceding the introduction of the kW-based peak demand charge, resulting in a balanced panel starting in January 2022. To mitigate the influence of outliers, we truncated monthly grid withdrawals (in kWh), monthly peak demand (in kW), and installed solar capacity (in kW) at the 99th percentile. The final sample consists of more than 1.5 million household-month observations across approximately 42,000 households during the 2022–2024 period. For the additional analysis on real-time pricing, we then add approximately 15,000 households to our sample that have an active real-time pricing contract somewhere in 2023 and 2024. We observe these households both before and after switching to a real-time pricing contract. However, we do not always observe these households for the complete three year period from 2022 to 2024, which is the reason they are not always included in the main analysis of the peak demand charge. We apply the same preprocessing for this additional sample of households on real-time pricing.

In addition to consumption data, we observe detailed metadata on the adoption of low-carbon technologies at the household level. These include heat pumps, electric vehicles, solar photovoltaic systems, and battery energy storage. Solar photovoltaic systems and battery energy storage are identified by the DSO using administrative records, based on the mandatory reporting of these systems. Electric vehicle and heat pump adoption is identified by the DSO through a combination of administrative records, based on the mandatory reporting of electric vehicle charging stations and heat pumps to the distribution system operator, and machine learning–based classification models. These machine learning-based classification models take households with electric vehicles and heat pumps, identified through mandatory reporting, as the training set. Using this approach, the DSO also identifies the month of installation of the low-carbon technologies.

In addition to high-frequency consumption data, we observe rich metadata on the adoption of low-carbon technologies at the household level, including heat pumps, electric vehicles, solar photovoltaic systems, and battery energy storage. The distribution system operator (DSO) identifies solar PV systems and batteries using administrative records, drawing on mandatory reporting requirements for these technologies. For electric vehicles and heat pumps, identification combines administrative data, based on the required registration of charging stations and heat pumps, with machine learning–based classification models. These models are trained on households with confirmed technology adoption (via reporting) and used to predict adoption status for the all other households. This approach also enables the DSO to infer the month of installation for each low-carbon technology.

Finally, we obtained further contract-level information for all households. First, we identify a subset of households designated as protected customers, who were exempted from the peak demand charge implemented under the otherwise mandatory new tariff. Second, we observe whether a household is voluntarily enrolled in a real-time pricing contract, including the date of real-time pricing contract start. The majority of real-time pricing households adopted this contract type only after the introduction of the peak demand charges on January 1st, 2023.

3.3. Sample description

Metering data Our analysis of peak demand charges relies on smart meter data recorded at 15-minute intervals for a balanced panel of 42,077 households over the 2022–2024 period. For each household-month, we construct several key measures of electricity consumption and injection. Monthly peak demand is defined as the highest load observed within any single 15-minute interval during the month, measured in watts (W). In addition to monthly peak withdrawal, we aggregate grid withdrawals and grid injections over the month to obtain household-level measures of total monthly withdrawals (kWh) and total monthly injection (kWh).

Table 1 summarizes the distribution of these monthly variables across the sample. The average monthly peak demand is approximately 4.1 kW, with an interquartile range (IQR) from roughly 3.0 kW to 5.0 kW. When broken down by year, monthly peak withdrawals are reduced across 2022 and 2023, but slightly increase in 2024. Total grid withdrawals average 256 kWh per month, with slightly higher withdrawals observed in 2024 compared to earlier years. Monthly grid injections, which occur through solar photovoltaic generation, average 163 kWh, though the distribution is highly skewed: the median injection is significantly lower, representing the share of households with zero or minimal injection. This sample structure reflects the characteristics of smart meter deployment, which prioritized households with solar PV and battery owners. Therefore, grid injections are a prominent feature of the dataset, and the distribution of withdrawals reflects the combined effects of total consumption, self-consumption from PV production, and injection into the electricity grid.

Table 1: Descriptive statistics: smart meter data and sample composition

	Mean	Std	25%	50%	75%
Monthly peak withdrawal [W]	4146	1814	2988	3884	4959
Monthly peak withdrawal (2022) [W]	4142	1745	3040	3920	4948
Monthly peak withdrawal (2023) [W]	4048	1747	2925	3801	4852
Monthly peak withdrawal (2024) [W]	4249	1936	3001	3931	5080
Grid withdrawals per month [kWh]	256	191	131	210	327
Grid withdrawals per month (2022) [kWh]	251	182	132	210	320
Grid withdrawals per month (2023) [kWh]	249	184	127	205	320
Grid withdrawals per month (2024) [kWh]	269	205	133	217	344
Grid injection per month [kWh]	163	206	0	73	274
Grid injection per month (2022) [kWh]	175	222	0	71	304
Grid injection per month (2023) [kWh]	165	209	0	75	274
Grid injection per month (2024) [kWh]	149	184	0	72	249
PV (01-01-2023)	0.69	0.46	0.00	1.00	1.00
Battery (01-01-2023)	0.16	0.37	0.00	0.00	0.00
EV (01-01-2023)	0.05	0.21	0.00	0.00	0.00
HP (01-01-2023)	0.17	0.38	0.00	0.00	0.00
Average solar capacity (2023) [kW]	4.26	1.74	3.00	4.00	5.00
Average battery size (2023) [kWh]	8.50	3.19	5.12	9.60	10.00
Average battery capacity (2023) [kVA]	4.48	1.66	3.00	4.00	5.00

Note: Descriptive statistics for the smart meter data and sample composition for households included in the main analysis. This table reports household-month statistics. There are 1,514,722 observations for 42077 households, 40630 treated households and 1717 control households.

Low-carbon technology adoption Table 1 summarizes the adoption of low-carbon technologies within the sample as of January 1, 2023. Administrative records indicate that 69 percent of households had installed solar photovoltaic systems, with an average installed capacity of 4.26 kW. Sixteen percent of households had adopted battery storage, with an average usable storage capacity of 8.50 kWh and a corresponding average power capacity of 4.48 kVA. Ownership of electric vehicles and heat pumps is identified using a combination of administrative sources and machine learning classification algorithms trained on household-level smart meter data. Based on this approach, 5 percent of households are identified as electric vehicle owners and 17 percent as heat pump owners.

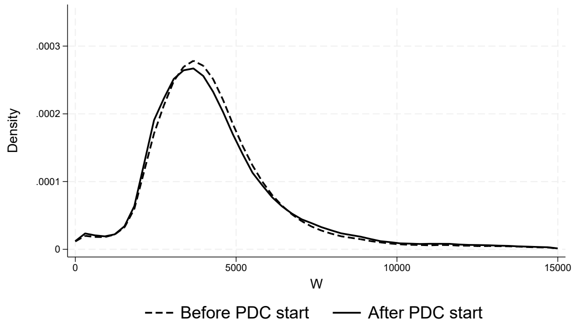
Real-time pricing sample In addition to the main balanced panel of 42,077 households, we construct a supplementary sample of 15,284 households for the analysis of real-time pricing. For these households, smart meter data become available on a staggered basis starting in early 2022. As a result, this sample is unbalanced, but data is typically available both before and after the real-time pricing enrollment. Descriptive statistics for the real-time pricing sample are reported in Appendix Table A.3. Relative to the main sample, households in the real-time pricing sample exhibit higher rates of battery and electric vehicle ownership, while solar photovoltaic adoption remains broadly similar and heat pump adoption rates are slightly lower.

3.4. *Descriptive evidence*

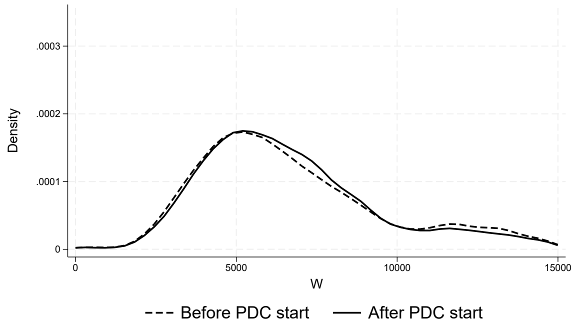
We begin by providing descriptive evidence on how households' monthly peak electricity demand evolves following the introduction of peak demand charges and enrollment in real-time pricing. Figures 3 and 4 illustrate the distribution of raw monthly peak electricity demand across different periods and subsamples. In each figure, dashed lines correspond to the distribution prior to the introduction of peak demand charges (Figure 3) or enrollment in real-time pricing (Figure 4), while solid lines depict the distribution afterward.

The top-left panel of Figure 3 plots the distribution for the full balanced sample. Following the implementation of the kW-based peak demand tariff, the distribution exhibits a slight leftward shift, suggesting a reduction in monthly peak demand. This shift is consistent with the patterns observed in Table 1, where mean monthly peak demand declines in the period following the reform. Figure 3 further suggests heterogeneity in the response across households. The top-right panel, focusing on households with an electric vehicle, reveals a more pronounced shift: the frequency of peaks above 10 kW diminishes significantly, with the probability mass moving toward the 5–10 kW range. While not expressing any causality, this pattern is consistent with households moderating their peak usage, possibly by shifting high-load activities such as electric vehicle charging or by reducing highest loads by adapting charging power. The lower two panels show the results for heat pumps and households without low-carbon technologies. Households with heat pumps typically have lower peaks than households with electric vehicles, and the shift in the peak distribution after peak demand charges is also less pronounced.

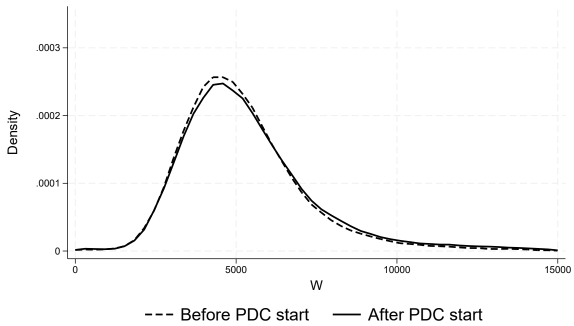
Figure 4 shows a markedly different pattern for households that adopt real-time pricing. Here, the distribution of monthly peak demand shifts to the right following adoption, indicating higher levels of peak usage. In addition to changes in the magnitude of monthly peaks, real-time pricing appears to influence the timing of peak demand events, as shown in Figures 5a and 5b. After adoption, households are less likely to reach their monthly peak during traditional evening system peak hours and more likely to do so during nighttime and afternoon periods, times when electricity prices are typically lower in the day-ahead market (Figure A.1).



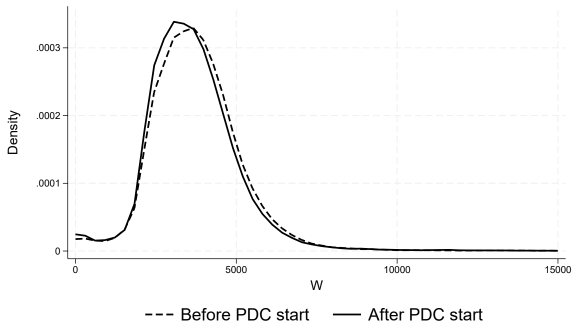
(a) Full sample



(b) Electric vehicles



(c) Heat pumps



(d) No low-carbon technologies

Figure 3: Kernel density plot for the distribution of monthly peaks before and after the introduction of peak demand charges for the full sample and three constituent subsamples. *Before PDC start* refers to the year 2022, when mandatory peak demand charges were not active. *After PDC start* refers to the years 2023 and 2024, after the mandatory introduction of peak demand charges

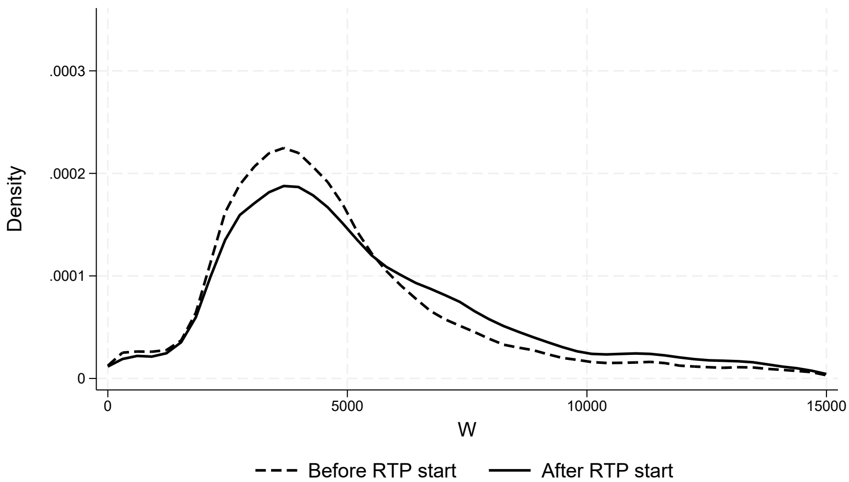
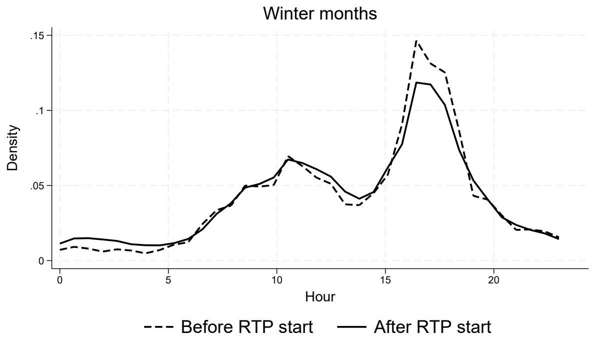
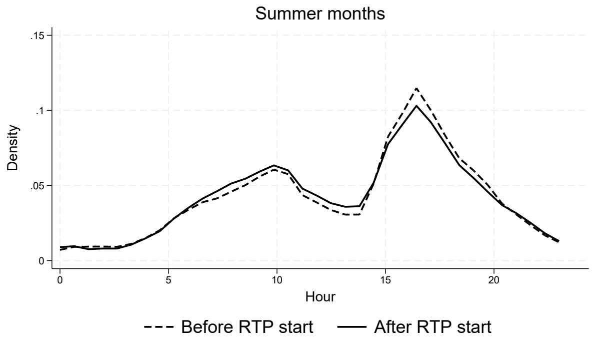


Figure 4: Kernel density plot for the distribution of monthly peaks before and after the voluntary uptake of a real-time pricing contract. *Before RTP start* refers to the monthly peak distribution of households that will adopt real-time pricing, but to observations prior to this adoption. *After RTP start* refers to households that have adopted real-time pricing



(a) Winter months



(b) Summer months

Figure 5: Kernel density plots for the distribution of monthly peak hours before and after the voluntary uptake of a real-time pricing contract.

4. Empirical Strategy

In this section, we describe our empirical strategy to estimate the causal effect of peak demand charges and real-time pricing on residential peak electricity demand. First, we estimate the average treatment effect for the treated (ATT) at the individual household level, for both treatments separately. Next, we turn to the aggregate impact of the treatments at the level of the local distribution grid. Finally, we explore the mechanisms underlying the overall treatment effects.

4.1. Monthly peak: Differences in Differences

Difference-in-Differences: Peak Demand Charges To identify the treatment effect of the introduction of the peak demand charge scheme, we exploit a large-scale natural experiment in Flanders. Under the policy change, a subset of the population, known as protected customers, was exempted from the newly introduced peak demand charge, which is otherwise mandatory. Instead of facing the newly introduced peak demand charge based on kilowatt (kW) peak usage, these protected customers continue to pay a fixed volumetric kilowatt-hour (kWh) rate. Eligibility status for being a protected customer is determined by pre-defined social criteria, including households with at least one chronically ill or disabled member receiving social assistance, recipients of unemployment benefits, low-income retirees, and residents of social housing.

Exploiting this natural experiment, we implement a difference-in-differences (DiD) design to estimate the treatment effect of peak demand charges. We compare the relative evolution of monthly peaks between households subject to the peak demand charges (treatment group) and protected customers who remain on the fixed volumetric kilowatt-hour (kWh). Define Peak_{it} as the monthly peak of household i in month-of-sample t. Furthermore, let $\mathbb{1}\{\text{Year}_t \geq 2023\}$ be a dummy variable that takes a value of one after the introduction of peak demand charges on January 1st, 2023, and define $\mathbb{1}\{\text{Protected}_i = 0\}$ an indicator variable equal to 1 if a household is in the treated group. We estimate the following regression model:

$$\text{Peak}_{it} = \beta_0 + \beta_1 \times \mathbb{1}\{\text{Year}_t \geq 2023\} \times \mathbb{1}\{\text{Protected}_i = 0\} + \mathbf{X}'_{it}\boldsymbol{\delta} + \lambda_i + \tau_t + \varepsilon_{it} \tag{4}$$

The term λ_i captures household fixed effects, τ_t accounts for month-of-sample fixed effects and ε_{it} represents the idiosyncratic error term, clustered at the household level. The main coeffient of interest, β_1, identifies the average treatment effect on the treated (ATT).

Identification issues: Peak Demand Charges If protected consumers are not an appropriate control group for the treated households, pre-treatment characteristics between the treated and control group might differ, and the parallel trends assumption underlying the difference-in-differences model might not hold unconditionally. To address these potential violations, we adopt multiple variations of a conditional difference-in-differences model.

First, as shown in Equation 4 we directly add a set of control variables $\mathbf{X}_{it}$ to our baseline TWFE difference-in-differences model to improve on covariate-balance between the treated and control group. More specifically, we include monthly electricity grid withdrawals (kWh), monthly electricity injection (kWh), solar capacity (kW), storage capacity (kW), and ownership of heat pumps and electric vehicles as household-level control variables. Temperature and electricity market-price effects do not vary between households and are thus captured in the month-of-sample fixed effects. Second, we implement the inverse-probability weighted (IPW) difference-in-differences estimator of Abadie (2005) with stabilised weights. This estimator estimates the propensity score of being treated, based on the same set of household-level covariates, and then computes a weighted mean of the outcome variable, where the weights are equal to the inverse of the propensity scores. Finally, we adopt the doubly-robust difference-in-differences estimator proposed by Sant'Anna and Zhao (2020). This method combines propensity score weighting with outcome regression, providing an unbiased estimate of the average treatment effect on the treated if at least one of the models is correctly specified. Again, the same set of covariates is used.

Difference-in-Differences: Real-time pricing For real-time pricing, we pursue a similar strategy and compare households who enrolled for real-time pricing (treatment group) with customers who did not adopt real-time pricing (never-takers). Let $\mathbb{1}\{\text{RTP}_{it} = 1\}$ be a binary variable taking a value of one if a household is currently on a real-time pricing contract. We estimate the following regression model:

$$\text{Peak}_{it} = \alpha_0 + \alpha_1 \times \mathbb{1}\{\text{RTP}_{it} = 1\} + \mathbf{X}_{it}'\boldsymbol{\delta} + \lambda_i + \tau_t + \varepsilon_{it} \tag{5}$$

The term α_1 is our coefficient of interest. The terms λ_i, τ_t and ε_{it} again represent household fixed-effects, month-of-sample fixed effects and the idiosyncratic error term. The control variables are the same as before.

Identification issues: Real-Time Pricing Identifying the effect of real-time pricing from observational data suffers from at least two problems. First, households self-select into real-time prices. We aim to accommodate for this self selection bias by again including the control variables used for the identification of peak demand charges. Second, Equation 5 would typically be estimated using a TWFE difference-in-differences model. Yet, it is shown in de Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2021) and Borusyak et al. (2024) that the TWFE difference-in-differences model delivers inconsistent estimates for the ATT if the treatment follows a staggered adoption or the treatment effect is heterogeneous across treatment groups or time. That is, because a TWFE model is a weighted average of all possible 2×2 difference-in-differences comparisons, it incorporates both "clean" comparisons between treated and not-yet-treated units and "forbidden" comparisons between units that are both already-treated, leading to negative weighting issues and inconsistent estimation of the ATT if treatment effects are heterogeneous across treatment groups or time (Roth et al., 2023). We aim to overcome these issues by estimating Equation 5 using recently introduced robust estimators. More specifically, we use the estimators introduced in, Callaway and Sant'Anna (2021). This procedure relies on a generalization of the parallel trends assumption to the setup of staggered adoption and isolates "clean" comparisons to produce consistent estimates of the ATT, using as building blocks doubly robust 2×2 difference-in-differences estimators.

Dynamic treatment effects To explore the dynamics of treatment effects we also estimate fully dynamic versions of our (robust) DiD models. More specifically, we estimate the following specifications:

$$\text{Peak}_{it} = \beta_0 + \sum_{\substack{k=-12 \\ k \neq -1}}^{24} (\beta_k \times \mathbb{1}\{\text{EventTime}_t = k\} \times \mathbb{1}\{\text{Protected}_i = 0\}) + \mathbf{X}_{it}'\boldsymbol{\delta} + \lambda_i + \tau_t + \varepsilon_{it} \tag{6}$$

$$\text{Peak}_{it} = \alpha_0 + \sum_{\text{moy}=1}^{12} \left(\alpha_{\text{moy}} \times \mathbb{1}\{\text{RTP}_{it} = 1\}\right) + \mathbf{X}_{it}'\boldsymbol{\delta} + \lambda_i + \tau_t + \varepsilon_{it}, \tag{7}$$

For peak demand charges, we specify a fully dynamic specification in which we obtain a month-of-sample specific treatment effect estimates. As in the baseline DiD approach, we augment this model in three ways to account for covariate imbalance. First, we directly add a set of control variables to our baseline event-study. Second and third, we implement dynamic versions of the IPW DiD estimator (Abadie, 2005) and the doubly-robust DiD estimator (Sant'Anna and Zhao, 2020).

To estimate the dynamic effect of real-time pricing, we continue with our difference-in-differences specification with staggered treatment timing, following the framework of Callaway and Sant'Anna (2021). Specifically, we estimate separate treatment effects for each adoption cohort, and then aggregate the results to calendar time. While some early adopters enter in early 2023, the majority of uptake occurs in late 2023 and 2024. Due to the limited sample size and resulting imprecision for the 2023 cohorts, we focus in our results on the 2024 calendar-month treatment effects. These estimates are therefore month-of-sample specific, but restricted to calendar year 2024. We include month-of-sample fixed effects (τ_t) and household fixed effects (λ_i) to control for common shocks and seasonal variation across households.

Grid level effects To simulate the impact of network charges and low-carbon technologies on the distribution grid, we adopt a strategy inspired by Bailey et al. (2025b). Households are randomly assigned to synthetic distribution circuits consisting of either 10 or 25 households. Assignment is based on the adoption of electric vehicles, heat pumps, and battery energy storage systems. For each technology, households are placed into circuits with a predetermined adoption level: 0%, 20%, 50%, 80%, or 100%. We then aggregate the load profiles for these 10 or 25 households, to obtain the aggregate load profile for the distribution circuit. This also allows determining the coincident grid-level monthly peak.

We believe our simulation strategy provides several key advantages. First, our design captures different stages of residential electrification. By varying the share of, for instance, electric vehicle adoption across circuits, the design enables the simulation of grid impacts under different scenarios of electric vehicle penetration. Second, our design allows maintaining realistic baseline demand profiles, without relying on ad-hoc assumptions. Because households are assigned to circuits conditional on their own low-carbon technology adoption status, the underlying heterogeneity in non-electric vehicle or non-heat pump electricity consumption is preserved. This allows for a more accurate representation of baseline electricity load conditions within each circuit.

To estimate the aggregate effect of peak demand charges, we estimate a variation on our main specification, Equation 4. More specifically, we run a regression with the coincident grid-level monthly peak as an outcome variable and a dummy variable indicating the post-treatment period as main explanatory variable. As the absolute number of household with low-carbon technologies in the control group is limited, we no longer make a direct comparison with the control group in our aggregate analysis. We do, however, further include an extensive set of circuit-level control variables. These are identical to the household-level control variables, but are now aggregated over all the household in the distribution circuit: the number of households with heat pumps and electric vehicles, aggregate solar capacity (kW) and battery energy storage capacity (kW), aggregate residential electricity production (kWh), and temperature, and added month-of-year and circuit fixed-effects.

For the analysis of real-time pricing at the grid level, we follow a similar strategy to that outlined in Equation 5, with an adjustment to account for treatment variation within circuits. We construct a set of categorical variables that indicate the share of households with an active real-time pricing contract within each synthetic distribution circuit. Specifically, we define indicators for adoption levels of approximately 0%, 20%, 50%, 80%, and 100%. This approach is motivated by the staggered nature of real-time pricing uptake: unlike peak demand charges, with a fixed start date, real-time pricing adoption evolves over time, making it infeasible to assign circuits a fixed level of treatment intensity at every point in time. As a result, we allow real-time pricing penetration to vary *within* circuits across time and estimate how different levels of adoption affect grid-level outcomes. We thus also exploit variation within circuits rather than only across circuits. The control variables are the same as the grid-level control variables for the analysis of peak demand charges.

4.2. Load profile: Difference in Differences

Potential explanations for changes in monthly peaks can be manyfold. For instance, households might shift consumption outside peak hours to off-peak hours, or they might reduce their overall consumption in response to peak demand charges and real-time pricing. These incentives and load shifting dynamics might be affected by information availability, knowledge or automation. In order to study to study the incentives and mechanisms behind the introduction of peak demand charges and real-time pricing, we use granular 15-minute interval electricity consumption data in a regression framework to examine changes in the daily household load profiles.

Our regression works as follows. From the raw 15-minute metering data, we first aggregate grid withdrawals per hour (in kWh). We thus obtain one observation per household-hour combination. In a subsequent step, we aggregate hourly observations to total daily withdrawals and total daily withdrawals within a specific time interval. kWh_{idb} represents these total electricity withdrawals for household i on day-of-sample d during time interval ("block") b. The time intervals include total withdrawals during night (22.00 - 06.00), morning (06.00 - 12.00), afternoon (12.00 - 17.00) and evening peak hours (17.00 - 20.00). kWh_{idb} is then used in a difference-in-differences regression, defined separately for real-time pricing and peak demand charges:

$$\text{kWh}_{idb} = \beta_0 + \beta_1 \times \mathbb{1}\{\text{Year}_t \geq 2023\} \times \mathbb{1}\{\text{Protected}_i = 0\} + \mathbf{X}'_{idb}\boldsymbol{\delta} + \alpha_{idb} + \varepsilon_{idb}. \tag{8}$$

$$\text{kWh}_{idb} = \alpha_0 + \alpha_1 \times \mathbb{1}\{\text{RTP}_{it} = 1\} + \mathbf{X}'_{idb}\boldsymbol{\delta} + \alpha_{idb} + \varepsilon_{idb}. \tag{9}$$

Again $\mathbb{1}\{\text{Year}_t \geq 2023\}$ takes a value of one after the introduction of peak demand charges, and $\mathbb{1}\{\text{Protected}_i = 0\}$ is an indicator variable taking a value of one for the treated households. Control variables X_{idb} include hourly temperature and household-specific variables on solar capacity (kW), storage capacity (kW), heat pump and electric vehicle adoption, and solar production (kWh). Finally, α_{idb} includes household-day-of-week, household-month-of-year and month-of-sample fixed effects. The effect of real-time pricing on the load profile is studied in a similar way, replacing only the peak demand charge treatment variables with the appropriate variables for real-time pricing.

5. Results

In this section, we present our treatment effect estimates. We first investigate the effect of the peak demand charge and real-time pricing on the individual monthly peak in Section 5.1 and the distribution grid peak in Section 5.2. We then proceed to our analysis of the mechanisms and the effect on the shape of the daily load profile in different seasons, which we present in Section 5.3.

5.1. Monthly Peak

5.1.1. Difference-in-Differences

Table 2 presents estimates of α_1 and β_1 in equations 4 and 5 and captures the effect of peak demand charges and real-time pricing on monthly household-level peaks, showing that the introduction of both pricing schemes had an opposing effect on peak electricity demand. The first three columns show the effects for peak demand charges. In the first column, we apply the TWFE-DID estimator, which includes control variables and month-of-sample and household fixed effects. In the second column, we apply the IPW-DID estimator (Abadie, 2005). The third column uses the DR-DID estimator (Sant'Anna and Zhao, 2020) and shows the largest point estimate. We show specification tests for our weighting procedures in Appendix B.1. Our results are relatively stable across specifications. The point estimates increase in size from -51 watts to -122 watts, but all carry the same sign and all are statistically significant at the 1 percent level.

In order to help build intuition about the magnitude of our baseline effects, we provide a few interpretations. First, the magnitude of our baseline effects corresponds to an approximate reduction of between 1 to 3 percent of the average household monthly peak. Second, we highlight that this reduction is equivalent to switching off close to ten energy-efficient LED lightbulbs rated at 10 W during peak periods but is significantly less than switching off a typical washing machine during peak hours. Third, we benchmark our baseline effects against those found in the literature. In response to a critical peak pricing experiment, Garnache et al. (2025) observe reductions of consumption up to 12.5% at critical peak hours. Similarly, Enrich et al. (2024) observe reductions of peak-hour electricity consumption up to 9% after the introduction of a time-of-use tariff. Our results are quantitatively smaller, which might indicate that it is more difficult to decrease monthly *peak* electricity demand than to shift *average* electricity usage in peak periods.

To prevent that our results are driven or attenuated by new low-carbon technology adoption, Appendix B.2 presents two robustness checks. In the first, we include only households in our analysis that do not acquire any new low-carbon technology after the introduction of the peak demand charge scheme (Table B.2). In the second, we do allow households that install new low-carbon technologies in our sample, and remove the control variables modelling adoption of low-carbon technologies from our regression specification (Table B.3). This should test the sensitivity of our coefficients to modelling choices around low-carbon technologies. Both robustness checks present results similar to our main specification, with statistically significant and negative coefficients.

Columns four and five of Table 2 present the estimated effect of real-time pricing. Column four employs the traditional TWFE-DID estimator, which should be interpreted with caution as it does not fully address the staggered rollout of real-time pricing in our sample. In contrast, column five implements the doubly robust difference-in-differences estimator proposed by Callaway and Sant'Anna (2021), which better accommodates treatment timing heterogeneity. Our results suggest that real-time pricing leads to a statistically significant increase in monthly peak demand, with an effect size comparable to that of peak demand charges. This implies that the introduction of real-time pricing could potentially offset most of the peak-reducing impact of peak demand charges. These findings offer a new perspective on the implications of real-time pricing: while Fabra et al. (2021) report an overall insignificant price elasticity, our evidence indicates that real-time pricing may nonetheless contribute to higher household peak electricity consumption.

Table 2: Main Specification using DiD

	PDC			RTP	
	(1)	(2)	(3)	(4)	(5)
	TWFE-DID	IPW-DID	DR-DID	TWFE-DID	CS-DID
$\mathbb{1}\{\text{Year}_t \geq 2023\} \times \mathbb{1}\{\text{Protected}_i = 0\}$	-51.40***	-95.67***	-122.22***		
	(-3.79)	(-3.11)	(-3.99)		
$\mathbb{1}\{\text{RTP}_{it} = 1\}$				38.00***	127.46**
				(4.06)	(2.35)
Fixed Effects	✓			✓	
Control variables	✓		✓	✓	✓
Weighting		✓	✓		✓
Observations	1,514,722	1,514,722	1,514,722	1,275,700	1,275,700
Households	42,077	42,077	42,077	57,361	57,361
Treated	40,360	40,360	40,360	N/A	N/A
Control	1717	1717	1717	N/A	N/A

Note: The monthly peak (W) over the period January 2022 - December 2024 is modelled in a difference-in-differences framework. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households on the social tariff serve as control group. Three specifications are used to estimate the model. Column (1) uses TWFE-DID with additional control variables. Control variables include grid withdrawals (kWh), solar capacity (kW), solar injection (kWh), storage capacity (kWh) and the dummy variables for the presence of heat pumps and electric vehicles. Household fixed effects and time fixed effects are included. In column (2), we apply the IPW-DID estimator with stabilised weights, weighting based on grid withdrawals (kWh), solar capacity (kW), solar injection (kWh), postal code, and dummy variables for the quarter of low-carbon technology adoption (separate for EV, HP, PV and battery storage). Column (3) shows the estimate for the Sant'Anna and Zhao (2020) Doubly Robust DID estimator using the same weighting variables. Finally, columns (4) and (5) show the results for real-time prices, using the TWFE-DID and Callaway and Sant'Anna (2021) Doubly Robust DID estimator with never-takers as the control group, respectively. The unit of observation is household-month-of-sample. For real-time pricing, the number of treated and control households varies per month-of-sample, as treatment follows staggered adoption. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1.2. Event study

Peak demand charges Beyond average effects, we now explore the dynamics of treatment effects over time using event studies. More specifically, in this section, we estimate a dynamic version of our difference-in-differences models. Figure 6 presents the event-study results for three specifications of our difference-in-differences model for peak demand charges: the TWFE-DID estimator with control variables, the IPW-DID estimator with stabilised weights, and the Doubly Robust DID estimator (Sant'Anna and Zhao, 2020). All specifications provide suggestive evidence that the parallel trends assumption holds using "pre-trends": the coefficients for the months prior to the introduction of peak demand charges are close to zero across all estimators, with no discernible trends. This suggests that, before the implementation of the peak demand charges on January 1st, 2023, treated and control households were following similar trajectories in terms of their monthly peak demand conditional on control variables. It is only after the policy intervention that treated households begin to reduce their peak demand relative to the control group.

Figure 6 also illustrates the temporal dynamics of the peak demand charge, showing a clear pattern of decay in the treatment effect over time. In the early months of 2023, treated households significantly reduce their monthly peak demand, but this reduction diminishes gradually in subsequent months. This decline is robust across the various model specifications. These findings indicate that the effect of the peak demand charge gradually decays away as time progresses, regardless of the estimator used. Response fatigue provides a plausible explanation for the diminishing effect, particularly among households that rely on manual demand response, those without low-carbon technologies. For these households, the sustained effort required to reduce peak demand manually may lead to a gradual decline in engagement. As these households are not able to leverage automated systems, continuously altering consumption patterns becomes increasingly difficult, likely explaining the attenuation of the peak reduction over time, as shown in Figure 7a. This response fatigue aligns with findings in Hofmann and Lindberg (2024), who document a decreased interest and attention to electricity prices in a randomized controlled trial setting.

Finally, some households are not incentivized to reduce their monthly peak after the introduction of peak demand charges, as the new tariff structure imposes a minimum peak of 2.5 kW. Therefore, those households with average pre-treatment monthly peaks below 2.5 kW, are not incentivized to reduce their peaks further. Figure 7b shows that these households do not change their monthly peaks after the introduction of the kW-based peak demand charge scheme. For these households, the minimum threshold of 2.5 kW serves as a financial constraint that makes it difficult to justify further reductions in demand, as a peak reduction does not translate into a lower electricity bill. Furthermore, even when they do attempt to reduce their peak consumption, the inherent difficulty in achieving substantial reductions when pre-treatment peaks are already low, means that the overall impact of the treatment is less pronounced, as illustrated in Figure 7b.

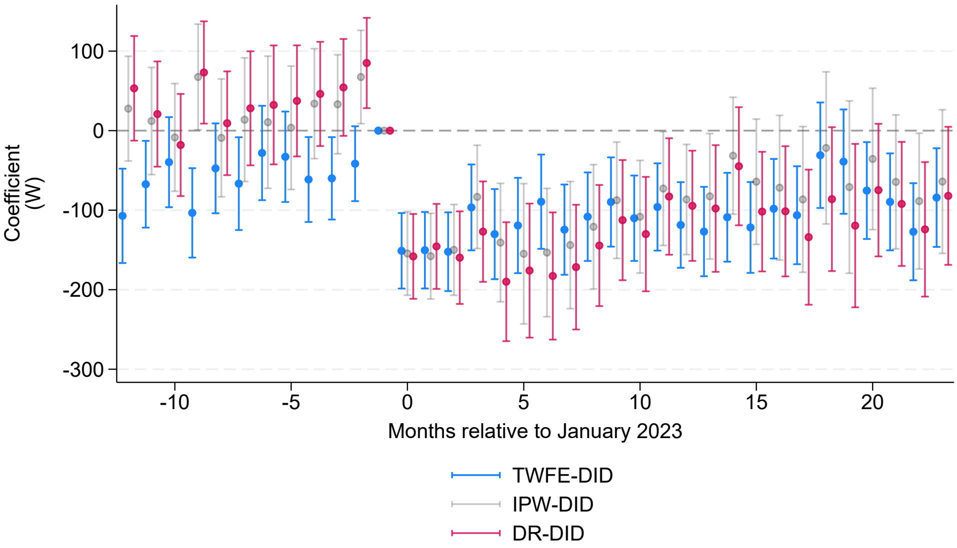
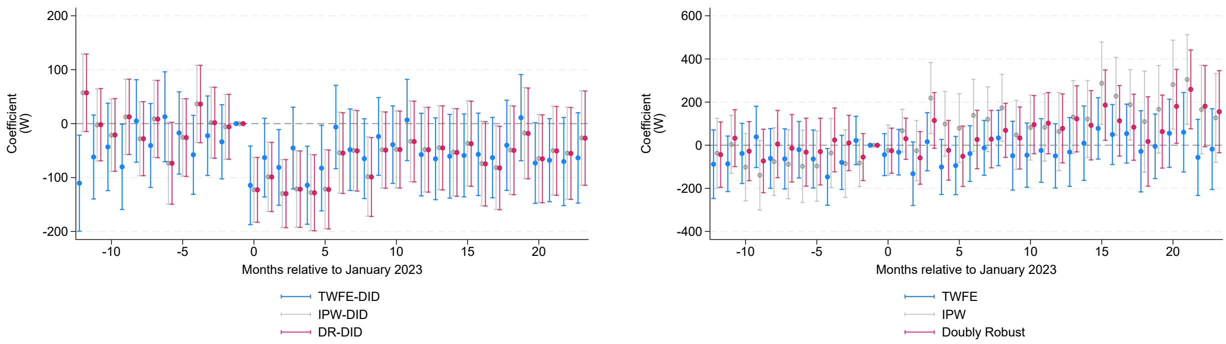


Figure 6: Estimates of the dynamic specification for peak demand charges in the full sample. Each dot represents the point estimate of the monthly peak reduction (in W) for a given month-of-sample t. Three different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects including control variables. Second, the IPW-DID estimator with stabilised weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. December 2022 is used as the reference category in both pre- and post-treatment periods. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.



(a) Households without low-carbon technologies (manual response)

(b) Households with 2022 peak < 2.5 kW

Figure 7: Each dot represents the point estimate of the monthly peak reduction (in W) for a given month-of-sample t. Three different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects including control variables. Second, the IPW-DID estimator with stabilised weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. December 2022 is used as the reference category in both pre- and post-treatment periods. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

Real-time pricing In this section, we turn our attention to the event-study effects of real-time pricing, which differs from the peak-demand charge policy's effects. Figure 8 shows statistically significant increases in monthly peak demand among households that voluntarily adopt real-time pricing on top of the compulsory peak demand charge, with additional seasonal variation. The peak-increasing effect of real-time pricing is most pronounced during the summer months, June, July, August, and September, when monthly peak demand rises by more than 150 W. These results suggest that the interaction between real-time pricing and peak demand charges is seasonally dependent, affecting the alignment of incentives across pricing schemes.

A possible explanation could be the following: in winter, day-ahead electricity prices tend to be elevated during both morning and evening peak periods, but are not consistently low during off-peak hours (Figure A.1). As a result, households on real-time pricing have less financial incentive to create so-called "shadow peaks" by shifting consumption to very low-priced hours. In contrast, during summer months, day-ahead prices can be substantially lower, or even negative, during periods of high solar PV generation. In this context, real-time pricing introduces a trade-off: households face incentives to both reduce their monthly peak (to minimize peak demand charges) and to increase consumption during low-price hours (to benefit from low marginal costs of electricity production). These competing incentives appear to largely offset each other, resulting in a smaller net effect on household monthly peak electricity demand during these months. As the number of negative price hours is increasing, and expected to increase further in the future (IEA, 2025), the economic significance of this finding is expected to increase even further.

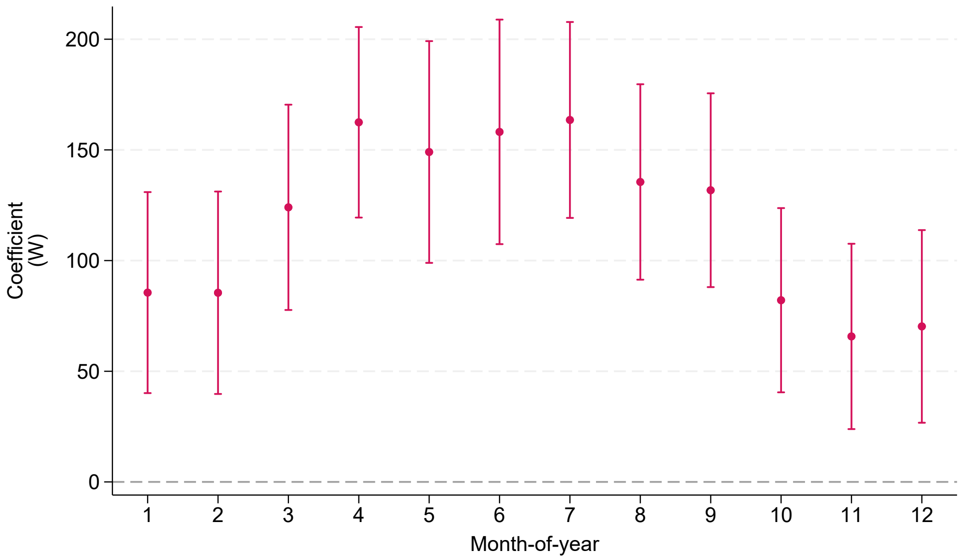


Figure 8: Estimates of the dynamic specification for real-time prices in the full sample, showing coefficients per month-of-year in 2024. Each dot represents the point estimate of the monthly peak change (in W) for a given month-of-year. The Callaway and Sant'Anna (2021) Doubly Robust DID estimator with never-takers as the control group is used to estimate the causal effect. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

5.1.3. Heterogeneity

Low-carbon technology To assess whether the introduction of peak demand charges generated heterogeneous treatment effects across household types, we examine treatment heterogeneity by low-carbon technology adoption. Our analysis proceeds in two steps. First, we classify each household into one or more categories based on the technologies installed prior to January 2023, the start of the peak demand charge tariff. These categories include households without any low-carbon technology, and those with electric vehicles (EVs), heat pumps (HPs), solar photovoltaics, or batteries. Second, we estimate Equation 4 separately by subgroup to identify heterogeneous effects.

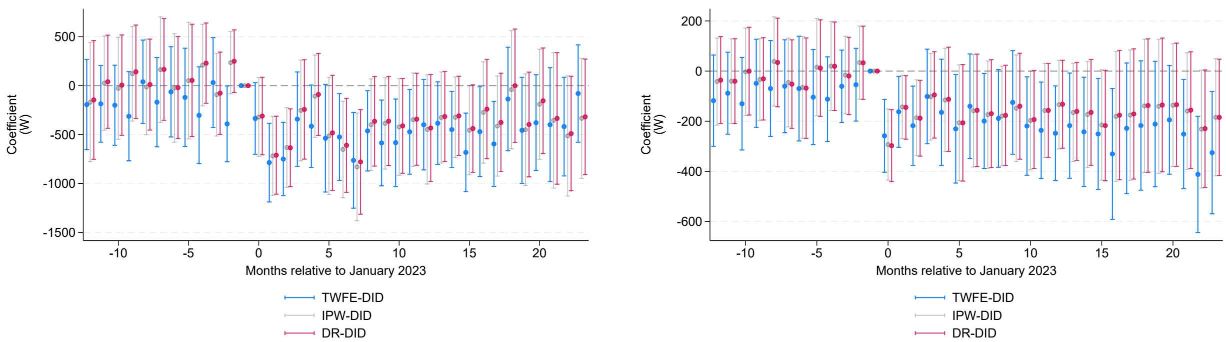
Table 3 reports the estimates of β_1 across household subsamples. All specifications use the TWFE-DID estimator and control for household and month-of-sample fixed effects. In addition, we include household-level covariates and account for adoption of new low-carbon technologies after the introduction of the kW-based peak demand charge scheme. The results reveal considerable heterogeneity in treatment effects. Households with heat pumps or no low-carbon technologies exhibit peak demand reductions lower in magnitude than the full-sample average. Battery-owning households reduce their peaks somewhat more, indicating a modest additional response capacity. The most notable finding concerns EV-owning households. These households reduce their monthly peak load by an average of 319 W following the reform, a reduction that is both economically and statistically significant. Relative to their 2022 pre-treatment baseline, this reduction amounts to roughly 5 percent of their average monthly peak. This contrasts both in absolute and relative terms with the more modest 1–3 percent reductions observed in the full sample and other subgroups. Appendix Table B.4 provides robustness checks using alternative estimators, which corroborate the main findings: the estimated treatment effects are larger for EV and battery owning households.

Figures 9a and 9b present the event-study estimates of the dynamic response of monthly peak demand to the introduction of kW-based peak demand charges, separately for households with EVs and those with battery storage. These figures show a sharp reduction in peak demand in the months immediately following the reform for both groups, with this effect persisting over time. The coefficients do not dissipate in the months following the reform and remain statistically significant. This treatment effect is consistent with the adoption of automated energy-management systems, such as smart EV chargers, as well as applications provided by EV manufacturers, both of which can incorporate the incentive from the peak demand charge into the charging schedule to help limit peak demand.By deferring EV charging to off-peak periods, these systems help reduce peak demand consistently, transforming what might otherwise be a one-time adjustment into a lasting change driven by automation. For robustness, Appendix Figure B.4 displays event-study estimates for all subgroups of low-carbon technologies. These results reinforce the finding that households with EVs exhibit the most stable and persistent reductions in peak demand over time.

Table 3: Heterogeneity analysis using DiD

	(1) Full sample	(2) EV	(3) HP Main	(4) HP Additional	(5) BAT	(6) No LCT
$\mathbb{1}\{\text{Year}_t \geq 2023\} \times \mathbb{1}\{\text{Protected}_i = 0\}$	-51.40***	-319.47***	-29.37	-88.70	-147.55***	-18.44
	(-3.79)	(-2.41)	(-0.45)	(-1.41)	(-2.61)	(-1.13)
Control variables	✓	✓	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	1,514,722	57,636	102,168	79,308	245,088	290,844
Households	42,077	1600	2838	2203	6808	8079
Treated	40,360	1547	2745	2107	6588	7513
Control	1717	54	93	96	220	566
Average Peak$_{it}$ 2022	4142.44	6331.26	5083.59	4966.90	3861.69	3706.10

Note: The monthly peak (W) over the period January 2022 - December 2024 is modelled in a difference-in-differences framework. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households on the social tariff serve as control group. Results are presented for the TWFE-DID estimator with additional control variables. Control variables include grid withdrawals (kWh), solar capacity (kW), solar injection (kWh), storage capacity (kWh) and the dummy variables for the presence of heat pumps and electric vehicles. Household fixed effects and time fixed effects are included. Households with heat pumps as main source of heating do not have significant gas consumption, whereas households with heat pumps as additional source of heating also have significant gas consumption. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a) Households with electric vehicle ownership

(b) Households with battery energy storage

Figure 9: Estimates of the dynamic specification for peak demand charges for households with electric vehicle ownership, relying on a manual demand response. Each dot represents the point estimate of the monthly peak reduction (in W) for a given month-of-sample t. Three different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects including control variables. Second, the IPW-DID estimator with stabilised weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. December 2022 is used as the reference category in both pre- and post-treatment periods. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

Peak demand charge price level Table 4 presents estimates from an extended specification that examines heterogeneity in treatment effects by the level of the peak demand charge. We introduce this specification for two reasons. First, while peak demand charges were introduced uniformly across Flanders on January 1st, 2023, the actual tariff levels vary by region, ranging from €35.18/kW-year to €50.05/kW-year in 2023 and from €35.12/kW-year to €53.39/kW-year in 2024. To capture this variation, we define $\widetilde{\text{Rate}}_{it}$ as the deviation of a household's peak demand charge rate from the annual average. Second, it is important to note that households typically receive their electricity bill annually, in a randomly assigned month that depends on the timing of their most recent retailer switch. As a result, it may take up to a year before all households have had the opportunity to observe the new peak demand charge on their bill. To capture this effect, we estimate the regression separately for 2023 and 2024, where in the latter period all households had observed the bill-impact of the peak demand charge.

Column (1) replicates our average treatment effect estimated with the TWFE-DID specification including control group and control variables, indicating a statistically significant reduction in monthly peaks of approximately 51.4 W. Columns (2) through (4) explore heterogeneity by interacting the treatment indicator with household-level deviations from the average peak demand charge rate. While the overall interaction term is not statistically significant in column (2), the year-specific analysis in columns (3) and (4) reveals that the effect of the rate deviation becomes significant in 2024. Specifically, a one-euro/kW-year increase in the deviation from the average rate is associated with a 2.75 W additional reduction in peak demand. These results suggest that while the introduction of peak demand charges had an immediate impact on consumption, the salience or responsiveness to the precise rate level appears to increase over time.

Table 4: Effect of Peak Demand Charge Rate

	Main	**Deviations**		
	All	All	2023	2024
$\mathbb{1}\{\text{Year}_t \geq 2023\} \times \mathbb{1}\{\text{Protected}_i = 0\}$	-51.40***	-53.06***	-58.08***	-46.00***
	(-3.79)	(-3.90)	(-4.60)	(-2.66)
$\mathbb{1}\{\text{Year}_t \geq 2023\} \times \mathbb{1}\{\text{Protected}_i = 0\} \times \widetilde{\text{Rate}}_{it}$		-1.311	-0.0921	-2.754*
		(-1.34)	(-0.10)	(-1.75)
Fixed Effects	✓	✓	✓	✓
Control variables	✓	✓	✓	✓
N	1,514,772	1,514,772	1,009,848	1,009,848
Clusters	42,077	42,077	42,077	42,077

Note: The monthly peak (W) over the period January 2022 - December 2024 is modelled in a difference-in-differences framework. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households on the social tariff serve as control group. Four specifications are used to estimate the model. Each specification uses the TWFE-DID estimator. Column (1) estimates the treatment effect for the full sample, and columns (4), (5) and (6) model add the deviation from the average peak demand rate as a covariate. All specifications include control variables: grid withdrawals (kWh), solar capacity (kW), solar injection (kWh), storage capacity (kWh), heat pump and electric vehicle ownership. Furthermore, all specifications include household and month-of-sample fixed effects. The unit of observation is household-month-of-sample. Standard errors are clustered at the household level. t-statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

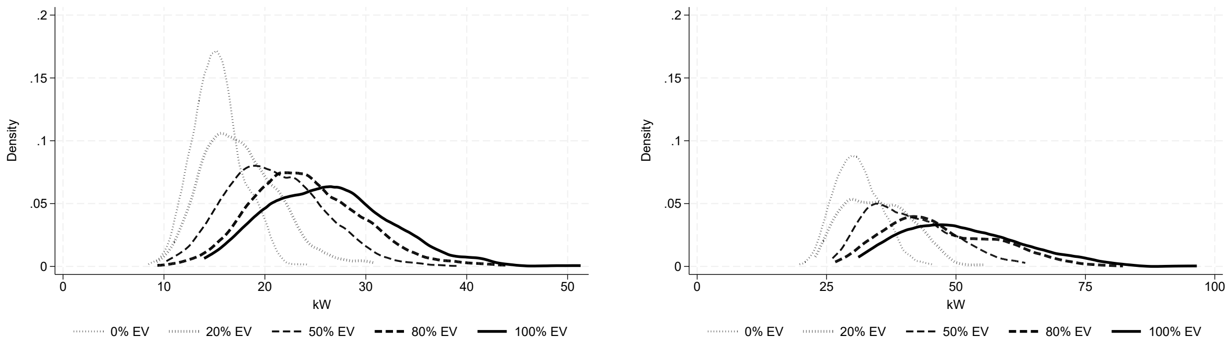
5.2. *Grid level effects*

The effects of the introduction of peak demand charges and real-time pricing thus far leverage data at the individual household-level. However, transmission and distribution grids are sized to ensure meeting future system peaks in demand (Joskow and Tirole, 2005; Fell et al., 2021; Schittekatte et al., 2023). Network charges should thus provide an incentive to spread consumption over time, particularly discouraging usage during periods of high coincident system peaks, in order to reduce the need for costly grid reinforcement and enhance overall system efficiency. This issue is becoming increasingly salient with the growing adoption of electric vehicles, as simultaneous fast charging events can generate substantially higher load peaks compared to conventional household appliances (Bailey et al., 2025b; Becker et al., 2025; Powell et al., 2022). For this reason, this section leverages the granularity of our dataset to assess how individual behavioral responses to tariffs and prices scale to the level of the distribution grid. Our approach proceeds in two steps. First, we generate synthetic distribution circuit-level data through a bootstrap procedure similar to Bailey et al. (2025b). Second, we estimate local distribution grid effects of peak demand charges and real-time pricing through regression analysis.

5.2.1. *Electric vehicles and peak demand charges*

To simulate the effect of network charges and electric vehicle adoption on the distribution grid, we randomly assigned households to distribution circuits comprising either 10 or 25 households. Conditional on their own electric vehicle adoption status, each household was then randomly placed into a circuit with a predetermined level of EV adoption: 0%, 20%, 50%, 80%, or 100%.

To understand the potential impact of electric vehicle charging on the distribution grid, Figure 10 shows the distribution of monthly peak electricity demand across varying levels of electric vehicle adoption. Across the groups, we observe that monthly peak electricity demand increases consistently with the percentage of households that has adopted an EV in the circuit. Distribution circuits of 10 households with 0% EV adoption, peak on average at 15.32 kW (31.01 kW for circuits with 25 households), while distribution circuits with 100% EV adoption peak on average at 26.41 kW (51.34 kW for circuits with 25 households). We provide further descriptives in Appendix Tables C.1 and C.2. These tables illustrates that EV charging exhibits highly coincident behavior: the coincidence factor for households with EVs remains comparable to that of non-EV households. Because EV charging significantly increases individual peak demand, the resulting circuit-level coincident peaks are substantially higher in absolute kilowatt terms. This increase in peak load places additional strain on the local distribution grid and lead to overload of distribution feeder cables and stations.



(a) 10 households aggregated

(b) 25 households aggregated

Figure 10: Kernel density for the distribution of monthly peaks in the distribution grid for circuits with 10 or 25 households connected, and varying levels of electric vehicle adoption

We now explore how the introduction of peak demand charges has changed these monthly peaks through a panel fixed effects regression model, with the coincident grid-level monthly peak as an outcome variable and a dummy variable indicating the post-treatment period as main explanatory variable. We further include an extensive set of circuit-level control variables, including the number of households with heat pumps, EVs, solar PV and battery energy storage installed, residential electricity production, and temperature, and added month-of-year and circuit fixed-effects.

The results from this exercise are shown in Table 5. The table makes several points. The results indicate a statistically significant reduction in coincident peaks in local distribution circuits following the introduction of peak demand charges. The reduction of the coincident peak is most pronounced in circuits with a higher level of EV-adoption. For instance, in circuits with 100% EV adoption and 10 connected households, the introduction of peak demand charges leads to a reduction in the monthly peak load of 1.8 kW. This represents a decline of approximately 6.8% relative to the pre-treatment mean monthly peak of 26.41 kW (see Table C.1). The effect scales with the size of the circuit: in circuits with 100% EV adoption and 25 connected households, the coincident peak declines by 3.09 kW, or 6.0% of the pre-treatment average.

In Appendix C.3 and Appendix C.4 we provide similar analysis, now for circuits with increased uptake of heat pumps or residential battery energy storage. For heat pumps we find similar results, although the reduction of the circuit-level peak after the introduction of peak demand charges is smaller for heat pumps than for electric vehicles in circuits with 10 households and 100% adoption. For larger circuits with 25 households and 100% heat pump adoption, the result turns insignificant. In circuits with higher levels of battery energy storage adoption, we find that battery installation itself reduces circuit-level coincident peaks (Figures C.2a and C.2b). However, introducing peak demand charges does not further reduce monthly peak demand in these circuits.

Table 5: Synthetic distribution level TWFE regression results by EV adoption level

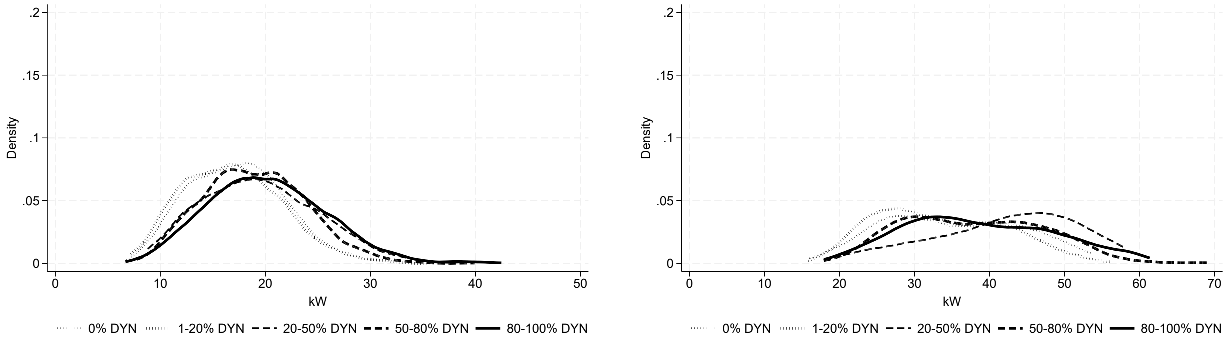
	Percentage of households with EV				
	0%	20%	50%	80%	100%
	PANEL A: 10 households				
Peak (kW)					
Daily	-0.111***	-0.315***	-0.536***	-0.648***	-0.673***
	(-3.37)	(-6.37)	(-7.88)	(-9.06)	(-9.24)
Monthly	-0.453***	-0.824***	-1.511***	-1.847***	-1.810***
	(-4.58)	(-4.97)	(-6.20)	(-6.60)	(-5.24)
	PANEL B: 25 households				
Peak (kW)					
Daily	-0.173**	-0.569***	-0.653***	-1.116***	-1.238***
	(-2.07)	(-5.01)	(-4.75)	(-6.44)	(-4.94)
Monthly	-0.508**	-0.798**	-1.988***	-1.861**	-3.093***
	(-2.10)	(-2.14)	(-3.59)	(-2.32)	(-3.23)

Note: The distribution grid level coincident monthly peak (kW) - aggregated over 10 households in Panel A or 25 households in Panel B - over the period January 2022 - December 2024 is modeled in a panel fixed effects regression model. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period. We employ a TWFE model without control group, but with additional control variables. Control variables include grid-level aggregate distributed solar production (kWh), aggregate grid withdrawals (kWh), solar capacity installed (kW), storage capacity installed (kWh), temperature, and the variables for the number of heat pumps and electric vehicles in the distribution circuit. Fixed effects include circuit and month-of-year fixed effects. Standard errors are clustered at the circuit level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.2. Real-time pricing

In Figure 11, we examine how the introduction of real-time pricing affects coincident monthly peak demand at the distribution grid level. The figure displays the distribution of monthly peak loads across synthetic circuits comprising 10 or 25 households, stratified by varying levels of real-time pricing adoption (0%, 1-20%, 20-50%, 50-80%, or 100%). Importantly, real-time pricing adoption is staggered over time, and the share of adopters in each circuit increases throughout the sampling period. Consequently, circuits with higher real-time pricing adoption are disproportionately observed later in the panel, introducing potential confounding due to seasonality or underlying time trends in electricity demand. While these descriptive results provide suggestive insights, they should be interpreted with caution given this potential confounding bias.

Across adoption levels in Figure 11, we observe a modest increase in coincident monthly peaks at the distribution level, although the effect is less pronounced than that observed under electric vehicle adoption. Specifically, in circuits where none of the 10 connected households has adopted real-time pricing, the average monthly coincident peak is 15.27 kW. This rises to 20.17 kW in circuits where all connected households have adopted real-time pricing. Additional summary statistics are provided in Appendix Tables C.3 and C.4. We next examine how real-time pricing adoption affects coincident peak demand in a regression framework, controlling for adoption of low-carbon technology, month-of-year, temperature and solar production effects. Table 6 presents results from a panel fixed effects regression model, estimating the impact of varying levels of real-time pricing penetration within synthetic distribution circuits of 10 and 25 households. Across both circuit sizes, we find limited evidence that real-time pricing also increases peak demand at the grid level. While daily peak demand increases modestly at intermediate and higher adoption levels, the effects are generally not statistically significant at any levels. Similarly, we do not observe a statistically significant pattern in monthly peak effects. These findings suggest that the impact of real-time pricing on grid-level coincident peaks is currently modest.



(a) 10 households aggregated

(b) 25 households aggregated

Figure 11: Kernel density for the distribution of monthly peaks in the distribution grid for circuits with 10 or 25 households connected, and varying levels of real-time pricing adoption.

Table 6: Synthetic distribution level TWFE regression results by real-time pricing adoption level

	Percentage of households with active real-time pricing contract				
	0%	20%	50%	80%	100%
			PANEL A: 10 households		
Peak (kW)					
Daily	Ref.	0.005	0.139	0.109	0.137
		(0.06)	(1.28)	(0.79)	(0.90)
Monthly	Ref.	0.0886	0.261	0.792	0.437
		(0.47)	(0.81)	(0.20)	(1.03)
			PANEL B: 25 households		
Peak (kW)					
Daily	Ref.	0.068	0.694*	0.408	0.478
		(0.31)	(1.93)	(0.94)	(1.08)
Monthly	Ref.	0.012	0.072	-0.380	-0.005
		(0.02)	(0.09)	(-0.31)	(-0.00)

Note: The distribution grid level coincident monthly peak (kW) - aggregated over 10 households in Panel A or 25 households in Panel B - over the period January 2022 - December 2024 is modeled in a panel fixed effects regression model. We employ a TWFE model with additional control variables. Control variables include grid-level aggregate distributed solar production (kWh), aggregate grid withdrawals (kWh), solar capacity installed (kW), storage capacity installed (kWh), temperature, and the variables for the number of heat pumps and electric vehicles in the distribution circuit. Fixed effects include circuit and month-of-year fixed effects. Standard errors are clustered at the circuit level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3. *Daily load profile*

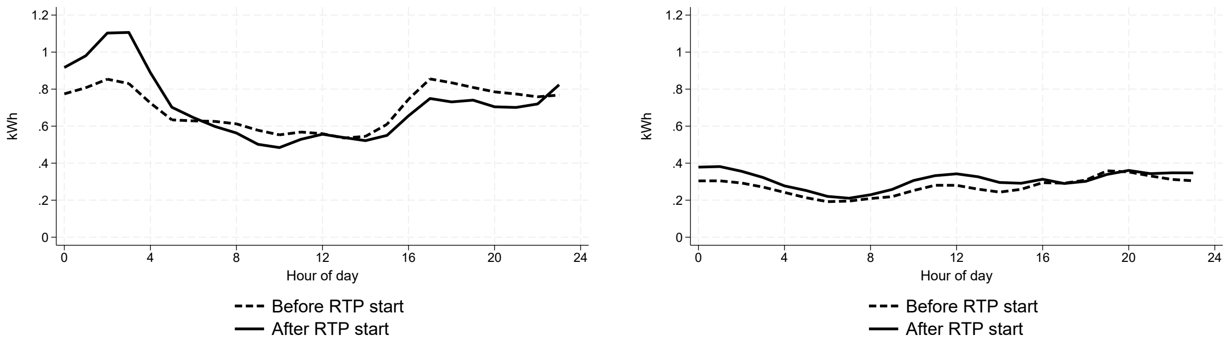
After presenting treatment effects for monthly peak demand at the individual household and distribution level, we now turn to the underlying behavioral mechanisms using complete daily load profiles. This section explores the individual behavior behind changes in monthly peak electricity demand, and discusses important enablers of the demand response, such as automation and information availability (Jessoe and Rapson, 2014; Bollinger and Hartmann, 2020; Blonz et al., 2025). Our evaluation focusses on two groups, who face significant financial incentives under under the peak-demand charge. We first discuss households who voluntarily adopted real-time pricing and then discuss the incentives and demand response for households owning an electric vehicle.

5.3.1. *Real-time pricing and peak demand charges*

Based on our results for monthly peaks we hypothesized a potential effect of day-ahead prices and seasonal effect on electricity consumption patterns for households on real-time pricing. Figure A.1 adds more detail to this hypothesis. This figure displays the raw mean day-ahead electricity prices on the Belgian market for 2023 and 2024, respectively. Each heatmap plots average hourly day-ahead prices by month-of-year, showing both seasonal and intraday variation. The figures indicate that day-ahead prices are generally higher during the winter months. Additionally, the lowest prices tend to occur during daytime hours in months with longer solar duration, reflecting the influence of solar PV generation. A consistent pattern across most months is the increase in day-ahead prices during evening system-level demand peaks, particularly between 17:00 and 20:00. For households on real-time pricing, this day-ahead electricity price translates immediately to a bill impact.

To assess the role of within-day variation of day-ahead prices, Figures 12a and 12b plot the average household-level hourly electricity consumption for winter months and summer months. The figure contains data for adopters of real-time pricing, plotting their consumption before and after adoption. The load profiles imply a clear response to price changes, as customers shift their load to hours with lower prices. After switching to real-time prices, nighttime electricity increases, while evening peak-hour electricity consumption decreases. This load shifting pattern correlates with the shape of real-time electricity prices, that are generally highest in winter evening peak-hours. In summer months, the observed shift is less pronounced, though some small increase in electricity consumption is observed for night and afternoon hours: hours with, on average, the lowest real-time electricity prices.

We then formalize this findings by estimating regression equation 9. This regression estimates the change in kWh electricity demand after the uptake of a real-time pricing contract, controlling for household characteristics, including the uptake of new low-carbon technologies. Table 7 shows the findings. In the first row of the table, we pool together the daily electricity consumption, and find that real-time pricing does not have an effect on total load. In the other rows of the table, we pool together electricity consumption in a specific block of hours. For instance, the second row pools together all morning consumption, and finds that real-time pricing decreases morning consumption by on average 0.127 kWh per day. The decomposition between winter and summer months adds intuition to our findings. Throughout winter months households clearly shift away from electricity consumption in morning hours and evening peak hours, almost substituting this demand one-to-one by an increase in nighttime consumption. For summer months, on the contrary, the observed load shifting is much smaller, in line with descriptive evidence. We do however observe an increase in average afternoon consumption.



(a) Winter months

(b) Summer months

Figure 12: Average kWh hourly electricity grid withdrawals for RTP adopters before and after adoption

Table 7: Load shifting for real-time pricing

	(1) All	(2) Winter	(3) Summer
Total grid withdrawals:			
All hours	0.404	0.074	0.655
	(1.45)	(0.10)	(1.20)
Morning hours (06.00 - 12.00)	-0.127**	-0.438**	0.077
	(-2.16)	(-2.22)	(0.61)
Afternoon hours (12.00 - 17.00)	0.065	0.008	0.303**
	(1.01)	(-1.64)	(2.11)
Peak hours (17.00 - 20.00)	-0.125**	-0.519***	-0.055
	(-2.49)	(-3.77)	(-0.44)
Night hours (22.00 - 06.00)	0.576***	1.442***	0.338
	(3.73)	(3.61)	(1.20)
Control variables	✓	✓	✓
Household × day-of-week FE	✓	✓	✓
Household × month-of-year FE	✓	✓	✓
Month-of-sample FE	✓	✓	✓
Observations	358,639	88,523	92,202
Clusters	1061	1061	1061

Note: The daily grid withdrawals (kWh) in a block of hours over the day over the period January 2023 - December 2024 are regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The uptake of real-time prices indicates the post period and not-yet-treated households serve as control group. The model is estimated for the full sample, and the different seasons separately. The unit of observation is household-day-of-sample. Control variables include solar capacity (kW), solar production (kWh), storage capacity (kWh), daily variables for temperature and the dummy variables for the presence of heat pumps and electric vehicles. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

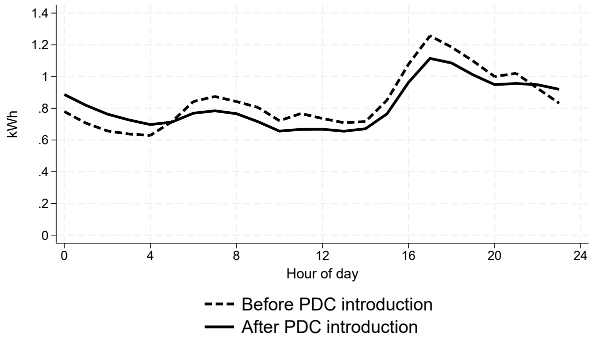
5.3.2. Electric vehicles, solar panels and peak demand charges

In this section, we present evidence showing the load shifting dynamics in response to the introduction of peak demand charges for EV-owning households. In Figures 13a and 13b, we first explore the change in the load profiles descriptively, and plot the average hourly electricity grid withdrawals for electric vehicle-owning households in summer and winter months, before and after the introduction of peak demand charges. "Before PDC introduction" refers to 2022, prior to the introduction of peak demand charges, while "After PDC introduction" refers to 2023 and 2024, when households were charged based on their kilowatt peak usage. To avoid confounding the figure by intermediate electric vehicle adoption, these figures only incorporate data for households that adopted their electric vehicle before the start of 2022. In analogy with the results for real-time pricing, we observe a more pronounced change in load profiles in winter months. Nighttime electricity grid withdrawals increases after the introduction of the peak demand charge scheme, while peak hour electricity withdrawals reduce.

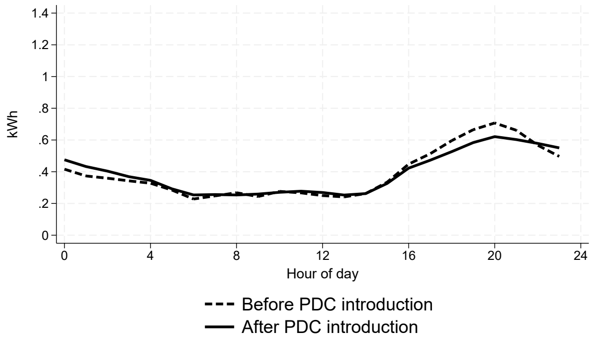
Table 8 presents the estimation results of Equation 8 for EV-owning households. In the first row, we again pool together the daily electricity grid withdrawals over all hours of the day, while the other rows pool together electricity grid withdrawals in a block of hours. The results corroborate our descriptive evidence and demonstrates the response of electric vehicle-owning households to the peak demand charges. Pooling together all hours of the day, we observe that peak demand charges have not led to an overall load reduction.

We do however observe patterns of load shifting. Specifically, in winter months we observe a reduction in grid withdrawals of 0.274 kWh during the [17.00; 20.00] interval, the evening peak. We also observe significant reductions throughout the rest of the morning and afternoon hours. An offsetting effect is observed at night, with increased grid withdrawals during the [22.00; 06.00] interval. The overall shift of load amounts to roughly 0.75 kWh per day. In summer months, we do not observe statistically significant load shifting effects. These results are robust to the inclusion of self-production, as we observe similar load shifting dynamics when substituting our outcome variable grid withdrawals (kWh) by consumption (kWh). Detailed results for total electricity consumption, the sum of withdrawals and production, minus injection, can be found in Appendix Figures D.2a and D.2b and Table D.2.

Several mechanisms may explain the effects we observe. First, the introduction of peak demand charges appears to shift electricity consumption from peak to off-peak hours, particularly during the night. Such load-shifting behavior reduces household-level monthly peaks, thereby lowering the peak component of the electricity bill. Similar patterns have been documented in response to time-of-use pricing schemes for electric vehicle owners in Arizona (Qiu et al., 2022) and price incentive programs in Australia (La Nauze et al., 2024). Second, we find that this nighttime charging effect diminishes during the summer months. In this period, households with rooftop solar panels exhibit relatively stable grid withdrawals following the introduction of peak demand charges. This likely reflects a pre-existing incentive for solar self-consumption among households that already owned both electric vehicles and solar panels prior to the tariff reform (Liang et al., 2022; La Nauze et al., 2024). These findings are also consistent with prior evidence showing that co-adoption of electric vehicles and solar panels induces a shift in charging behavior, from nighttime to daytime, to align electricity demand with solar generation profiles (Qiu et al., 2022; Liang et al., 2022; Astier et al., 2023; La Nauze et al., 2024). In Appendices Appendix D.3 and Appendix D.4, we extend this analysis to households with heat pumps and battery energy storage. For these groups, we do not find evidence of load shifting in response to peak demand charges. However, we do observe an increase in overall grid withdrawals for heat pump households, which is statistically significant during winter months.



(a) Winter months



(b) Summer months

Figure 13: Average kWh hourly electricity grid withdrawals for EV adopters before and after the introduction of peak demand charges

Table 8: Load shifting for EV owners

	(1) All	(2) Winter	(3) Summer
Total grid withdrawals:			
All hours	0.349	-0.434	0.790
	(0.83)	(-0.61)	(1.51)
Morning hours (06.00 - 12.00)	0.00164	-0.386**	0.217
	(0.02)	(-2.44)	(1.50)
Afternoon hours (12.00 - 17.00)	-0.0118	-0.394*	0.152
	(-0.12)	(-1.86)	(1.41)
Peak hours (17.00 - 20.00)	-0.0600	-0.274**	0.0813
	(-0.69)	(-2.07)	(0.66)
Night hours (22.00 - 06.00)	0.460**	0.788*	0.277
	(2.10)	(1.77)	(1.26)
Control variables	✓	✓	✓
Household × day-of-week FE	✓	✓	✓
Household × month-of-year FE	✓	✓	✓
Month-of-sample FE	✓	✓	✓
Observations	2,106,068	516,362	531,802
Households	2021	2021	2021

Note:The daily grid withdrawals (kWh) in a block of hours over the day over the period January 2022 - December 2024 are regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households serve as control group. The model is estimated for the full sample, and the different seasons separately. The unit of observation is household-day-of-sample. Control variables include solar capacity (kW), solar production (kWh), storage capacity (kWh), daily variables for temperature and the dummy variables for the presence of heat pumps and electric vehicles. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusion

The transition to a zero-carbon energy system is reshaping how electricity is priced and consumed. On the production side, real-time pricing promotes productive efficiency by aligning consumption with temporal variations in the marginal cost of electricity production, encouraging demand shifts toward periods of lower supply costs (Borenstein, 2005; Burkhardt et al., 2023). Recent research has emphasized a second, increasingly important constraint: local distribution network capacity. Rising residential electrification and the adoption of electric vehicles are intensifying coincident peak demand at the local distribution level, accelerating the need for costly grid upgrades (Bailey et al., 2025b; Powell et al., 2022). Time-of-use charges and real-time pricing may exacerbate these challenges by inducing synchronized consumption responses to low wholesale prices, thereby increasing local coincident peak loads and overloading distribution infrastructure.

Using high-frequency consumption data of over 42,000 low-voltage consumers, we find that peak demand charges are effective at reducing the individual and distribution grid-level coincident monthly peaks. The average treatment effect equals between 51 and 122 watts, which is 1-3 percent of the pre-treatment average. Households with an electric vehicle show the most pronounced peak reduction of 300 watts, 5 percent of their average pre-treatment monthly peak (in line with the findings in Bailey et al. (2025a)), an effect that remains statistically significant over time. This reduction of monthly peak electricity demand is obtained largely through load shifting to night hours, with a shift of up to 0.75 kWh per day in winter months. The individual-level effects further translate to the low-voltage grid, especially when more of the connected households own electric vehicles. The voluntary adoption of real-time pricing conditional on peak demand charges can partially counteract this reduction by concentrating consumption during lower-cost periods, leading to new peaks, an effect that is particularly pronounced during summer months. These peak increases amount on average to 127 watts. Furthermore, the effects of real-time prices do not seem to propagate to the distribution grid, alleviating the concern that real-time prices increase grid congestion.

Rather than generating conflicting incentives, the two pricing mechanisms can operate in a complementary manner when carefully designed: real-time pricing addresses energy system efficiency by signaling marginal production costs (Fabra et al., 2021; Allcott, 2011; Borenstein, 2005), while peak demand charges internalize distribution-level constraints that are otherwise invisible to consumers (Bailey et al., 2025b; Becker et al., 2025; Powell et al., 2022). In increasingly automated households (Bollinger and Hartmann, 2020; Blonz et al., 2025), this complementarity is required for scalable demand-side flexibility that does not violate local grid constraints. While our empirical analysis focuses on such joint implementation of real-time pricing and peak demand charges in Flanders, Belgium, the underlying mechanisms are likely to be relevant in broader contexts. Several neighboring countries, including Germany, France, and the Netherlands, exhibit comparable levels of per capita household electricity consumption and are similarly characterized by winter peak demand. Furthermore, the observed price variation in the day-ahead wholesale prices observed in Belgium, which serve as the basis for the real-time pricing contracts, follow a similar shape in other Western European countries (see Figures A.1 and A.2 in Appendix A.1).

These findings contribute to a growing literature recognizing the importance of aligning price signals across the electricity supply chain to address both production and network-level challenges in the energy transition. More broadly, our findings highlight a challenge inherent in vertically structured electricity markets: the coexistence of multiple tariff components makes coordination across different stages of the supply chain – generation, transmission, and distribution – a necessary condition for avoiding unintended outcomes such as inefficient load shifting or the exacerbation of local network constraints.

References

Abadie, A., 2005. Semiparametric difference-in-differences estimators. The Review of Economic Studies 72, 1–19. doi:10.1111/0034-6527.00321.

ACER, 2024. Electricity Infrastructure Development to Support a Competitive and Sustainable Energy System: 2024 Monitoring Report. Technical Report. European Union Agency for the Cooperation of Energy Regulators. Ljubljana, Slovenia. URL: https://www.acer.europa.eu/sites/default/files/documents/Publications/ACER_2024_Monitoring_Electricity_Infrastructure.pdf.

Allcott, H., 2011. Rethinking real-time electricity pricing. Resource and Energy Economics 33, 820–842. doi:10.1016/j.reseneeco.2011.06.003.

Astier, N., Rajagopal, R., Wolak, F.A., 2023. Can distributed intermittent renewable generation reduce future grid investments? evidence from france. Journal of the European Economic Association 21, 367–412.

Bailey, M., Brown, D., Shaffer, B., Wolak, F., 2025a. Show me the money! a field experiment on electric vehicle charge timing. American Economic Journal: Economic Policy May.

Bailey, M., Brown, D.P., Myers, E., Shaffer, B., 2025b. Electric vehicles and the energy transition: Unintended consequences of a common retail rate design. American Economic Review: Insights .

Becker, T., Smet, R., Macharis, B., Vanthournout, K., 2025. Effect of electric vehicles, heat pumps, and solar panels on low-voltage feeders: Evidence from smart meter profiles. Sustainable Energy, Grids and Networks 42. doi:10.1016/j.segan.2025.101705.

Berg, S., Savvides, A., 1983. The theory of maximum kw demand charges for electricity. Energy Economics 5, 258–266. doi:10.1016/0140-9883(83)90030-0.

Bernard, L., Hackett, A., Metcalfe, R., Schein, A., 2024. The impact of heat pumps and a time-of-use heat pump tariff on energy demand. NBER URL: https://www.nber.org/papers/w33036, doi:10.3386/w33036.

Blonz, J., Palmer, K., Wichman, C.J., Wietelman, D.C., 2025. Smart thermostats, automation, and time-varying prices. American Economic Journal: Applied Economics 17, 90–125. doi:10.1257/app.20210618.

Bollinger, B.K., Hartmann, W.R., 2020. Information vs. automation and implications for dynamic pricing. Management Science 66, 290–314. doi:10.1287/mnsc.2018.3225.

Borenstein, S., 2005. The long-run efficiency of real-time electricity pricing. The Energy Journal 26, 93–116. URL: https://journals.sagepub.com/doi/abs/10.5547/ISSN0195-6574-EJ-Vol26-No3-5, doi:10.5547/ISSN0195-6574-EJ-Vol26-No3-5.

Borenstein, S., Holland, S., 2005. On the efficiency of competitive electricity markets with time-invariant retail prices. RAND Journal of Economics 36, 469–493.

Borusyak, K., Jaravel, X., Spiess, J., 2024. Revisiting event-study designs: Robust and efficient estimation. Review of Economic Studies 91, 3253–3285. doi:10.1093/restud/rdae007.

Burkhardt, J., Gillingham, K., Kopalle, P.K., 2023. Experimental Evidence on the Effect of Information and Pricing on Residential Electricity Consumption. Management Science Forthcoming. doi:10.2139/ssrn.3336385.

Callaway, B., Sant'Anna, P.H.C., 2021. Difference-in-differences with multiple time periods. Journal of Econometrics 225, 200–230. doi:10.1016/j.jeconom.2020.12.001.

de Chaisemartin, C., D'Haultfœuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. American Economic Review 110, 2964–2996. doi:10.1257/aer.20181169.

Enrich, J., Li, R., Mizrahi, A., Reguant, M., 2024. Measuring the impact of time-of-use pricing on electricity consumption: Evidence from spain. Journal of Environmental Economics and Management 123. doi:10.1016/j.jeem.2023.102901.

Eurelectric, 2024. Grids for speed. Technical Report. Eurelectric.

Fabra, N., Rapson, D., Reguant, M., Wang, J., 2021. Estimating the elasticity to real-time pricing: Evidence from the spanish electricity market. AEA Papers and Proceedings 111, 425–429. doi:10.1257/pandp.20211007.

Fell, H., Kaffine, D.T., Novan, K., 2021. Emissions, transmission, and the environmental value of renewable energy. American Economic Journal: Economic Policy 13, 241–72. doi:10.1257/pol.20190258.

Garnache, C., Hernæs, Ø., Imenes, A.G., 2025. Demand-side management in fully electrified homes. Journal of the Association of Environmental and Resource Economists 12, 257–283.

Gillingham, K., Ovaere, M., Xingchi, S., 2025. Effects of rooftop solar on the distribution grid: Evidence from connecticut.

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. Journal of Econometrics 225, 254–277. doi:10.1016/j.jeconom.2021.03.014.

Harding, M., Lamarche, C., 2016. Empowering Consumers Through Data and Smart Technology: Experimental Evidence on the Consequences of Time-of-Use Electricity Pricing Policies. Journal of Policy Analysis and Management 35, 906–931. doi:10.1002/pam.

Harding, M., Sexton, S., 2017. Household Response to Time-Varying Electricity Prices. Annual Review of Resource Economics 9, 337–359. doi:10.1146/annurev-resource-100516-053437.

Hofmann, M., Lindberg, K.B., 2024. Evidence of households' demand flexibility in response to variable hourly electricity prices – results from a comprehensive field experiment in norway. Energy Policy 184. doi:10.1016/j.enpol.2023.113821.

IEA, 2025. Electricity 2025: Analysis and Forecast to 2027. Technical Report. International Energy Agency. URL: https://www.iea.org/reports/electricity-2025.

Ito, K., 2014. Do consumers respond to marginal or average price? evidence from nonlinear electricity pricing. American Economic Review 104, 537–563. doi:10.1257/aer.104.2.537.

Ito, K., Zhang, S., 2025. Do consumers distinguish fixed cost from variable cost?" schmeduling" in two-part tariffs in energy. American Economic Journal: Economic Policy .

Jessoe, K., Rapson, D., 2014. Knowledge is (Less) Power : Experimental Evidence from Residential Energy Use. American Economic Review 104, 1417–1438.

Joskow, P., Tirole, J., 2005. Merchant transmission investment. The Journal of Industrial Economics 53, 233–264. doi:10.1111/j.0022-1821.2005.00253.x.

La Nauze, A., Friesen, L., Li Lim, K., Menezes, F., Page, L., Philip, T., Whitehead, J., 2024. Can electric vehicles aid the renewable transition? evidence from a field experiment incentivising midday charging. CESifo Working Paper Series 11386.

Leuven, E., Sianesi, B., 2003. PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Statistical Software Components, Boston College Department of Economics. URL: https://ideas.repec.org/c/boc/bocode/s432001.html.

Liang, J., Qiu, Y., Xing, B., 2022. Impacts of the co-adoption of electric vehicles and solar panel systems: Empirical evidence of changes in electricity demand and consumer behaviors from household smart meter data. Energy Economics 112. doi:10.1016/j.eneco.2022.106170.

Powell, S., Cezar, G.V., Min, L., Azevedo, I.M.L., Rajagopal, R., 2022. Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption. Nature Energy 7, 932–945. doi:10.1038/s41560-022-01105-7.

Qiu, Y., Kahn, M.E., Xing, B., 2019. Quantifying the rebound effects of residential solar panel adoption. Journal of Environmental Economics and Management 96, 310–341. doi:10.1016/j.jeem.2019.06.003.

Qiu, Y.L., Wang, Y.D., Iseki, H., Shen, X., Xing, B., Zhang, H., 2022. Empirical grid impact of in-home electric vehicle charging differs from predictions. Resource and Energy Economics 67. doi:10.1016/j.reseneeco.2021.101275.

Roth, J., Sant'Anna, P.H.C., Bilinski, A., Poe, J., 2023. What's trending in difference-in-differences? a synthesis of the recent econometrics literature. Journal of Econometrics 235, 2218–2244. doi:10.1016/j.jeconom.2023.03.008.

Sant'Anna, P.H.C., Zhao, J., 2020. Doubly robust difference-in-differences estimators. Journal of Econometrics 219, 101–122. doi:10.1016/j.jeconom.2020.06.003.

Schittekatte, T., Mallapragada, D., Joskow, P.L., Schmalensee, R., 2023. Reforming retail electricity rates to facilitate economy-wide decarbonization. Joule 7, 831–836. doi:10.1016/j.joule.2023.03.012.

Shaffer, B., 2020. Misunderstanding nonlinear prices: Evidence from a natural experiment on residential electricity demand. American Economic Journal: Economic Policy 12, 433–461.

Stokke, A.V., Doorman, G.L., Ericson, T., 2010. An analysis of a demand charge electricity grid tariff in the residential sector. Energy Efficiency 3, 267–282. doi:10.1007/s12053-009-9071-9.

Turk, G., Schittekatte, T., Duenas-Martinez, P., Joskow, P., Schmalensee, R., 2025. Designing distribution network tariffs in the us with an application to increased electric vehicle penetration. The Energy Journal .

US Energy Information Administration, 2023. Annual Energy Outlook 2023. Technical Report. U.S. Energy Information Administration.

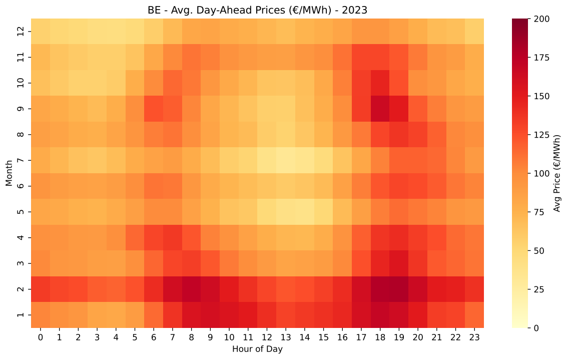
Appendix

This appendix contains additional descriptive statistics (Appendix A), additional econometric results for the main specification on individual-level effects (Appendix B), aggregated grid-level effects (Appendix C) and mechanisms using daily load profiles (Appendix D).

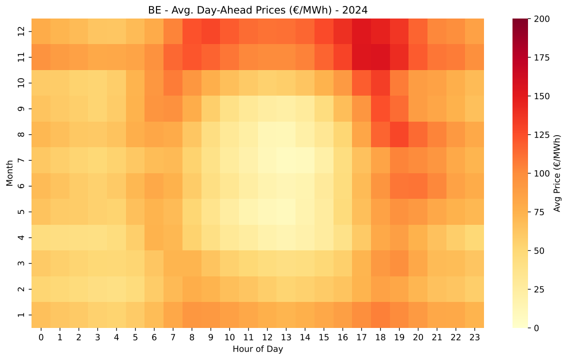
Appendix A. Supplementary Descriptives

Appendix A.1. Real-time prices

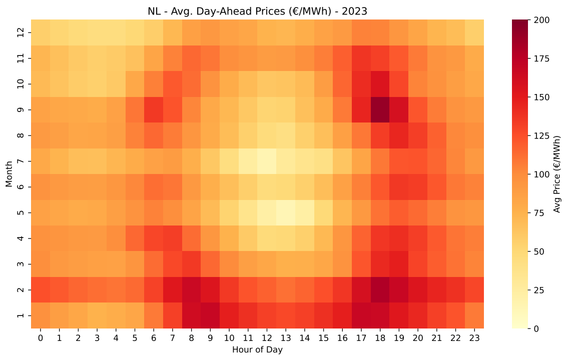
Figure A.1 displays heatmaps for day-ahead electricity price by hour of day and month of year for 2023 and 2024 in Belgian and other European bidding zones. Prices exhibit clear seasonal and within-day variation, with higher prices concentrated during winter evenings and lower prices during midday hours, especially in the summer months. The patterns are somewhat less pronounced in 2024, reflecting milder price volatility compared to 2023. Figure A.2 shows correlation matrices for pairwise correlation between day-ahead electricity prices (€/MWh) for four European bidding zones. Correlations are high, ranging from between 0.7 to 0.97.



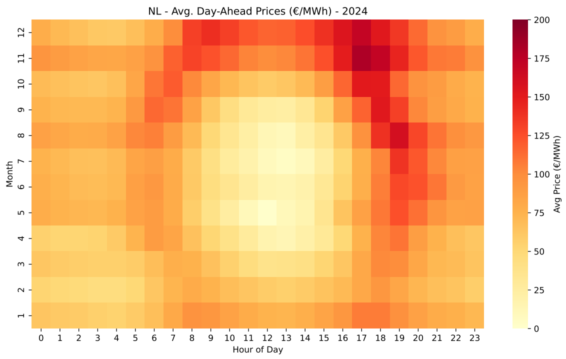
(a) Bidding Zone Belgium, 2023



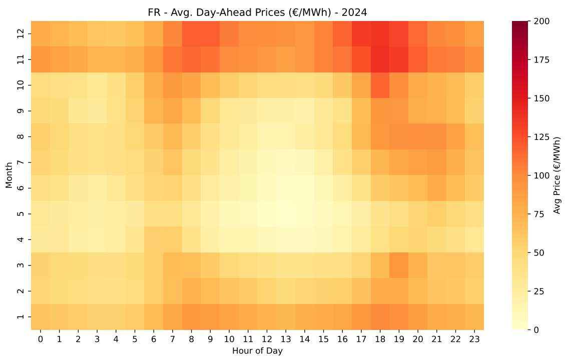
(b) Bidding Zone Belgium, 2024



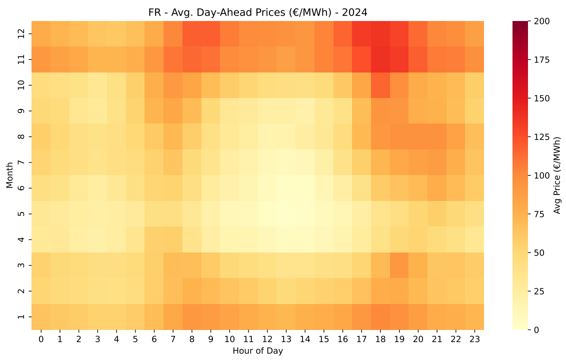
(c) Bidding Zone Netherlands, 2023



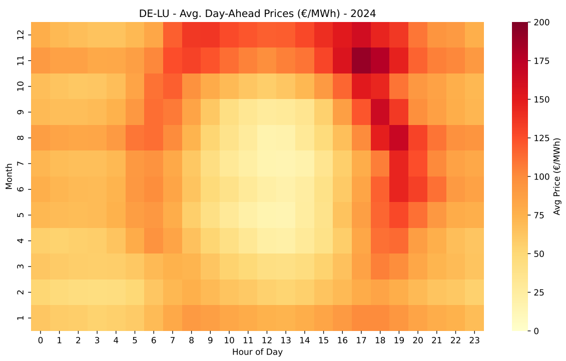
(d) Bidding Zone Netherlands, 2024



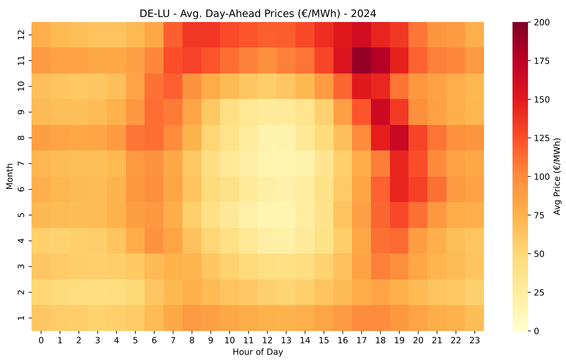
(e) Bidding Zone France, 2023



(f) Bidding Zone France, 2024

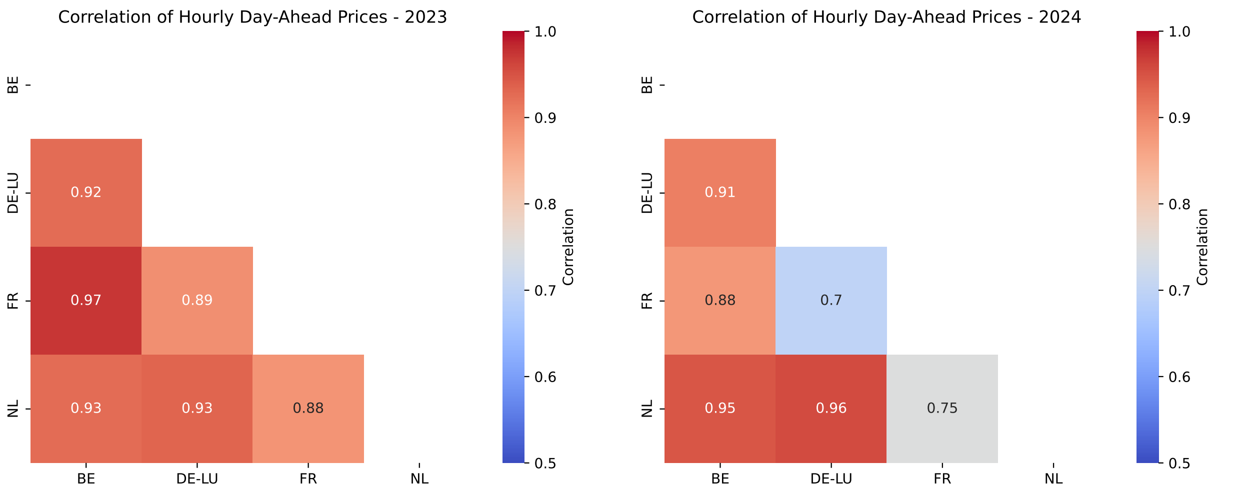


(g) Bidding Zone Germany-Luxembourg, 2023



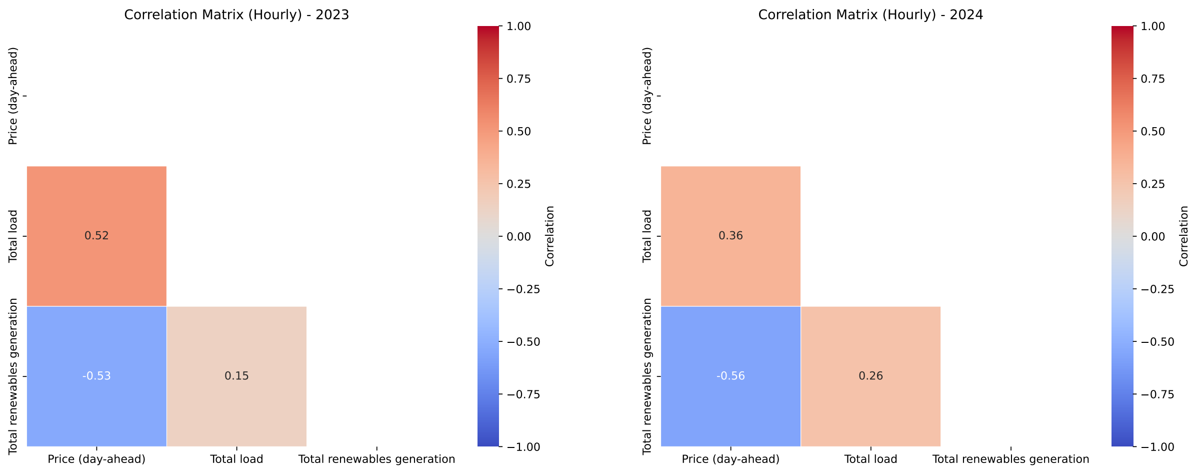
(h) Bidding Zone Germany-Luxembourg, 2024

Figure A.1: Heatmaps for hour-by-month average day-ahead electricity prices (€/MWh)



(a) 2023 (b) 2024

Figure A.2: Correlation matrix for pairwise correlation between day-ahead electricity prices (€/MWh) for four European bidding zones



(a) 2023 (b) 2024

Figure A.3: Correlation matrix for pairwise correlation between day-ahead electricity prices (€/MWh), actual total load (MWh) and actual total renewables generation (solar, offshore wind, onshore wind, MWh)

Appendix A.2. Sample composition - Peak Demand Charges

Table A.1 summarizes the smart meter readings for the 42,077 households included in our sample for the evaluation of peak demand charges. We summarize meter readings for total monthly grid withdrawals, total monthly grid injection and monthly peak electricity demand.

Table A.2 describes the composition of the 42,077 households that are included in our final sample for the evaluation of peak demand charges. We present summary statistics separately for the treatment and control group. Columns (1) shows the total number of households included in the final sample. Columns (2) and (3) presents the household counts separately for the treated and control group. The control group consists of the protected households that are not exposed to the introduction of peak demand charges. Finally, column (4) represents the same results, but now represented as the percentage of households adopting a specific combination of low-carbon technologies. Percentages are computed separately for each year. Columns (5) and (6) further split up the sample into treated and control households.

Table A.1: Descriptive statistics: smart meter data

Treated	Mean	Std	25%	50%	75%
Monthly peak withdrawal [W]	4152	1821	2990	3886	4963
Monthly peak withdrawal (2022) [W]	4148	1752	3040	3924	4952
Monthly peak withdrawal (2023) [W]	4051	1753	2926	3801	4854
Monthly peak withdrawal (2024) [W]	4257	1944	3005	3934	5087
Grid withdrawals per month [kWh]	256	191	130	210	326
Grid withdrawals per month (2022) [kWh]	251	182	132	209	319
Grid withdrawals per month (2023) [kWh]	248	184	126	204	319
Grid withdrawals per month (2024) [kWh]	268	205	132	216	344
Grid injection per month [kWh]	165	206	0	76	277
Grid injection per month (2022) [kWh]	177	223	0	74	307
Grid injection per month (2023) [kWh]	167	210	0	78	277
Grid injection per month (2024) [kWh]	151	184	0	74	252
Control	Mean	Std	25%	50%	75%
Monthly peak withdrawal [W]	4016	1626	2926	3847	4865
Monthly peak withdrawal (2022) [W]	4020	1557	2984	3884	4860
Monthly peak withdrawal (2023) [W]	3968	1590	2892	3798	4804
Monthly peak withdrawal (2024) [W]	4059	1726	2905	3856	4931
Grid withdrawals month [kWh]	267	185	141	227	345
Grid withdrawals month (2022) [kWh]	266	181	144	227	341
Grid withdrawals month (2023) [kWh]	263	180	139	224	341
Grid withdrawal month (2024) [kWh]	272	194	140	229	353
Grid injection month [kWh]	121	188	0	10	193
Grid injection month (2022) [kWh]	130	205	0	2	215
Grid injection month (2023) [kWh]	121	189	0	11	191
Grid injection month (2024) [kWh]	111	169	0	16	179

Note: Descriptive statistics for the smart meter data included in the main analysis. This table reports household-month statistics. There are 1,514,722 observations for 42,077 households, 40630 treated households and 1717 control households.

Table A.2: Descriptive statistics: sample composition

		(1) Households (All)	(2) Households (Treated)	(3) Households (Control)	(4) % (All)	(5) % (Treated)	(6) % (Control)
1-1-2022							
	EV	175	173	2	0.4%	0.4%	0.1%
	PV	26613	25774	839	63.2%	63.9%	48.9%
	HP	615	601	14	1.4%	1.5%	0.8%
	Battery	3845	3722	123	9.1%	9.2%	7.1%
	Total	42077	40360	1717			
1-1-2023							
	EV	2023	1957	66	4.8%	4.8%	3.8%
	PV	28287	29199	912	67.2%	72.3%	53.1%
	HP	7257	6990	267	17.2%	17.3%	15.5%
	Battery	6859	6636	223	16.3%	16.4%	12.9%
	Total	42077	40360	1717			
All	**Total**	42077	40360	1717			

Note: Characteristics of the households studied. This table reports household-level statistics. There are 40,360 households observed for the full three year period from 2022 up to and including 2024. We classify the households based on low-carbon technology adoption. Percentages represent the proportion of households with a specific type of low-carbon technology adoption, relative to the total number of households in the metering regime.

Appendix A.3. Sample composition - Real-Time Pricing

Table A.3 summarizes the characteristics of the 15,284 households included in the final sample for the evaluation of real-time pricing. For these households, smart meter data become available on a staggered basis beginning in early 2022. We report summary statistics for total monthly grid withdrawals, total monthly grid injections, and monthly peak electricity demand. In addition, we present information on the adoption of low-carbon technologies, reflecting the status as of January 1, 2024.

Table A.3: Descriptive statistics: smart meter data and sample composition for real-time pricing households

	Mean	Std	25%	50%	75%
Monthly peak withdrawal [W]	4274	2152	2896	3900	5188
Monthly peak withdrawal (2023) [W]	4210	1928	3000	3916	5020
Monthly peak withdrawal (2024) [W]	4299	2237	2848	3892	5264
Grid withdrawals per month [kWh]	268	222	117	209	354
Grid withdrawals per month (2023) [kWh]	262	201	132	216	341
Grid withdrawals permonth (2024) [kWh]	270	230	111	206	360
Grid injection per month [kWh]	136	204	0	24	218
Grid injection per month (2023) [kWh]	125	194	0	9	199
Grid injection per month (2024) [kWh]	141	207	0	29	226
PV (01-01-2024)	0.61	0.49	0.00	1.00	1.00
Battery (01-01-2024)	0.28	0.45	0.00	0.00	1.00
EV (01-01-2024)	0.09	0.28	0.00	0.00	0.00
HP (01-01-2024)	0.11	0.32	0.00	0.00	0.00
Average solar capacity (2024) [kW]	4.94	2.04	3.68	5.00	5.00
Average battery size (2024) [kWh]	9.25	3.25	7.20	10.00	10.00
Average battery capacity (2024) [kVA]	4.96	1.79	4.00	5.00	5.00

Note: Descriptive statistics for the smart meter data and sample composition for households included in the additional analysis for real-time pricing. This table reports household-month statistics. We add 15,284 households on a real-time pricing contract in 2023 or 2024, for which there are 253,682 observations. For this group, not the full three year period is available.

Appendix A.4. Consumer survey data

Table A.4: Familiarity with peak demand charges

		Do you know the "capacity tariff"		
		Yes	No	Total
Is the price you pay for electricity the social maximum price, also referred to as the social tariff?	Yes	33	90	123
		(26.83%)	(73.17%)	(100%)
	No	381	451	832
		(45.79%)	(54.21%)	(100%)
	Do not know	3	43	46
		(6.52%)	(93.48%)	(100%)
	Total	417	854	1001
		(41.66%)	(58.34%)	(100%)

Note: Familiarity with peak demand charges by customer type. This Table shows a crosstabulation of two survey questions from the VREG Marktmonitor (2024). Differences between categories are statistically significant, Pearson $\chi^2 = 40.35$, p-value = 0.00.

Table A.5: Correct definition of peak demand charges

		Give correct definition of "capacity tariff"		
		Yes	No	Total
Is the price you pay for electricity the social maximum price, also referred to as the social tariff?	Yes	14	19	33
		(42.42%)	(57.58%)	(100%)
	No	271	110	381
		(71.73%)	(28.87%)	(100%)
	Do not know	3	0	3
		(100%)	(0%)	(100%)
	Total	288	129	417
		(69.06%)	(30.94%)	(100%)

Note: Correct definition of peak demand charges by customer type. This Table shows a crosstabulation of two survey questions from the VREG Marktmonitor (2024). Differences between categories are statistically significant, Pearson $\chi^2 = 13.07$, p-value = 0.00.

Table A.6: Financial impact of peak demand charges

		What impact has the "capacity tariff" had on overall bill?					
		Remarkable decrease	Slight decrease	No change	Slight increase	Remarkable increase	Total
Is the price you pay for electricity the social maximum price, also referred to as the social tariff?	Yes	6	15	43	17	19	100
		(6.00%)	(15.00%)	(43.00%)	(17.00%)	(19.00%)	(100%)
	No	42	53	258	188	95	636
		(6.60%)	(8.33%)	(40.57%)	(29.56%)	(14.94%)	(100%)
	Do not know	1	3	15	8	4	31
		(3.23%)	(9.68%)	(48.39%)	(25.81%)	(12.90%)	(100%)
	Total	49	71	316	213	118	767
		(6.39%)	(9.26%)	(41.20%)	(27.77%)	(15.38%)	(100%)

Note: Estimated impact of peak demand charges on annual bill by customer type. This Table shows a crosstabulation of two survey questions from the VREG Marktmonitor (2024). Differences between categories are not statistically significant, Pearson $\chi^2 = 11.25$, p-value = 0.19.

Appendix B. Supplementary Results: Differences-in-Differences

Appendix B.1. Specification Tests

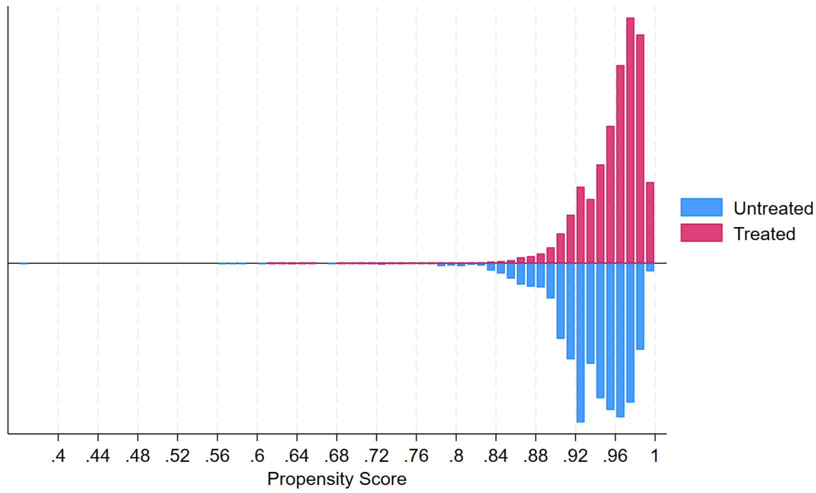


Figure B.1: Common support graph. This figure plots the distribution of estimated propensity scores for the Doubly Robust DiD model (Sant'Anna and Zhao, 2020) estimated for the full sample of 42,077 households.

Table B.1: Balancing Table

Variable	Matched	Treated	Control	Bias (%)	Bias reduction (%)	t	p
Solar capacity (kW)	U	2.97	2.22	30.5		12.42	0.000
	M	2.97	2.88	3.6	88.1	5.05	0.000
Storage capacity (kWh)	U	1.39	1.08	9.7		3.72	0.000
	M	1.39	1.41	-0.4	95.4	-0.58	0.562
Grid withdrawals (kWh)	U	385.62	383.89	0.7		0.30	0.767
	M	386.62	383.63	0.8	-15.0	1.20	0.232
Grid injection (kWh)	U	20.77	15.20	20.5		7.83	0.000
	M	20.77	19.75	3.7	81.8	5.04	0.000

Note: Balancing Table for observable covariates. Balancing statistics are shown for the unmatched (U) and matched (M) sample. The matched sample uses the weights generated by the DR-DID model Sant'Anna and Zhao (2020) estimated for the full sample of 42,077 households. Outlier observations (eleven observations with inverse probability weights > 100) are excluded from this table. t-statistics are based on a regression of the variable on a treatment indicator, the bias is the percentage difference in sample means in the treated and non-treated groups. Rubin's B = 32.8 for the unmatched sample and B = 4.4 for the matched sample. Table constructed using the Stata command psmatch from Leuven and Sianesi (2003).

Appendix B.2. Robustness Checks

Table B.2: Robustness using DID: new low-carbon technology adopters excluded

	(1) TWFE-DID	(2) IPW-DID	(3) DR-DID
$\mathbb{1}\{\text{Year}_t \geq 2023\} \times \mathbb{1}\{\text{Protected}_i = 0\}$	-10.28	-68.26***	-70.51**
	(-0.83)	(-2.81)	(-2.53)
Observations	734,688	734,688	734,688
Households	20,408	20,408	20,408
Treated	19,436	19,436	19,436
Control	972	972	972

Note: The monthly peak (W) over the period January 2022 - December 2024 is modelled in a difference-in-differences framework. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households on the social tariff serve as control group. We exclude all households that adopt any new low-carbon technology over the period 2023-2024. Three specifications are used to estimate the model. Column (1) uses TWFE-DID with additional control variables. Control variables include grid withdrawals (kWh), solar capacity (kW), solar injection (kWh), storage capacity (kWh). Household fixed effects and time fixed effects are included. In column (2), we apply the IPW-DID estimator with stabilised weights, weighting based on grid withdrawals (kWh), solar capacity (kW), solar injection (kWh), postal code, and dummy variables for the quarter of low-carbon technology adoption (separate for EV, HP, PV and battery storage). Column (3) shows the estimate for the Sant'Anna and Zhao (2020) Doubly Robust DID estimator using the same weighting variables. The unit of observation is household-month-of-sample. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

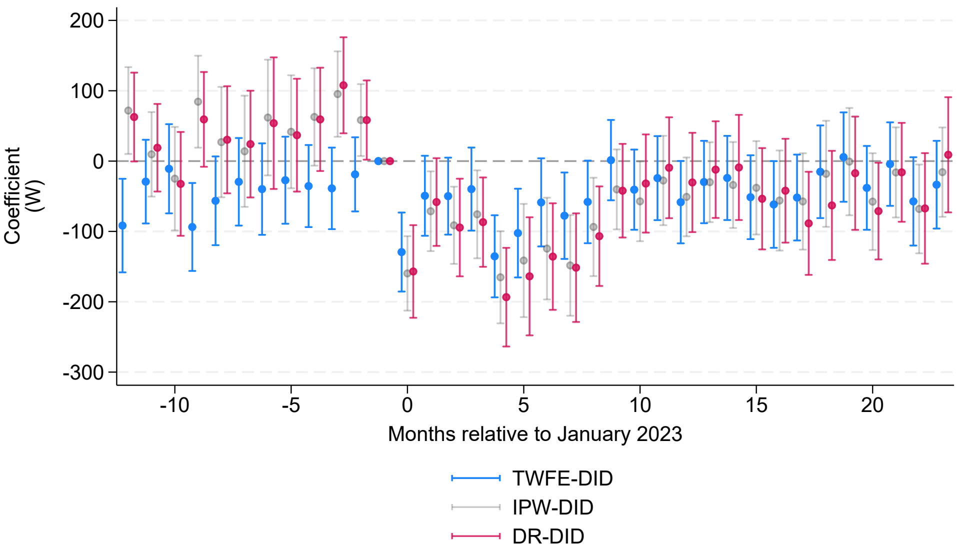


Figure B.2: Estimates of the dynamic specification for peak demand charges in the sample of households that does not adopt any new low carbon technology throughout the period 2022-2024. Each dot represents the point estimate of the monthly peak reduction (in W) for a given month-of-sample t. Three different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects, excluding control variables for low-carbon technology adoption. Second, the IPW-DID estimator with stabilised weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. December 2022 is used as the reference category in both pre- and post-treatment periods. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

Table B.3: Robustness using DID: no controls for new low-carbon technologies

	(1) TWFE-DID	(2) IPW-DID	(3) DR-DID
$\mathbb{1}\{\text{Year}_t \geq 2023\} \times \mathbb{1}\{\text{Protected}_i = 0\}$	-32.90***	-85.95***	-106.22***
	(-2.61)	(-3.43)	(-4.36)
Observations	2,012,724	2,012,724	2,012,724
Households	55,909	55,909	55,909
Treated	53,522	53,522	53,522
Control	2387	2387	2387

Note: The monthly peak (W) over the period January 2022 - December 2024 is modelled in a difference-in-differences framework. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households on the social tariff serve as control group. We do not explicitly control for the adoption of new low-carbon technologies over the period 2022-2024 using EV or heatpump adoption dummy variables. Three specifications are used to estimate the model. Column (1) uses TWFE-DID with additional control variables. Control variables include grid withdrawals (kWh), solar capacity (kW), solar injection (kWh), storage capacity (kWh). Household fixed effects and time fixed effects are included. In column (2), we apply the IPW-DID estimator with stabilised weights, weighting based on grid withdrawals (kWh), solar capacity (kW), and solar injection (kWh). Column (3) shows the estimate for the Sant'Anna and Zhao (2020) Doubly Robust DID estimator using the same weighting variables. The unit of observation is household-month-of-sample. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

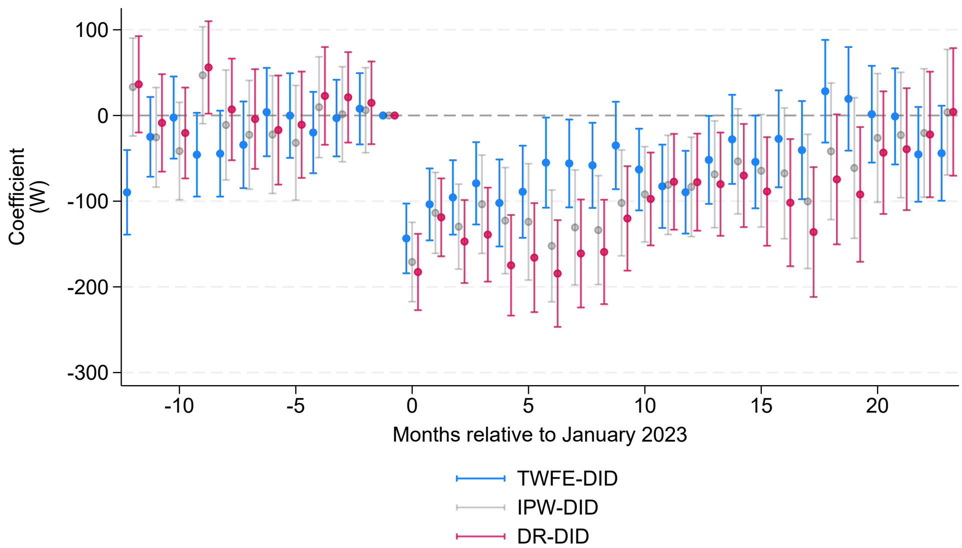


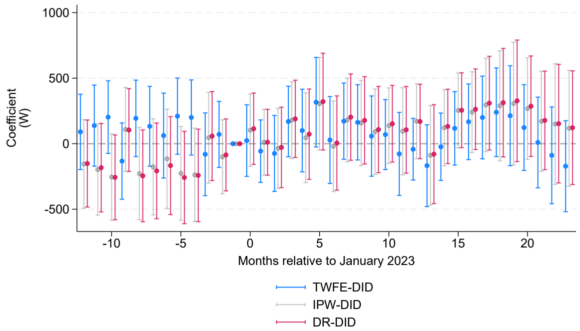
Figure B.3: Estimates of the dynamic specification for peak demand charges in the full sample, without controls for new low carbon technologies. Each dot represents the point estimate of the monthly peak reduction (in W) for a given month-of-sample t. Three different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects, excluding control variables for low-carbon technology adoption. Second, the IPW-DID estimator with stabilised weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. December 2022 is used as the reference category in both pre- and post-treatment periods. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

Appendix B.3. Heterogeneity

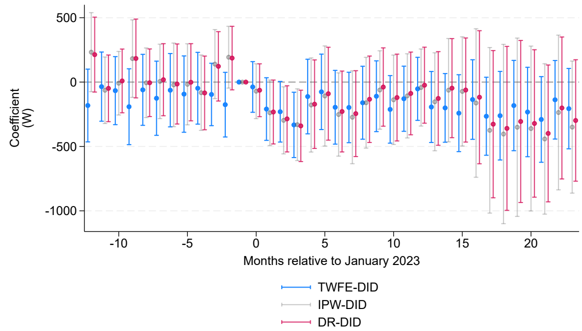
Table B.4: Heterogeneity analysis using DiD

	(1) Full sample	(2) Electric vehicle	(3) Heat pump (main)	(4) Heat pump (additional)	(5) Battery storage	(6) No low-carbon technology
TWFE-DID (no controls)	12.71	-173.67**	94.42	38.01	-153.92**	-2.27
	(0.71)	(-1.05)	(-0.41)	(0.46)	(-2.35)	(-0.11)
TWFE-DID (controls)	-51.40**	-319.47***	-29.37	-88.70	-147.55***	-18.44
	(-3.79)	(-2.41)	(-0.45)	(-1.41)	(-2.61)	(-1.13)
IPW-DID	-95.67***	-404.02**	147.88	-217.62	-170.79**	-69.94**
	(-3.11)	(-2.05)	(1.10)	(-1.44)	(-2.09)	(-2.22)
DR-DID	-122.22***	-380.89**	161.01	-192.72	-168.33**	-70.20**
	(-3.99)	(-2.02)	(1.20)	(-1.35)	(-2.63)	(-2.06)
Observations	1,514,722	57,636	102,168	79,308	245,088	290,844
Households	42,077	1600	2838	2203	6808	8079
Treated	40,360	1547	2745	2107	6588	7513
Control	1717	54	93	96	220	566
Average Peak$_{it}$ 2022	4142.44	6331.26	5083.59	4966.90	3861.69	3706.10

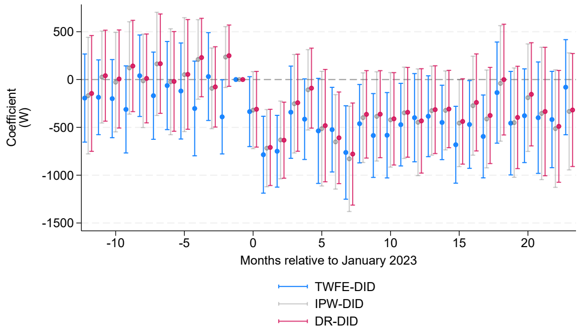
Note: The monthly peak (W) over the period January 2022 - December 2024 is modelled in a difference-in-differences framework. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households on the social tariff serve as control group. Four specifications are used to estimate the model. Row (1) uses the TWFE-DID estimator without control variables. In row (2) we use TWFE-DID with additional control variables. Control variables include grid withdrawals (kWh), solar capacity (kW), solar injection (kWh) and storage capacity (kWh). Household fixed effects and time fixed effects are included. In row (3), we apply the IPW-DID estimator with stabilised weights, weighting based on grid withdrawals (kWh), solar capacity (kW), solar injection (kWh) and dummy variables for the quarter of low-carbon technology adoption (separate for EV, HP, PV and battery storage). Finally, row (4) shows the estimate for the (Sant'Anna and Zhao, 2020) Doubly Robust DID estimator using the same weighting variables. The unit of observation is household-month-of-sample. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



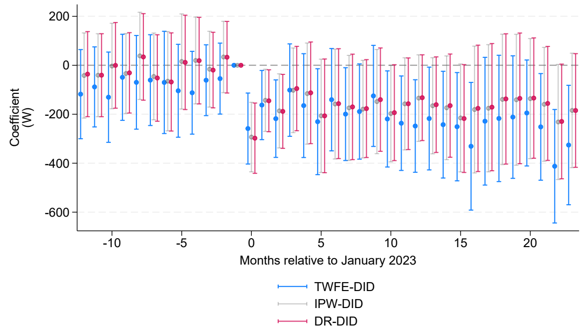
(a) Heat pump as main heating



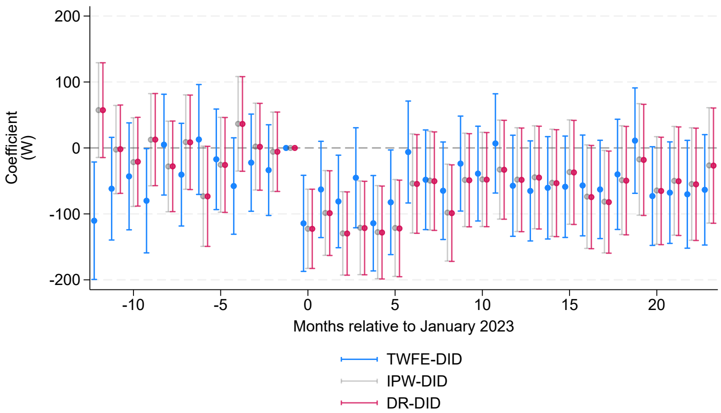
(b) Heat pump as additional heating



(c) Electric vehicle



(d) Battery energy storage



(e) No low-carbon technologies

Figure B.4: Estimates of the dynamic specification for peak demand charges in the five subsamples. Each dot represents the point estimate of the monthly peak reduction (in W) for a given month-of-sample t. Three different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects including control variables. Second, the IPW-DID estimator with stabilised weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. December 2022 is used as the reference category in both pre- and post-treatment periods. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

Appendix C. Supplementary Results: Grid-Level Effects

Appendix C.1. Electric vehicles

Table C.1: Synthetic distribution grid descriptive statistics by EV adoption level, 10 households

	Percentage of households with EV				
	0%	20%	50%	80%	100%
Peak (kW)					
Daily	10.48	11.69	13.58	15.51	16.83
	(2.46)	(3.39)	(4.37)	(5.23)	(5.84)
Monthly	15.32	17.64	21.04	24.15	26.41
	(2.43)	(3.76)	(4.75)	(5.45)	(6.08)
Yearly	18.15	21.67	26.70	30.81	34.55
	(2.01)	(3.36)	(4.17)	(4.64)	(4.94)
Grid withdrawals (kWh)					
Daily	78.99	88.70	104.82	120.82	131.98
	(14.68)	(23.11)	(35.99)	(47.87)	(56.69)
Monthly	2424.22	2719.98	3214.23	3703.68	4047.56
	(357.05)	(556.08)	(910.80)	(1231.36)	(1480.50)
Yearly	14534.67	16317.52	19285.36	22235.04	24285.35
	(1722.49)	(2028.85)	(2621.46)	(3040.05)	(3415.60)
Coincidence factor					
Daily	0.53	0.54	0.54	0.54	0.54
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
Monthly	0.40	0.41	0.41	0.41	0.41
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Yearly	0.35	0.37	0.38	0.38	0.40
	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)

Note: Synthetic distribution grid descriptive statistics based on an aggregation of 10 households. The rows indicate the percentage of households with an electric vehicle (EV). All other households in the synthetic distribution grid do not have any low-carbon technologies. Values represent mean peak electricity withdrawals (kW), total electricity withdrawals (kWh) and coincidence factors for the peak electricity demand with corresponding standard deviations between parenthesis.

Table C.2: Synthetic distribution level descriptive statistics by EV adoption level. 25 households

	Percentage of households with EV				
	0%	20%	50%	80%	100%
Peak (kW)					
Daily	23.24	25.57	29.12	33.49	36.28
	(4.38)	(5.95)	(7.66)	(9.68)	(10.97)
Monthly	31.01	34.98	40.81	47.24	51.34
	(4.38)	(6.32)	(7.99)	(10.55)	(11.50)
Yearly	36.62	43.11	52.63	62.86	68.75
	(3.29)	(4.11)	(5.11)	(6.64)	(7.88)
Grid withdrawals (kWh)					
Daily	196.99	221.56	259.19	303.40	329.67
	(26.75)	(45.43)	(72.59)	(105.58)	(125.43)
Monthly	6041.04	6795.35	7948.53	9305.05	10110.41
	(646.72)	(1155.71)	(1928.94)	(2873.05)	(3439.30)
Yearly	36246.26	40772.10	47691.15	55830.29	60662.48
	(2773.84)	(3033.09)	(3407.96)	(5200.31)	(5049.57)
Coincidence factor					
Daily	0.47	0.47	0.46	0.47	0.47
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
Monthly	0.32	0.32	0.32	0.32	0.32
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)
Yearly	0.28	0.29	0.31	0.31	0.31
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)

Note: Synthetic distribution grid descriptive statistics based on an aggregation of 25 households. The rows indicate the percentage of households with an electric vehicle (EV). All other households in the synthetic distribution grid do not have any low-carbon technologies. Values represent mean peak electricity withdrawals (kW), total electricity withdrawals (kWh) and coincidence factors for the peak electricity demand with corresponding standard errors between parenthesis.

Appendix C.2. Real-time pricing

Table C.3: Synthetic distribution level descriptive statistics by real-time pricing adoption level. 10 households

	Percentage of households with real-time pricing				
	0%	1-20%	20-50%	50-80%	80-100%
Peak (kW)					
Daily	11.05	10.83	12.86	12.41	13.31
	(4.24)	(4.31)	(4.94)	(4.52)	(5.02)
Monthly	15.27	16.25	17.86	18.55	20.17
	(6.27)	(5.29)	(6.26)	(5.14)	(5.58)
Yearly	36.62	43.11	52.63	62.86	68.75
	(3.29)	(4.11)	(5.11)	(6.64)	(7.88)
Grid withdrawals (kWh)					
Daily	84.79	83.99	104.27	99.57	111.89
	(40.34)	(40.60)	(50.32)	(45.93)	(52.64)
Monthly	2101.31	2323.88	2499.30	2784.41	3398.93
	(1358.80)	(1208.83)	(1708.84)	(1381.36)	(1440.69)
Yearly	36246.26	40772.10	47691.15	55830.29	60662.48
	(2773.84)	(3033.09)	(3407.96)	(5200.31)	(5049.57)
Coincidence factor					
Daily	0.53	0.53	0.54	0.54	0.54
	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)
Monthly	0.36	0.39	0.39	0.40	0.42
	(0.12)	(0.09)	(0.10)	(0.07)	(0.06)
Yearly	0.28	0.29	0.31	0.31	0.31
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)

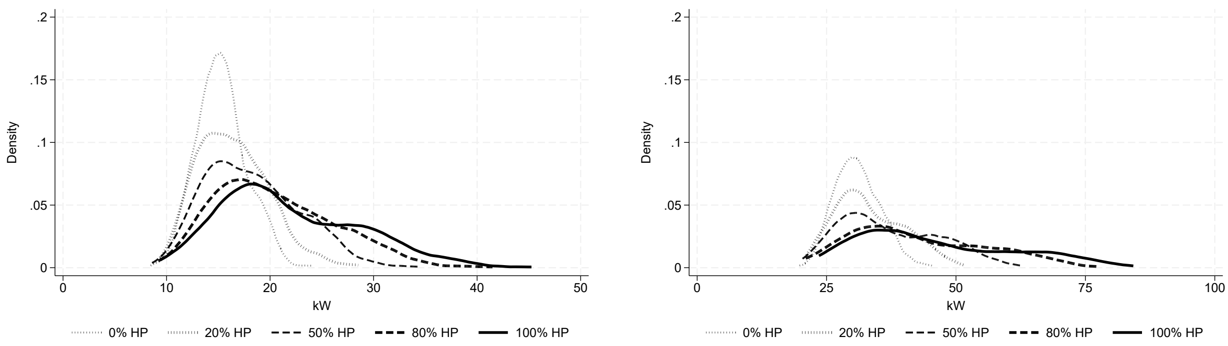
Note: Synthetic distribution grid descriptive statistics based on an aggregation of 10 households. The rows indicate the percentage of households with an active real-time pricing contract. All other households in the synthetic distribution grid are not-yet takers, households who have not yet adopted real-time pricing, but will be adopting later in the sample period. Values represent mean peak electricity withdrawals (kW), total electricity withdrawals (kWh) and coincidence factors for the peak electricity demand with corresponding standard errors between parenthesis.

Table C.4: Synthetic distribution level descriptive statistics by real-time pricing adoption level. 10 households

	Percentage of households with real-time pricing				
	0%	20%	50%	80%	100%
Peak (kW)					
Daily	24.59	23.18	31.01	26.99	27.86
	(8.85)	(8.18)	(8.95)	(8.93)	(9.36)
Monthly	26.91	33.34	39.36	36.96	38.71
	(13.31)	(8.77)	(9.65)	(9.83)	(9.83)
Yearly	36.62	43.11	52.63	62.86	68.75
	(3.29)	(4.11)	(5.11)	(6.64)	(7.88)
Grid withdrawals (kWh)					
Daily	214.21	208.22	291.50	254.74	272.50
	(95.32)	(87.54)	(112.29)	(106.27)	(115.48)
Monthly	4009.11	6081.38	6432.30	7204.51	8275.29
	(3737.30)	(2498.20)	(4514.44)	(3328.15)	(3298.40)
Yearly	36246.26	40772.10	47691.15	55830.29	60662.48
	(2773.84)	(3033.09)	(3407.96)	(5200.31)	(5049.57)
Coincidence factor					
Daily	0.46	0.46	0.48	0.46	0.46
	(0.08)	(0.07)	(0.09)	(0.07)	(0.06)
Monthly	0.25	0.32	0.32	0.32	0.33
	(0.11)	(0.05)	(0.06)	(0.06)	(0.05)
Yearly	0.28	0.29	0.31	0.31	0.31
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)

Note: Synthetic distribution grid descriptive statistics based on an aggregation of 25 households. The rows indicate the percentage of households with an active real-time pricing contract. All other households in the synthetic distribution grid are not-yet takers, households who have not yet adopted real-time pricing, but will be adopting later in the sample period. Values represent mean peak electricity withdrawals (kW), total electricity withdrawals (kWh) and coincidence factors for the peak electricity demand with corresponding standard errors between parenthesis.

Appendix C.3. Heat pumps



(a) 10 households aggregated

(b) 25 households aggregated

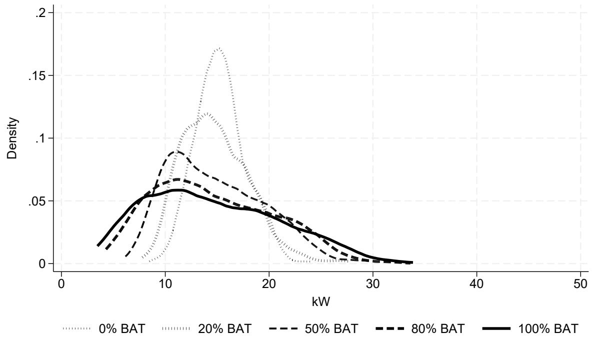
Figure C.1: Kernel density for the distribution of monthly peaks in the distribution grid for circuits with 10 or 25 households connected, and varying levels of heat pump adoption

Table C.5: Synthetic distribution level TWFE regression results by heat pump adoption level

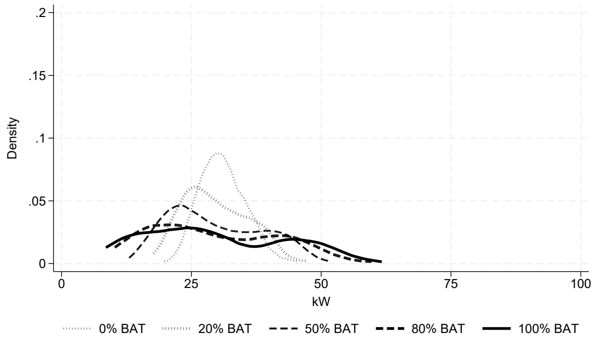
	Percentage of households with heat pump				
	0%	20%	50%	80%	100%
			PANEL A: 10 households		
Peak (kW)					
Daily	-0.111***	-0.103**	-0.158***	-0.145**	-0.203**
	(-3.37)	(-2.04)	(-2.78)	(-2.15)	(-2.45)
Monthly	-0.453***	-0.284**	-0.405**	-0.366*	-0.573**
	(-4.58)	(-2.12)	(-2.14)	(-1.75)	(-2.08)
			PANEL B: 25 households		
Peak (kW)					
Daily	-0.173**	-0.240**	-0.220	-0.239	-0.370
	(-2.07)	(-2.24)	(-1.49)	(-1.11)	(-1.28)
Monthly	-0.508**	-0.674*	-0.411	-0.770	-1.240
	(-2.10)	(-1.99)	(-0.73)	(-1.00)	(-1.26)

Note: The distribution grid level coincident monthly peak (kW) - aggregated over 10 households in Panel A or 25 households in Panel B - over the period January 2022 - December 2024 is modeled in a panel fixed effects regression model. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period. We employ a TWFE model without control group, but with additional control variables. Control variables include grid-level aggregate distributed solar production (kWh), aggregate grid withdrawals (kWh), solar capacity installed (kW), storage capacity installed (kWh), temperature, and the variables for the number of heat pumps and electric vehicles in the distribution circuit. Fixed effects include circuit and month-of-year fixed effects. Standard errors are clustered at the circuit level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C.4. Battery energy storage



(a) 10 households aggregated



(b) 25 households aggregated

Figure C.2: Kernel density for the distribution of monthly peaks in the distribution grid for circuits with 10 or 25 households connected, and varying levels of battery energy storage adoption

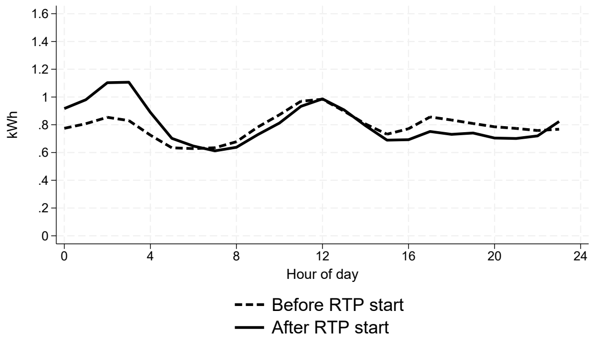
Table C.6: Synthetic distribution level TWFE regression results by battery energy storage adoption level

	Percentage of households with battery energy storage				
	0%	20%	50%	80%	100%
			PANEL A: 10 households		
Peak (kW)					
Daily	-0.111***	-0.200***	-0.202***	-0.119*	-0.174***
	(-3.37)	(-4.84)	(-3.81)	(-1.74)	(-3.16)
Monthly	-0.453***	-0.518***	-0.681***	-0.151	-0.338
	(-4.58)	(-3.84)	(-2.84)	(-0.58)	(-1.42)
			PANEL B: 25 households		
Peak (kW)					
Daily	-0.173**	-0.283***	-0.325**	-0.210	-0.173
	(-2.07)	(-3.34)	(-2.03)	(-1.57)	(-1.14)
Monthly	-0.508**	-0.942**	-1.028*	-0.841	0.527
	(-2.10)	(-2.45)	(-1.97)	(-1.48)	(0.64)

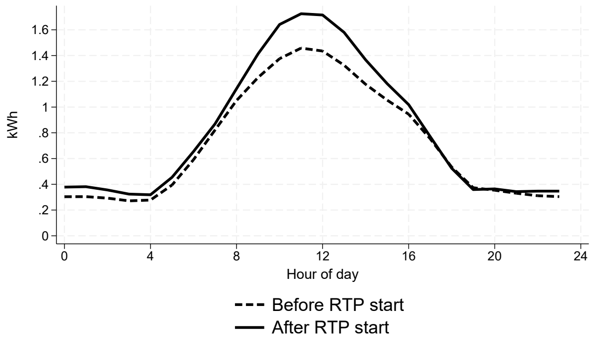
Note: The distribution grid level coincident monthly peak (kW) - aggregated over 10 households in Panel A or 25 households in Panel B - over the period January 2022 - December 2024 is modeled in a panel fixed effects regression model. The introduction of the peak demand tariff on January 1st, 2023 indicates the post period. We employ a TWFE model without control group, but with additional control variables. Control variables include grid-level aggregate distributed solar production (kWh), aggregate grid withdrawals (kWh), solar capacity installed (kW), storage capacity installed (kWh), temperature, and the variables for the number of heat pumps and electric vehicles in the distribution circuit. Fixed effects include circuit and month-of-year fixed effects. Standard errors are clustered at the circuit level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D. Supplementary Results: Load Profile

Appendix D.1. Real-time pricing



(a) Winter months



(b) Summer months

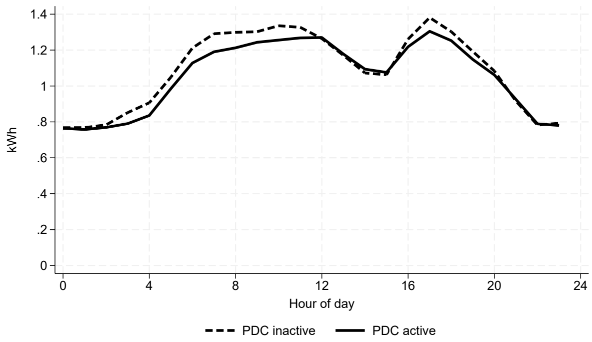
Figure D.1: Average kWh hourly electricity consumption for RTP adopters before and after adoption

Table D.1: Load shifting for real-time pricing

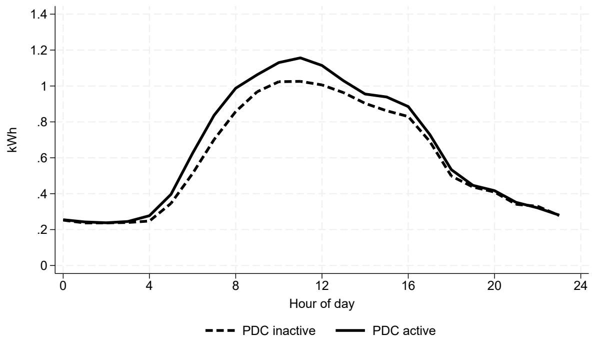
	(1) All	(2) Winter	(3) Summer
Total grid withdrawals:			
All hours	-0.0616	-0.612	-1.347
	(-0.16)	(-0.76)	(-1.33)
Morning hours (06.00 - 12.00)	-0.180	-0.535**	-1.132**
	(-1.16)	(-2.27)	(-2.39)
Afternoon hours (12.00 - 17.00)	-0.292*	-0.422*	-1.221
	(-1.73)	(-1.84)	(-1.54)
Peak hours (17.00 - 20.00)	-0.132*	-0.390***	0.0886
	(-1.84)	(-2.64)	(0.37)
Night hours (22.00 - 06.00)	0.491***	0.768*	0.767*
	(2.77)	(1.87)	(1.94)
Control variables	✓	✓	✓
Household × day-of-week FE	✓	✓	✓
Household × month-of-year FE	✓	✓	✓
Month-of-sample FE	✓	✓	✓
Observations	358,639	88,523	92,202
Clusters	1061	1061	1061

Note: The daily electricity consumption (kWh) in a block of hours over the day over the period January 2023 - December 2024 is regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The uptake of real-time prices indicates the post period and not-yet-treated households serve as control group. The model is estimated for the full sample, and the different seasons separately. The unit of observation is household-day-of-sample. Control variables include solar capacity (kW), solar production (kWh), storage capacity (kWh), daily variables for temperature and the dummy variables for the presence of heat pumps and electric vehicles. *t*-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D.2. Electric vehicles



(a) Winter months



(b) Summer months

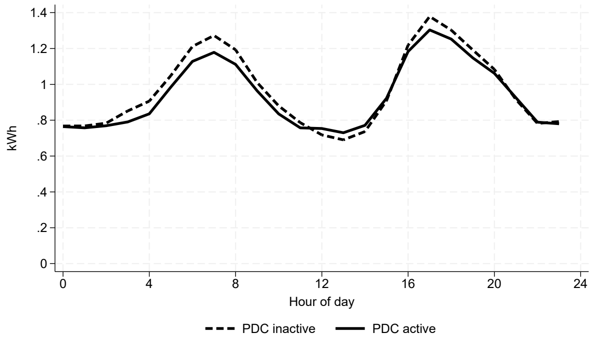
Figure D.2: Average kWh hourly electricity grid withdrawals for EV adopters before and after the introduction of peak demand charges

Table D.2: Load shifting for EV owners

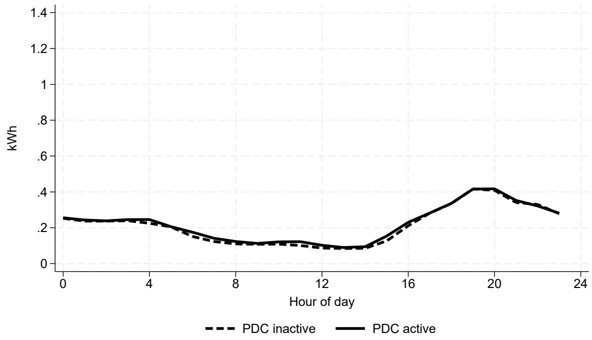
	(1) All	(2) Winter	(3) Summer
Total electricity consumption:			
All hours	0.461	-0.379	1.027*
	(1.11)	(-0.50)	(1.80)
Morning hours (06.00 - 12.00)	0.0305	-0.338*	0.299
	(0.18)	(-1.81)	(1.20)
Afternoon hours (12.00 - 17.00)	0.0787	-0.389	0.341*
	(0.63)	(-1.54)	(1.65)
Peak hours (17.00 - 20.00)	-0.0655	-0.271**	0.0716
	(-0.71)	(-2.05)	(0.53)
Night hours (22.00 - 06.00)	0.458**	0.788*	0.250
	(2.08)	(1.77)	(1.12)
Control variables	✓	✓	✓
Household × day-of-week FE	✓	✓	✓
Household × month-of-year FE	✓	✓	✓
Month-of-sample FE	✓	✓	✓
Observations	2,106,068	516,362	531,802
Households	2021	2021	2021

Note: The daily electricity consumption (kWh) over the period January 2022 - December 2024 is regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households serve as control group. The model is estimated for the full sample, and the different seasons separately. The unit of observation is household-day-of-sample. Control variables include solar capacity (kW), solar production (kWh), storage capacity (kWh), daily variables for temperature and the dummy variables for the presence of heat pumps and electric vehicles. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D.3. Heat pumps



(a) Winter months



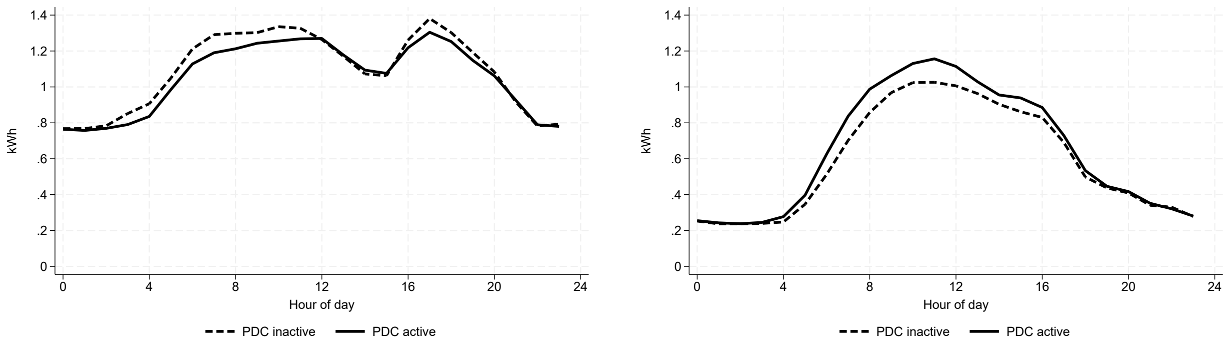
(b) Summer months

Figure D.3: Average kWh hourly electricity grid withdrawals for HP adopters before and after the introduction of peak demand charges

Table D.3: Load shifting for HP owners

	(1) All	(2) Winter	(3) Summer
Total grid withdrawals:			
All hours	0.483**	0.754**	0.330
	(2.06)	(2.16)	(1.26)
Morning hours (06.00 - 12.00)	-0.00378	-0.0677	0.0675
	(-0.06)	(-0.64)	(1.05)
Afternoon hours (12.00 - 17.00)	-0.000743	0.0125	0.00693
	(-0.02)	(0.14)	(0.15)
Peak hours (17.00 - 20.00)	0.0733*	0.112	0.0125
	(1.68)	(1.57)	(0.27)
Night hours (22.00 - 06.00)	0.355***	0.643***	0.198
	(2.87)	(3.11)	(1.52)
Control variables	✓	✓	✓
Household × day-of-week FE	✓	✓	✓
Household × month-of-year FE	✓	✓	✓
Month-of-sample FE	✓	✓	✓
Observations	1,165,941	285,859	294,362
Households	1123	1123	1123

Note: The daily grid withdrawals (kWh) in a block of hours over the day over the period January 2022 - December 2024 are regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households serve as control group. The model is estimated for the full sample, and the different seasons separately. The unit of observation is household-day-of-sample. Control variables include solar capacity (kW), solar production (kWh), storage capacity (kWh), daily variables for temperature and the dummy variables for the presence of heat pumps and electric vehicles. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01



(a) Winter months (b) Summer months

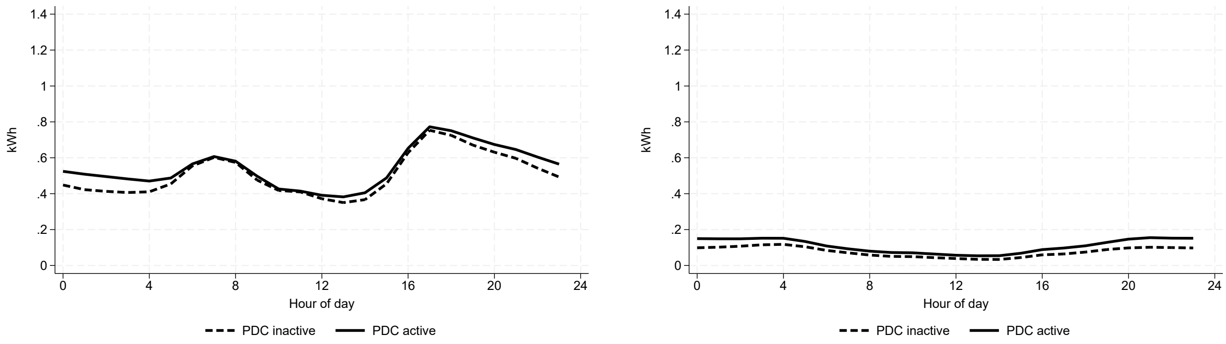
Figure D.4: Average kWh hourly electricity grid withdrawals for HP adopters before and after the introduction of peak demand charges

Table D.4: Load shifting for HP owners

	(1) All	(2) Winter	(3) Summer
Total electricity consumption:			
All hours	0.549**	0.748**	0.438
	(2.08)	(2.12)	(1.24)
Morning hours (06.00 - 12.00)	-0.0108	-0.0697	0.0989
	(-0.10)	(-0.63)	(0.63)
Afternoon hours (12.00 - 17.00)	0.0945	0.00842	0.131
	(0.91)	(0.08)	(0.90)
Peak hours (17.00 - 20.00)	0.0740*	0.113	0.0177
	(1.65)	(1.58)	(0.28)
Night hours (22.00 - 06.00)	0.332***	0.643***	0.146
	(2.69)	(3.11)	(1.16)
Control variables	✓	✓	✓
Household × day-of-week FE	✓	✓	✓
Household × month-of-year FE	✓	✓	✓
Month-of-sample FE	✓	✓	✓
Observations	1,165,941	285,859	294,362
Households	1123	1123	1123

Note: The daily electricity consumption (kWh) over the period January 2022 - December 2024 is regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households serve as control group. The model is estimated for the full sample, and the different seasons separately. The unit of observation is household-day-of-sample. Control variables include solar capacity (kW), solar production (kWh), storage capacity (kWh), daily variables for temperature and the dummy variables for the presence of heat pumps and electric vehicles. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D.4. Battery energy storage



(a) Winter months

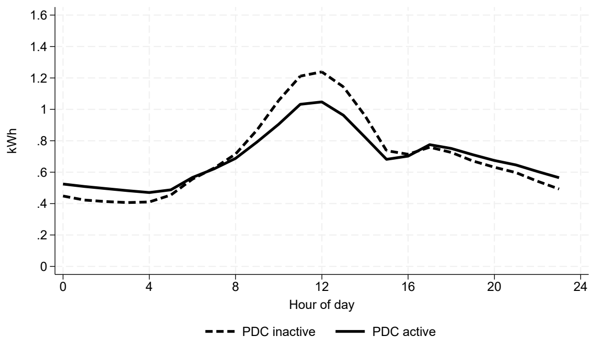
(b) Summer months

Figure D.5: Average kWh hourly electricity grid withdrawals for battery energy storage adopters before and after the introduction of peak demand charges

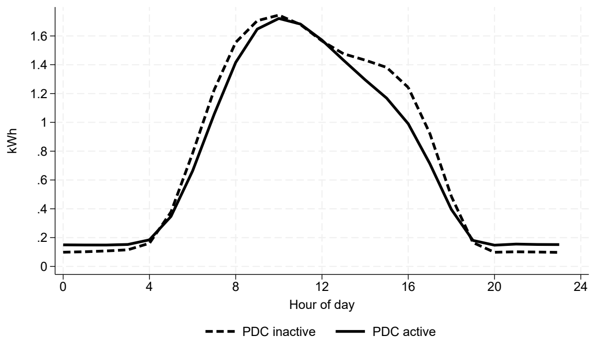
Table D.5: Load shifting for battery energy storage owners

	(1) All	(2) Winter	(3) Summer
Total grid withdrawals:			
All hours	-0.330	0.119	-0.706*
	(-1.18)	(0.28)	(-1.86)
Morning hours (06.00 - 12.00)	-0.126**	-0.0447	-0.155**
	(-2.05)	(-0.49)	(-2.02)
Afternoon hours (12.00 - 17.00)	-0.0684	-0.0710	-0.0691*
	(-1.51)	(-0.65)	(-1.86)
Peak hours (17.00 - 20.00)	-0.0722	-0.0381	-0.112*
	(-1.42)	(-0.45)	(-1.92)
Night hours (22.00 - 06.00)	-0.0193	0.335	-0.307
	(-0.13)	(1.61)	(-1.48)
Control variables	✓	✓	✓
Household × day-of-week FE	✓	✓	✓
Household × month-of-year FE	✓	✓	✓
Month-of-sample FE	✓	✓	✓
Observations	1,595,908	392,510	405,197
Households	2000	2000	2000

Note: The daily grid withdrawals (kWh) in a block of hours over the day over the period January 2022 - December 2024 are regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households serve as control group. The model is estimated for the full sample, and the different seasons separately. The unit of observation is household-day-of-sample. Control variables include solar capacity (kW), solar production (kWh), storage capacity (kWh), daily variables for temperature and the dummy variables for the presence of heat pumps and electric vehicles. *t*-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01



(a) Winter months



(b) Summer months

Figure D.6: Average kWh hourly electricity grid withdrawals for battery energy storage adopters before and after the introduction of peak demand charges

Table D.6: Load shifting for battery energy storage owners

	(1) All	(2) Winter	(3) Summer
Total electricity consumption:			
All hours	-0.267	0.137	-0.706
	(-0.74)	(0.31)	(-1.17)
Morning hours (06.00 - 12.00)	0.00565	-0.0420	0.00123
	(0.02)	(-0.26)	(0.00)
Afternoon hours (12.00 - 17.00)	-0.118	-0.0509	-0.195
	(-0.45)	(-0.34)	(-0.45)
Peak hours (17.00 - 20.00)	-0.0662	-0.0402	-0.0844
	(-0.81)	(-0.48)	(-0.52)
Night hours (22.00 - 06.00)	-0.0431	0.333	-0.365
	(-0.27)	(1.60)	(-1.48)
Control variables	✓	✓	✓
Household × day-of-week FE	✓	✓	✓
Household × month-of-year FE	✓	✓	✓
Month-of-sample FE	✓	✓	✓
Observations	1,165,941	285,859	294,362
Households	1123	1123	1123

Note: The daily electricity consumption (kWh) over the period January 2022 - December 2024 is regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of the peak demand tariff on January 1st, 2023 indicates the post period and protected households serve as control group. The model is estimated for the full sample, and the different seasons separately. The unit of observation is household-day-of-sample. Control variables include solar capacity (kW), solar production (kWh), storage capacity (kWh), daily variables for temperature and the dummy variables for the presence of heat pumps and electric vehicles. *t*-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$