WORKING PAPER

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

REVISED

CAPACITY CONSTRAINTS AND ELECTRIFICATION: EVIDENCE FROM RESIDENTIAL ELECTRICITY DEMAND AND PRICING

Marten Ovaere
Mark Vergouwen

June 2025 / June 2026 Revised
2025/1115

GHENT UNIVERSITY

Department of Economics

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

Capacity Constraints and Electrification: Evidence from Residential Electricity Demand and Pricing

Marten Ovaere
Ghent University

Mark Vergouwen
Ghent University

June 17, 2026

Abstract

We study how electrification and pricing affect household peak electricity demand, and whether these effects strain local electric grids. Using high-frequency consumption data from over 42,000 households, we find that adopting an electric vehicle raises a household's monthly peak by about 2 kilowatts. Real-time prices also raise household peak demand, but have limited grid-level effects. Peak demand charges reduce peaks by 3 percent on average, and by 5 percent or 320 watts among electric vehicle owners, who shift charging to nighttime. By lowering coincident demand, household-level peak reductions aggregate to lower local grid peaks and reduce costly grid investment.

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, Severin Borenstein, David Brown, James Bushnell, Paul Joskow, Blake Shaffer, Christopher Sullivan, Paige Weber, Reyer Gerlagh, and conference and seminar participants at UC Berkeley, Paris School of Economics, Technische Universität München, Groningen University, UCalgary, UAlberta, UC Louvain Saint-Louis, the 2026 POWER Conference on Energy Research and Policy, the 13th Mannheim Conference on Energy and the Environment, IAEE Paris, and the 2025 Manchester Workshop on the Economics of Energy Transition for valuable comments. This research was supported by the "Interflex" (Unlocking the barriers to accelerate and scale up residential flexibility in Belgium) project funded by the Energy Transition Fund of the Belgian federal government, managed by the FPS Economy, SMEs, Self-employed and Energy. M. Vergouwen was funded by Research Foundation - Flanders (FWO) (mandate no. 1108926N)

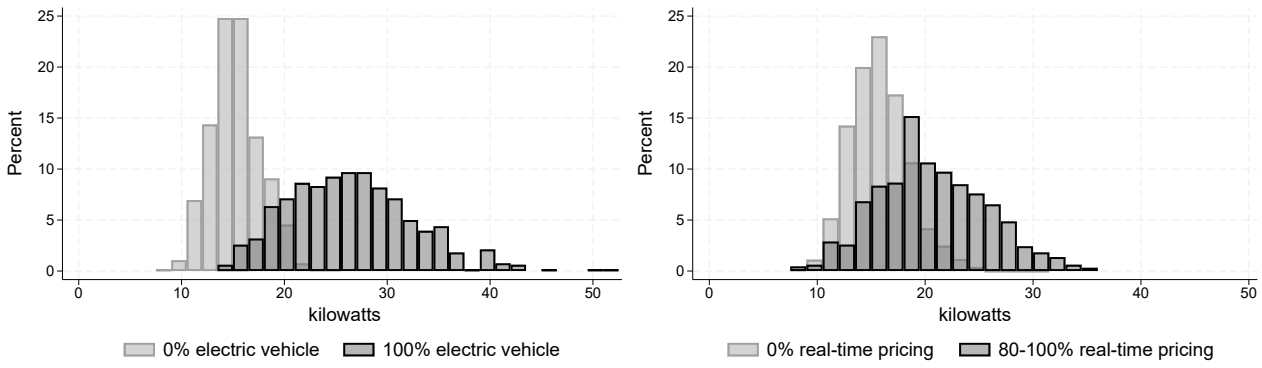
1 Introduction

In network industries, pricing must reconcile two fundamental objectives. On the one hand, prices should promote allocative efficiency by guiding consumption across time in line with marginal operating costs. On the other hand, because network capacity must be built to meet peak demand, prices must also reflect the long-run cost of maintaining and expanding grid capacity that is used only intermittently (Vickrey, 1969; Williamson, 1966).

Electricity markets provide a particularly salient setting in which this tradeoff between energy and capacity matters. Households are increasingly meeting heating and mobility needs with electricity, through heat pumps and electric vehicles. This adoption increases peak loads on distribution networks, which strains transformers, feeders, and distribution substations, and accelerates the need for costly distribution grid investments to maintain sufficient capacity (Bailey et al., 2025b; Powell et al., 2022; Rapson and Shaffer, 2025). As an illustration, Figure 1a shows that the average monthly peak demand in local distribution circuits rises by about 80 percent when electric vehicle adoption increases from 0% to 100%, based on high-frequency electricity consumption data from households in our dataset. Electrification also raises the elasticity of residential electricity demand, as heat pumps (Bernard et al., 2024; Blonz et al., 2025) and electric vehicles (Bailey et al., 2025c) add large, shiftable loads, whose demand is increasingly automated (Bollinger and Hartmann, 2020; Harding and Lamarche, 2016).

At the same time, the expansion of variable renewable generation makes wholesale prices more volatile, raising the gains from real-time prices, which pass this volatility through to consumers. These prices reduce production costs and improve allocative efficiency (Borenstein and Holland, 2005; Borenstein, 2005, 2016; Ito et al., 2023). Yet real-time prices could also raise peaks on local grids, by concentrating consumption in the lowest-price hours (Bailey et al., 2025b; Rapson and Shaffer, 2025). Consistent with this, peak demand in local distribution circuits in our data rises modestly when connected consumers switch to real-time pricing (see Figure 1b). Because networks must still be sized to meet these peaks, and the investments required to reinforce them are large and long-lived, capacity-related network costs account for a growing share of total grid expenditures (Schittekatte et al., 2018; Turk et al., 2025). Conventional volumetric tariffs recover these costs in proportion to energy consumed, setting the marginal price of capacity to zero and leaving households no incentive to avoid the peak hours that drive network costs. Given their scale, mitigating future costs requires grid tariffs that price scarce capacity.

In this study, we focus on individual peak demand charges. By pricing a household's peak rather than its energy use, this grid tariff gives households an incentive to lower demand in peak periods and smooth consumption across the day, making better use of existing network capacity. We develop a conceptual framework showing how electrification and renewable generation affect household peaks, and how this depends on whether consumers respond to



(a) 10 households with varying levels of electric vehicle adoption

(b) 10 households with varying levels of real-time pricing adoption

Figure 1. Histograms of coincident monthly peak demand (kW) at the circuit level in synthetic distribution grids with 10 households per circuit. For each circuit, we vary electric vehicle adoption and real-time pricing participation rates and compute the maximum coincident monthly peak (the maximum 15-minute aggregate load within each month). The histograms summarize the distribution of these peaks across simulated circuits.

prices. Real-time pricing has an ambiguous effect: it reduces demand during high-price periods but increases consumption when renewable supply is abundant and prices are low, so its net effect on peak demand is an empirical question. Peak demand charges, by contrast, internalize the capacity cost of peak load by discouraging consumption in any period that might set the peak. We then empirically examine the effects of electrification, peak demand charges, and real-time pricing on residential customers and distribution grids, using a high-frequency panel of 15-minute consumption data of over 42,000 low-voltage residential consumers in the region of Flanders (Belgium), between 2022 and 2024. Over this period, 17.3% of these households adopted a low-carbon technology, such as electric vehicles, heat pumps, batteries, or solar panels. Both the individual peak demand charges and real-time prices were introduced during our sample period. First, as of January 2021, every consumer had the voluntary option to switch from a flat energy price contract to real-time pricing. Second, as of January 2023, the volumetric tariff for network costs was partially replaced by an individual peak demand charge of roughly €35 to €53 per kW-year, applied to a consumer's monthly 15-minute peak demand, with a minimum of 2.5 kW. As these real-time energy prices and individual peak demand charges collectively contribute to the total retail price, they each affect the consumers' electricity load profiles.

We estimate how electrification, peak demand charges, and real-time pricing each affect monthly peak demand. For each, we use a difference-in-differences (DID) design that exploits a distinct source of variation. First, to estimate the effects of residential electrification, specifically electric vehicle and heat pump adoption, we implement a DID design that accounts for staggered adoption (Callaway and Sant'Anna, 2021). We find that electric vehicles increase peak demand consistently throughout the year by approximately 2 kW, while heat pumps have smaller,

seasonally varying effects. Second, we identify the effect of peak demand charges by exploiting a natural experiment in which protected consumers were exempt from the newly introduced tariff. To address differences in pre-treatment load profiles and observable characteristics, we implement a range of estimators, including two-way fixed effects DID, inverse probability weighting DID (Abadie, 2005), and doubly robust DID (Sant'Anna and Zhao, 2020). Across specifications, the introduction of individual peak demand charges reduces household monthly peak demand by 51 to 118 watts, approximately 1-3 percent of the average pre-treatment peak of around 4,100 watts. The reduction is larger among households with electric vehicles: 5 percent, or about 320 watts. Moreover, households seem to respond to the introduction of the charge but less to its level, consistent with a salience effect rather than a marginal-price response. Third, to estimate the effect of real-time prices, we exploit their staggered rollout, using not-yet-treated or never-treated households as controls. Using a doubly robust DID framework adjusted for variation in treatment timing (Callaway and Sant'Anna, 2021), we find that real-time prices increase monthly peak demand by around 56 to 76 watts per household. The net increase indicates that the concentration of load in low-price hours outweighs the dampening of peak-hour consumption.

Event-study estimates reveal heterogeneous and time-varying treatment effects of prices and tariffs. The effect of real-time prices is relatively stable throughout seasons, and only slightly more pronounced during summer months. The effect of peak demand charges shows little seasonal variation but is strongly moderated by low-carbon technology adoption. Households with electric vehicles show a sustained reduction in peak demand by shifting charging to nighttime and hours of high solar production. By contrast, households without low-carbon technologies–relying on manual demand response–see their peak demand gradually reverting to pre-treatment levels five months after 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 metered households to randomly assigned circuits of 10 or 25 households, simulating local distribution feeders and cables, following an approach inspired by Bailey et al. (2025b). Within each synthetic distribution circuit, we simulate varying levels of electric vehicle adoption and real-time pricing participation rates to capture different stages of electrification. Our findings reveal that individual peak demand charges also significantly reduce coincident peak load at the grid level, particularly in highly electrified circuits. In circuits with 100% electric vehicle adoption, we estimate that monthly distribution circuit-level peak demand decreases 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, reducing grid expansion costs by approximately €16.40 per household per year. This grid-level effect arises because electric vehicle 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. By contrast, household-level effects

of real-time pricing attenuate at the circuit-level. 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 residential electricity flexibility and household electricity demand response. Earlier observational studies have estimated household price elasticities under real-time pricing (Fabra et al., 2021) and time-of-use tariffs (Enrich et al., 2024), and others have relied on experimental designs to evaluate time-of-use tariffs (Bollinger and Hartmann, 2020; Blonz et al., 2025), critical-peak pricing (Jessoe and Rapson, 2014; Garnache et al., 2025), exceedance tariffs (van Montfoort et al., 2026), and real-time price interventions (Allcott, 2011; Hofmann and Lindberg, 2024). We extend this literature in four key ways. To begin, our study is among the first to examine the interaction between pricing schemes with distinct incentive structures. We show the effect of co-existing incentives in the same residential electricity bill. Second, we present one of the first large-scale empirical evaluations of individual peak demand charges as a tool for managing grid congestion in electrified grids. 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 extensive heterogeneity analysis of household responses to real-time prices and peak demand charges. 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 electric vehicle charging and electric vehicle-specific time-of-use tariffs (Qiu et al., 2022; La Nauze et al., 2024), and smart heating incentives (Bernard et al., 2024; Blonz et al., 2025), we document substantial heterogeneity in responsiveness to real-time pricing and individual peak demand charges for these distinct household types. In particular, households owning electric vehicles exhibit peak reductions up to six times larger than the average. Finally, a related literature examines whether households respond to average versus marginal price incentives (Ito, 2014; Shaffer, 2020; Ito and Zhang, 2025). Individual peak demand charges create a highly non-linear price schedule, with a marginal cost of zero except in the household's highest-demand hour, while real-time pricing exposes consumers to marginal prices that vary daily. We add evidence on the limits of marginal-price response: households above the billing minimum of 2.5 kW face a nonzero marginal incentive to lower their peak, yet react to the introduction of the charge but show no detectable response to its level. This pattern is consistent with a salience response. Households whose peak was already below the minimum, for whom the charge had no marginal incentive, show no detectable response at all.

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) and Rapson and Shaffer (2025), 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)). Further, a recent branch of the literature emphasizes the importance of high-voltage transmission grids for renewables integration and the energy transition (Gonzales et al., 2023; Hausman, 2025). Although important, these largely neglect the role of local 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 electric vehicle 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), and requiring grid tariffs that are forward-looking (Schittekatte et al., 2023). 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., 2025c,b; Turk et al., 2025). These shadow peaks can also arise under real-time electricity pricing, as real-time prices incentivize a coincident shift of electricity consumption towards periods with low cost of generation. Our findings indicate that the introduction of individual peak demand charges 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 electric vehicle 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 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). In an event-study estimation of our main model, we find results consistent with response fatigue only for households who need to rely on a manual demand response. Conversely, the literature also discusses factors that enhance demand responsiveness to pricing: the availability of information (Jessoe and Rapson, 2014) and the role of automation (Bollinger and Hartmann, 2020; Blonz et al., 2025; Bailey et al., 2025a; Metcalfe et al., 2026). We complement this work by linking the mechanisms underlying the demand response to the incentives provided by individual peak demand charges and real-time prices. We show that the largest reductions in monthly peak electricity demand occur among households adopting low-carbon technologies–particularly battery storage and electric vehicles–where demand adjustments can be largely automated.

The remainder of this paper is structured as follows. Section 2 provides a stylized model of electricity consumption, aiming to clarify the incentives for retail electricity pricing. Section 3 introduces our institutional setting and data. In Section 4 we detail our research design and empirical strategy. Section 5 presents the main results and extensions. Finally, Section 6 concludes.

2 Conceptual Framework

In this section, we develop a stylized model of electricity supply and demand to formalize the link between residential electrification, the cost of grid capacity, and real-time prices. The model demonstrates how coincident and individual peak demand charges internalize the capacity externality, thereby affecting production decisions, market equilibrium, and grid investment costs. We assume demand (Q_d) and supply (Q_s) for electricity are at any point in time given by:

$$Q_d = e - \beta P \quad , \quad Q_s = q_{renewable} + b_{fossil} P \tag{1}$$

Demand is decreasing linearly with the market price (P) and can shift with the level of residential electrification (e). Electricity supply consists of renewable generation ($q_{renewable}$), which has zero marginal cost and production depending on weather conditions, and fossil generation, which has a positive marginal cost that is increasing with supply.

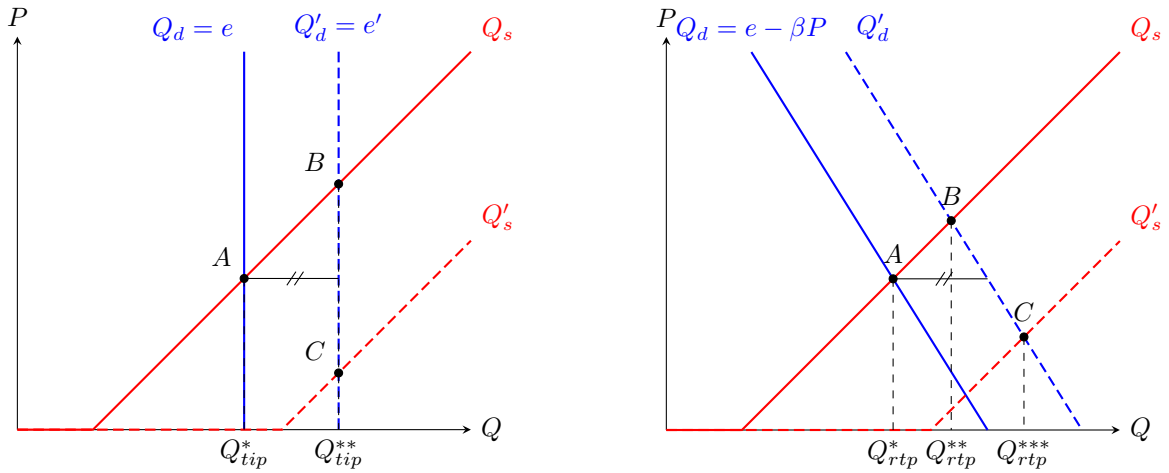
Electrification and renewable supply We are interested in the effect of increasing electrification and renewable generation on equilibrium quantities and grid expansion costs. We examine the comparative statics for increased electrification (e) through an outward shift of the demand curve, and for increased generation of renewables ($q_{renewable}$) through an outward shift of the supply curve. After solving for equilibrium (P^*, Q^*) and differentiating with respect to $q_{renewable}$ and e we find that the effect of an electrification or renewables shock on equilibrium quantities (Q^*) can be expressed as:

$$\frac{dQ^*}{de} = \frac{b_{fossil}}{\beta + b_{fossil}} \quad , \quad \frac{dQ^*}{dq_{renewable}} = \frac{\beta}{\beta + b_{fossil}}. \tag{2}$$

The proof for Equation 2 is given in Supplemental Appendix A. In this appendix, we also link the result to elasticities and prove the result more generally, for nonlinear supply and demand functions. It follows from Equation 2 that the comparative statics effects of electrification and renewable generation ultimately depend on consumers' price responsiveness β. We therefore distinguish between two scenarios: a baseline scenario with time-invariant retail electricity pricing and hence price-unresponsive consumers ($\beta = 0$), and a scenario in which consumers respond to prices through real-time retail electricity pricing ($\beta > 0$).

In the baseline scenario of time-invariant electricity pricing, shown in Figure 2a, demand does not respond to prices, implying a price elasticity of demand equal to zero, or $\beta = 0$ (point A). A positive demand shock from increased electrification then passes one-for-one into quantity ($\frac{dQ^*_{tip}}{de} = 1$), with no behavioral adjustment or load shifting in response to the increased price, raising peak demand from Q^*_{tip} to Q^{**}_{tip} (point B). Adding a positive supply shock from increased renewable generation does not further affect equilibrium quantity ($\frac{dQ^{**}_{tip}}{dq_{renewable}} = 0$) and is entirely passed onto lower prices (point C).

Under real-time electricity pricing, consumers do respond to prices, meaning that $\beta > 0$. These price responses reduce production costs. We show this in Figure 2b. For the same outward electrification shift as before, the increase in peak demand is now smaller, because price-responsive households reduce consumption in reaction to the higher peak-hour price (point B). Working in the opposite direction, the positive renewables shock lowers the price and price-responsive consumers increase consumption, so the peak rises from Q^{**}_{rtp} to Q^{***}_{rtp} (point C). The hour in which the peak occurs may itself shift toward times of abundant renewable supply, but this does not change the interpretation of the model. Real-time pricing thus pulls household peaks in two directions: it reduces demand during high-price periods but increases consumption when renewable supply is abundant and prices are low. Which effect dominates depends on the relative size of the demand and supply shocks and on how strongly consumers respond, making the net effect an empirical question. Peak demand under real-time pricing, Q^{***}_{rtp}, will be higher than under time-invariant pricing, Q^{**}_{tip}, when the price in the peak period is below the price in the initial equilibrium (point A).



(a) Increased electrification under time-invariant pricing increases peak demand from Q^*_{tip} to Q^{**}_{tip}.

(b) Joint increased electrification and real-time pricing increases peak demand from Q^*_{rtp} to Q^{***}_{rtp}.

Figure 2. Market equilibrium under time-invariant pricing (left) and real-time pricing (right), without internalizing capacity constraints

In summary, under time-invariant pricing, electrification adds directly to capacity constraints in local distribution circuits, since unresponsive demand passes the full shock into peak load. Real-time pricing makes demand responsive but does not resolve the problem: it prices energy rather than grid scarcity, dampening peaks in some circumstances and raising them in others. In particular, when increased demand from electrification shifts to times with abundant and low-price renewable generation, this raises local peaks–a pattern documented by Bailey et al.

(2025b) for electric vehicle charging under a time-of-use tariff. This motivates an instrument that prices grid capacity directly, to which we now turn.

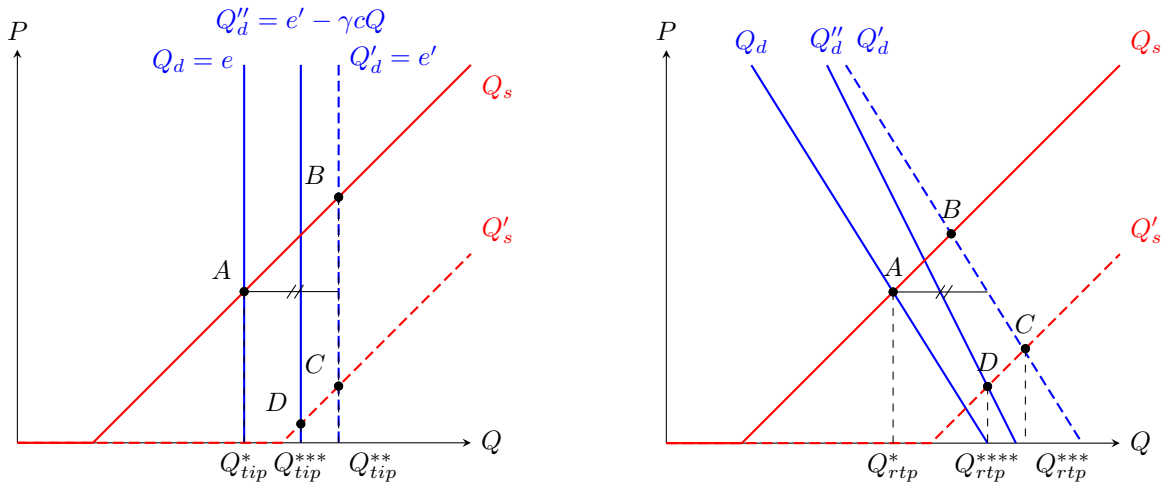
Coincident peak demand charges To internalize the network cost of peak demand, we introduce a coincident peak demand charge. This mechanism charges consumers a capacity cost c (in euro/kW) based on their demand during the system's highest-load hour within a billing period (e.g. month or season). This coincident peak demand charge changes the demand curve to $Q_d'' = e - \beta P - \gamma c Q$, where γ is consumers' responsiveness to the coincident peak demand charge. The charge rotates the original demand curve inward, as consumers internalize the marginal network cost of higher aggregate load.

With this adjustment, the responsiveness of equilibrium quantity to an electrification demand shock or renewable supply shock becomes:

$$\frac{dQ^*}{de} = \frac{b_{fossil}}{\beta + b_{fossil} + \gamma c b_{fossil}} \quad , \quad \frac{dQ^*}{dq_{renewable}} = \frac{\beta}{\beta + b_{fossil} + \gamma c b_{fossil}}. \tag{3}$$

Complete proofs are available in Supplemental Appendix A. Effectively, the introduction of a coincident peak demand charge reduces the quantity response to an increased electrification shock, thereby also mitigating the grid expansion costs as shown visually in Figure 3a, where the peak falls from Q_{tip}^{**} to Q_{tip}^{***} (point D). This finding should not be interpreted as a general reduction in overall electricity consumption. Rather, with a coincident peak demand charge, the household is given an incentive to reduce its maximum demand and to smooth their consumption over time. A similar argument holds for a positive supply shock and households on real-time pricing, which we show visually in Figure 3b: a coincident peak demand charge balances the productive efficiency from increased renewable supply with existing capacity constraints, reducing peak demand from Q_{rtp}^{***} to Q_{rtp}^{****}.

The coincident peak demand charge in the model differs from the individual peak demand charge we study empirically, which is based on each household's own maximum demand rather than the system-wide coincident peak. Only coincident charges directly target system congestion. The two instruments move closer together when individual peaks are highly synchronized. In feeders with strongly coincident load, for instance under high electrification and electric vehicle adoption (Bailey et al., 2025b), individual peaks increasingly coincide with the system peak, so an individual charge generates much the same incentive to curtail demand during peak hours. This incentive is not confined to a single hour. Because households cannot identify the peak in advance, both coincident and individual peak demand charges discourage high consumption across all periods that might turn out to be the maximum. This effect is largest for electric vehicle charging, whose load is large enough that almost any charging event risks setting the household's peak.



(a) A coincident peak demand charge under increased electrification and time-invariant pricing reduces peak demand from Q^{**}_{tip} to Q^{***}_{tip}.

(b) A coincident peak demand charge under increased electrification and real-time pricing reduces peak demand from Q^{***}_{rtp} to Q^{****}_{rtp}.

Figure 3. Market equilibrium under time-invariant pricing (left) and real-time pricing (right), with a peak demand charge that internalizes capacity constraints.

3 Data

As formalized in the conceptual framework in the previous section, electrification, real-time prices, and the introduction of individual peak demand charges affect peak electricity demand and hence grid capacity costs. The model also highlights heterogeneity through differences in price elasticity. We evaluate the empirical impact of electrification, individual peak demand charges, and real-time pricing on peak electricity demand, at the household and distribution-system level. We use as a case study the region of Flanders, for which we obtained a balanced panel of 15-minute level smart-meter electricity consumption data for over 42,000 residential low-voltage consumers between 2022 and 2024.

3.1 Institutional Setting

As of 2021, all residential electricity consumers in Flanders were given the voluntary option to switch from a flat-rate time-invariant electricity price contract to a real-time pricing contract where the electricity price changes every hour following 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, with an average daily price spread of €90/MWh. We describe day-ahead prices in further detail in Supplemental Appendix Figure B.1.

Secondly, as of January 2023, the grid tariff design changed. The volumetric kWh-based tariff for grid costs was replaced by a tariff for grid costs based on a combination of a volumetric kWh-

based tariff, representing 20% of overall grid tariffs, and a kW-based individual peak demand charge, representing the other 80% of overall grid tariffs. The volumetric kWh-based tariff was reduced, such that the total tariff reform was budget-neutral. The kW-based individual peak demand charge is based on a household'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.

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 preprocessing. The data were provided by Fluvius, the Flemish distribution system operator.

Metering data 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 inverter capacity (in kVA)[1]. The final sample consists of more than 1.5 million household-month observations for 42,077 households during the 2022–2024 period.

Low-carbon technology adoption In addition to high-frequency electricity 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 identifies solar photovoltaic 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 subsidy applications for heat pumps, with machine learning–based classification models. These models are trained on households with confirmed technology adoption (via reporting) and are used to predict adoption status for all other households[2]. This approach also enables the distribution system operator to infer the month

[1]Monthly grid withdrawals are truncated at 1500 kWh/month, monthly peak withdrawals at 15 kW and installed solar inverter capacity at 10 kVA. In Flanders, once the total inverter capacity exceeds 10 kVA, households must register as self-employed and comply with additional tax and administrative obligations. Households outside these thresholds are dropped from the sample

[2]The distribution system operator verifies the presence of electric vehicles by analyzing the distribution of household electricity consumption. When recurring peaks are observed at typical charging speeds, such as 5.4 kW, 7.7 kW, or 11 kW, the presence of an electric vehicle is confirmed. The detection of heat pumps relies on a supervised machine learning approach, in which the distribution system operator employs a decision tree model to detect heat pump

of installation for each low-carbon technology.

Electricity contracts 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 individual peak demand charges implemented under the otherwise mandatory new grid tariff. We describe this group of customers in more detail in our empirical strategy. Second, in addition to the main balanced panel of 42,077 households, we construct a supplementary sample of 16,197 households for the analysis of real-time pricing. The majority of real-time pricing households adopted this contract type only after the introduction of individual peak demand charges on January 1st, 2023. For these households, smart meter data become available on a staggered basis. As a result, this supplementary sample is unbalanced, but data is typically available both before and after the real-time pricing enrollment.

In summary, we obtain two final samples. A first, balanced, sample consisting of more than 42,000 households to estimate the effects of residential electrification and peak demand charges, introduced uniformly on January 1st, 2023. The second sample consists of households that additionally adopted real-time pricing. This second sample contains more than 16,000 households, but is unbalanced and reflects the staggered adoption of real-time pricing throughout 2023 and 2024.

3.3 Sample description

Metering data Our analysis of electrification and peak demand charges relies on the 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 grid withdrawal observed over any 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 electricity withdrawals (kWh) and total monthly electricity injection (kWh).

Table 1 summarizes the distribution of these monthly variables across the sample. The average monthly peak demand is approximately 4.1 kilowatt, with 50% of the households realizing a peak between 3 and 5 kilowatts. When broken down by year, monthly peak withdrawals decrease from 2022 to 2023, but increase in 2024. Total grid withdrawals average 256 kWh per month. 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. Overall, these sample descriptives reflect the characteristics of smart meter deployment, where installation of smart meters was prioritized for households with solar PV and battery owners.

ownership.

Low-carbon technology adoption Table 1 also describes the adoption of low-carbon technologies within the sample as of January 1, 2023. The data indicate that 69 percent of households had installed solar photovoltaic systems, with an average installed inverter capacity of 4.26 kVA. Sixteen percent of households had adopted battery storage, with an average usable storage capacity of 8.50 kWh and a corresponding average power rate of 4.48 kW.

Real-time pricing sample Descriptive statistics for the additional, unbalanced, real-time pricing sample are reported in Supplemental Appendix Table B.4. Relative to the main sample, households in the real-time pricing sample have higher rates of battery and electric vehicle ownership, while solar photovoltaic adoption remains broadly similar and heat pump adoption rates are slightly lower. Supplemental Appendix Figure B.5 shows the evolution of real-time pricing adoption over time, with households adopting in a staggered fashion over 2023 and 2024.

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

	Mean	Std	25%	50%	75%
Monthly peak withdrawal [W]	4,146	1,814	2,988	3,884	4,959
Monthly peak withdrawal (2022) [W]	4,142	1,745	3,040	3,920	4,948
Monthly peak withdrawal (2023) [W]	4,048	1,747	2,925	3,801	4,852
Monthly peak withdrawal (2024) [W]	4,249	1,936	3,001	3,931	5,080
Grid withdrawals per month [kWh]	256	191	131	210	327
Grid injection per month [kWh]	163	206	0	73	274
Solar PV (01-01-2023)	0.69	0.46	0.00	1.00	1.00
Battery storage (01-01-2023)	0.16	0.37	0.00	0.00	0.00
Electric vehicle (01-01-2023)	0.05	0.21	0.00	0.00	0.00
Heat pump (01-01-2023)	0.17	0.38	0.00	0.00	0.00
Average solar capacity (2023) [kVA]	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 power (2023) [kW]	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 1,514,772 observations for 42,077 households, 40,360 treated households and 1,717 control households.

3.4 Descriptive evidence

We begin by presenting descriptive evidence on how households' monthly peak electricity demand evolves across different stages of residential electrification, following enrollment in real-time pricing, and after the introduction of individual peak demand charges. Figure 4 shows the distribution of individual household monthly peak demand across these scenarios.

Electrification The distributions in Figure 4 are consistent with the model's prediction that residential electrification increases peak loads. Panels 4a and 4b show that households with electric vehicles and heat pumps display systematically higher monthly peak demand relative to non-electrified households. In both cases, the distributions visibly shift to the right, indicating more frequent high monthly peak demand values. This shift is most pronounced for electric

vehicle ownership. Further, the pattern aligns with the comparative statics in Figure 2a, where increases in electrification, in the absence of mechanisms that internalize capacity constraints, translate into higher peak electricity demand.

Real-time pricing Figure 4c examines how peak demand relates to real-time pricing. The observed shift in the distribution of monthly peaks is relatively small, and from a visual inspection alone, the sign is unclear looking at the distributions only, suggesting that exposure to real-time pricing by itself may not substantially reduce monthly peak demand. This finding is consistent with the theoretical framework, in which responsiveness to real-time prices ($\beta \neq 0$) induces demand adjustments but does not necessarily reduce peak demand when consumption is coordinated during low-price periods (Figure 2b).

Individual peak demand charges Finally, Figure 4d presents the distribution of monthly peaks for households with electric vehicles—those with the highest observed peak demand—before and after the introduction of peak demand charges. Following the introduction of this grid tariff, the highest peak values (10–15 kW) become less common, and the distribution shifts toward lower levels. This pattern is consistent with households adjusting charging behavior, either by reducing charging intensity or shifting load to off-peak periods. Consistent with the model in Figure 3, peak demand charges are associated with a shift away from high peak periods and, correspondingly, lower monthly peak demand, independent of real-time pricing.

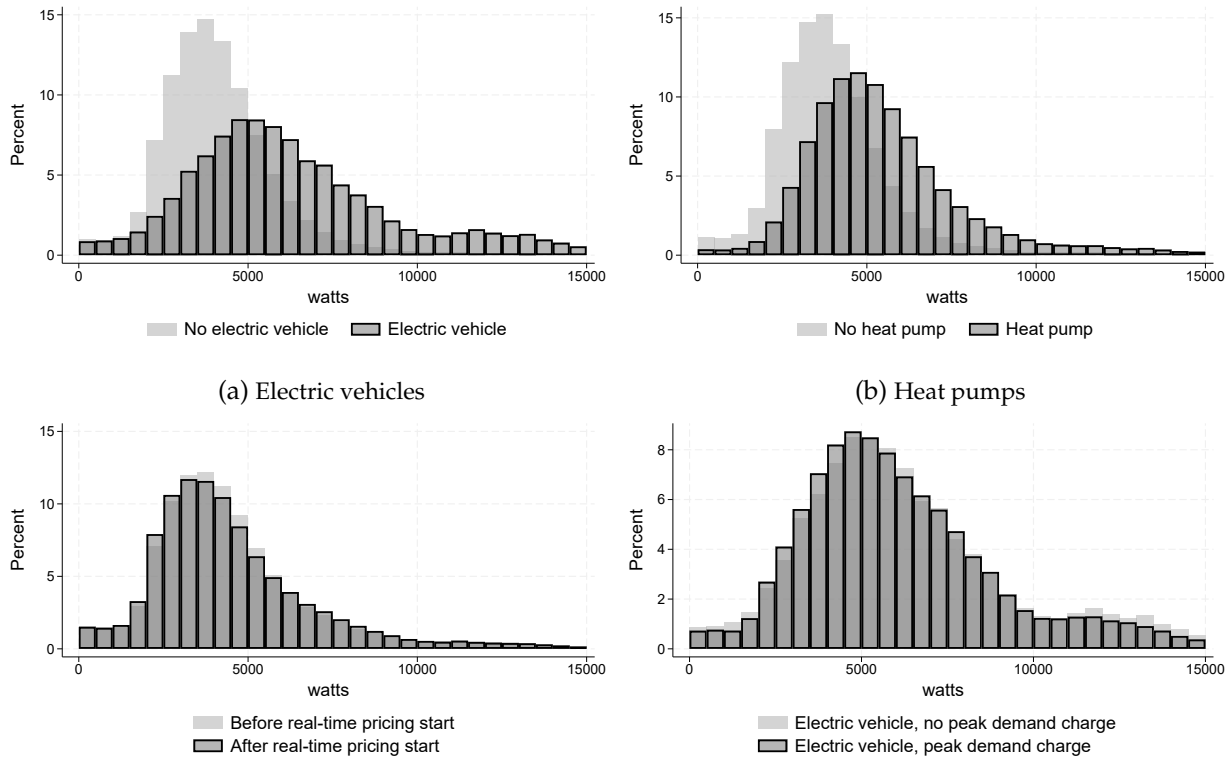
4 Empirical Strategy

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

4.1 Monthly peak

This section describes our analysis at the household level. To identify the treatment effects of each of the three treatments – residential electrification, real-time pricing and peak demand charges – on the household-level monthly peak electricity demand (Peak_{it}), we implement a series of difference-in-difference (DID) designs. While the empirical specifications differ across treatments and estimators, the treatment effects are estimated in the following generic DID framework:

$$\text{Peak}_{it} = \beta_0 + \beta_1 \times \mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat}_i = 1\} + \mathbf{X}_{it}'\boldsymbol{\delta} + \lambda_i + \tau_t + \varepsilon_{it}. \tag{4}$$



(a) Electric vehicles

(b) Heat pumps

(c) Real-time pricing

(d) Peak demand charges and electric vehicles

Figure 4. Histograms of individual household monthly peak demand (W). Panels (a) and (b) examine the impact of residential electrification by comparing households with and without electric vehicles and heat pumps. Panel (c) shows the effect of real-time pricing on monthly peak demand, while panel (d) shows the impact of peak demand charges among electrified households with at least one electric vehicle.

In this equation, $\mathbb{1}\{\text{Treat}_i\}$ defines one of the following treatment of variables of interest: household-level electric vehicle or heat pump adoption (indicating residential electrification), adoption of real-time electricity pricing, or exposure to peak demand charges. $\mathbf{X}_{it}$ defines a set of time-varying controls, 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. In each of the three difference-in-difference designs, the main coefficient of interest, β_1, identifies the ATT. In what follows, we discuss in more detail the identification of the treatment effects of electrification, peak demand charges and real-time prices on individual household monthly peaks.

Electrification To estimate the effects of residential electrification, we focus on electric vehicle and heat pump adoption[3]. Using Equation 4, we compare the relative evolution of monthly

[3]We use only those households with administratively confirmed electric vehicle adoption in the treated group, while for heat pumps we combine administrative data with the supervised machine learning approach developed by the distribution system operator. Because the detection algorithm identifies heat pump adoption with a lag, we shift the inferred adoption date one month earlier to better approximate the true installation date.

peak electricity demand for households who adopted an electric vehicle (treatment group) with households who did not adopt any electric vehicle (never-treated). To avoid confounding our treatment effect estimate due to observable differences between the treatment and control group, we include installed solar inverter capacity (kVA), installed battery energy storage size (kWh) and heat pump ownership as covariates in the estimation. The fixed effects include household and month-of-sample fixed effects. After estimating the effect of electric vehicles, we also estimate the effect of heat pump ownership on monthly peak electricity demand.

Equation 4 would typically be estimated using a TWFE-DID estimator. Yet, as is shown in de Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2021) and Borusyak et al. (2024), the TWFE-DID estimator delivers inconsistent estimates for the treatment effect if the treatment follows a staggered adoption and the treatment effect is heterogeneous across treatment groups or time (Roth et al., 2023), as is the case for electric vehicle or heat pump adoption. We overcome these issues by estimating Equation 4 for electric vehicle and heat pump adoption using the heterogeneity-robust estimators introduced in Callaway and Sant'Anna (2021).

Individual peak demand charges To identify the ATT of individual peak demand charges, we exploit the design of the tariff introduction in Flanders. Under the policy reform, 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. Protected customers are thus exempt from being charged based on peak electricity usage. Eligibility status for being a protected customer is determined by predefined social criteria[4]. If protected consumers are not an appropriate control group for treated households, pre-treatment characteristics between the treatment and control group might differ, and the parallel trends assumption underlying the DID model might not hold unconditionally. To address these potential violations, we adopt multiple variations of a conditional DID model.

First, as shown in Equation 4 we directly add a set of control variables $\mathbf{X}_{it}$ to our baseline TWFE-DID model to improve on covariate balance between the treated and control group. More specifically, we include monthly electricity grid withdrawals (kWh)[5], monthly electricity injection (kWh), installed solar capacity (kVA), installed battery energy storage size (kWh), and dummy

[4]These criteria include households with at least one chronically ill or disabled member receiving social assistance, recipients of unemployment benefits, low-income retirees, residents of social housing, and families receiving increased child allowances for children with a physical or mental disability (Vlaanderen, 2025).

[5]Grid withdrawals could be a bad control if they are directly affected by the treatment and mediate part of the treatment effect. In Supplemental Appendix Figure C.6, we show that the relative evolution of grid withdrawals between treated and control groups is statistically indistinguishable from zero in the 24 months surrounding the introduction of peak demand charges. This suggests that the observed peak reductions are not driven by changes in total electricity demand.

variables for the ownership of heat pumps and electric vehicles as household-level control variables. We interact each of the technology-specific variables with month-of-year dummies to capture heterogeneity between seasons. Second, we implement the inverse-probability weighted (IPW) DID estimator of Abadie (2005) with stabilized weights. This estimator estimates the propensity score of being treated, based on the same set of household-level control variables. For technology adoption, we now include for each technology the quarter-of-sample of adoption as a variable in the weighting procedure. The IPW-DID estimator 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 DID 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.

Real-time pricing Finally, to estimate the ATT of real-time pricing using Equation 4, we compare the relative evolution of monthly peak electricity demand for households who enrolled for real-time pricing (treatment group) with households who did not, or not-yet, adopt real-time pricing (not-yet-treated and never-treated). We account for two challenges in the identification of the effect of real-time pricing. First, households self-select into real-time prices. We accommodate for this self-selection bias by including a broad set of control variables, including monthly electricity grid withdrawals (kWh) and monthly electricity grid injection (kWh), installed solar capacity (kVA), installed battery energy storage size (kWh), and dummy variables for the adoption of heat pumps and electric vehicles. Second, as before, we account for the staggered adoption of real-time pricing by estimating Equation 4 using the estimator of Callaway and Sant'Anna (2021).

Dynamic treatment effects To explore the dynamics of treatment effects we also estimate fully dynamic versions of our three DID models. We estimate the following specification, separately for each treatment:

$$\text{Peak}_{it} = \beta_0 + \sum_k \left(\beta_k \times \mathbb{1}\{\text{EventTime}_t = k\} \times \mathbb{1}\{\text{Treat}_i = 1\}\right) + \mathbf{X}'_{it}\boldsymbol{\delta} + \lambda_i + \tau_t + \varepsilon_{it} \tag{5}$$

For peak demand charges, we specify a fully dynamic event-study specification in which we obtain a month-of-sample specific treatment effect estimate from January 2022 (12 months prior to treatment) to December 2024 (24 months after treatment). To estimate the dynamic effect of residential electrification and real-time pricing, we follow the framework of Callaway and Sant'Anna (2021): we estimate separate group-time specific treatment effects for each adoption cohort, and then aggregate the results to event time or calendar time.

4.2 Grid level effects

To simulate the impact of electrification, real-time pricing, and peak demand charges on the distribution grid, we adopt a strategy inspired by Bailey et al. (2025b). In our strategy, households are randomly assigned to synthetic distribution circuits consisting of either 10 or 25 households, representing a typical low-voltage cable or feeder in Flanders. Within each synthetic distribution circuit, we also vary the level of technology adoption. For each technology – electric vehicles, heat pumps, and battery storage – households are placed into circuits with a predetermined adoption level: 0%, 20%, 50%, 80%, or 100% adoption. We then aggregate the load profiles for these 10 or 25 households, to obtain the aggregate load profile for the synthetic distribution circuit, for varying levels of technology adoption. Afterwards, we determine the coincident grid-level monthly peak. As shown in Supplemental Appendix Table B.2, the relative uptake of low-carbon technologies in the group of protected customers is lower than in the treated group. We therefore generate our synthetic distribution circuits using only the households that are subject to the introduction of peak demand charges.

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 and the underlying coincidence in electric vehicle charging. Second, our design allows maintaining realistic baseline demand profiles, without relying on ad-hoc assumptions. Because households are assigned to circuits conditional on only 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. Third, this design allows us to estimate, within one coherent framework, the effects of electrification, real-time prices, and peak demand prices on distribution circuit monthly peaks.

To estimate these effects at the distribution circuit level, we implement a series of panel fixed effects regression models, which we summarize in their general form as:

$$\text{Circuit Peak}_{ct} = \beta_0 + \sum_{s=1}^{S} \beta_s \times \mathbb{1}\{\text{Adoption}_{ct} = s\} + \mathbf{X}'_{ct}\boldsymbol{\delta} + \tau_t + \varepsilon_{ct}. \tag{6}$$

In this equation the Circuit Peak_{ct} is defined at the circuit (c) month-of-sample (t)-level. $\mathbb{1}\{\text{Adoption}_{ct} = s\}$ reflects a set of dummy variables indicating electric vehicle or real-time pricing adoption bins (0%, 20%, 50%, 80%, or 100%), with 0% adoption as the omitted category[6]. For

[6]For electrification, it is possible to compare variation *between* circuits that always have a high (or low) share of electric vehicles or heat pumps. Real-time pricing adoption evolves staggered and only starts throughout 2023 and 2024, making it infeasible to assign circuits a fixed level of treatment intensity at every point in time. Within the same circuit, adoption levels can, for instance, increase from 20% to 50% throughout a year. As a result, we allow real-time pricing adoption to vary *within* circuits across time and estimate how different levels of real-time pricing adoption

the estimation of the effect of individual peak demand charges, we replace $\mathbb{1}\{\text{Adoption}_{ct} = s\}$ with $\mathbb{1}\{\text{Adoption}_{ct} = s\} \times \mathbb{1}\{\text{Post}_t = 1\}$, indicating that we are interested in the heterogeneous effect of peak demand charges when varying the level of low-carbon technology adoption in the distribution circuit. As before $\mathbf{X}_{ct}$ defines a set of time-varying controls, τ_t accounts for time fixed effects, and ε_{ct} represents the idiosyncratic error term, clustered at the distribution circuit level. The control variables are identical to the household-level control variables to mimic our main regression, but are now aggregated over all the households in the distribution circuit: total number of heat pumps and electric vehicles, aggregate solar inverter capacity (kVA), aggregate battery energy storage capacity (kWh), aggregate residential electricity production (kWh) and aggregate withdrawals (kWh).

4.3 Load profile

Changes in monthly peak demand at the household level can arise through multiple channels. Households may shift consumption from peak to off-peak hours or change overall electricity use in response to peak demand charges and real-time pricing. The extent of these responses may depend on information, knowledge, and the availability of automation technologies. To examine these mechanisms driving changes in peak demand, we exploit granular 15-minute interval electricity consumption data in a regression framework estimating load shifting behavior.

We construct the outcome variable of this regression as the sum of electricity consumption for specific intra-day time blocks and the overall daily total. Specifically, let Demand_{idb} denote total electricity demand from grid withdrawals (in kWh) of household i on day d in time block b. Time blocks are defined as night (22:00–06:00), morning (06:00–12:00), afternoon (12:00–17:00), and evening peak (17:00–20:00). We then use Demand_{idb} as the outcome variable in a DID specification:

$$\text{Demand}_{idb} = \beta_0 + \beta_1 \times \mathbb{1}\{\text{Treat}_i = 1\} \times \mathbb{1}\{\text{Post}_t = 1\} + \mathbf{X}'_{idb}\boldsymbol{\delta} + \alpha_{idb} + \varepsilon_{idb}. \tag{7}$$

As before, $\mathbb{1}\{\text{Treat}_i = 1\}$ is the treatment variable of interest: household-level adoption of real-time electricity pricing, or exposure to peak demand charges. For the response to peak demand charges, protected customers again serve as the control group. For real-time pricing, we use the not-yet-treated as control group. Control variables $\mathbf{X}_{idb}$ include daily temperature variables and household-specific variables on solar inverter capacity (kVA), battery storage size (kWh), heat pump and electric vehicle adoption, and solar production (kWh), interacted with month-of-year dummy variables. Finally, α_{idb} represents a flexible set of fixed effects.

within circuits affects grid-level outcomes.

5 Results

We investigate the effect of electrification, peak demand charges, and real-time pricing on the household-level 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 of treatment on the shape of the daily electricity consumption profile, which we present in Section 5.3.

5.1 Monthly Peak

5.1.1 Electrification

Main results Table 2 reports the estimated effects (ATT) of electric vehicle and heat pump adoption on monthly household peak demand. We first present results from a TWFE-DID specification with controls, followed by estimates based on the CS-DID approach (Callaway and Sant'Anna, 2021). Electric vehicle adoption leads to the largest increase in peak demand, raising monthly household peaks by approximately 1.9–2.2 kW on average. For heat pump adoption, the treatment effect estimates are considerably lower, with monthly peaks increasing by 0.15 kW, approximately, on average.

Calendar time treatment effects In Figure 5 we aggregate the treatment effects to calendar time. We exclude the first months of 2022 from this figure, as treatment effects are imprecisely estimated in these months. As described in Section 3.2, this occurs because we use a combination of administrative data and machine learning-based classification to detect low-carbon technology adoption. For this reason, the algorithm requires a few months of initial data – the first months of 2022 – before detection is reliably possible, and we thus exclude the initial months of the dataset. For reference, we report the event-time treatment effects and the calendar time treatment effects for the full three years in Supplemental Appendix C.1.

The aggregation to calendar time serves two purposes. First, it allows for an informal inspection of structural breaks with the introduction of the compulsory peak demand charge scheme, on January 1st 2023. Second, it allows to capture the seasonal variation in treatment effects which is especially present in the treatment effects for heat pump adoption[7].

Figure 5a presents the calendar-time treatment effect aggregations for electric vehicles. While there is *some* seasonality present in these results, electric vehicles increase households' monthly peak demand consistently throughout the year, and with a stable order of magnitude around 2 kW. After the introduction of the peak demand charge grid tariff on January 2023, there seems to be a fall in

[7]Presenting event-study estimates for heat pump adoption will confound the strong seasonality in electricity demand with the actual dynamic treatment effect. Because heat pump usage, and thus its impact on peak demand, is highly concentrated in winter months, event time becomes mechanically correlated with calendar time. As a result, the estimated event-study coefficients largely reflect seasonal variation rather than clean dynamic treatment effects.

monthly peak electricity demand. For heat pumps, in Figure 5b, results show pronounced seasonality. Treatment effects for heat pump ownership are insignificant in summer months, while heat pumps do increase peak electricity demand in winter months up to 400 to 600 watts, depending on the specification. The overall ATT of 152 to 160 watt increase in peak electricity demand, is thus indeed an *average* treatment effect, averaging away seasonal variation.

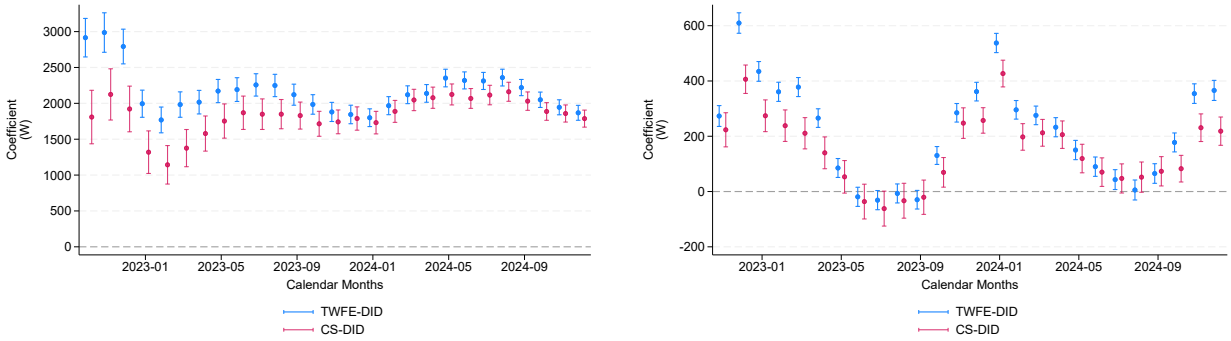
Table 2: Effects of electrification (electric vehicle and heat pump adoption) on households' monthly peaks

	Electric vehicle		**Heat pump**	
	(1)	(2)	(3)	(4)
	TWFE-DID	CS-DID	TWFE-DID	CS-DID
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat EV}_i = 1\}$	2198.78***	1891.37***		
	(45.32)	(31.46)		
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat HP}_i = 1\}$			178.35***	152.10***
			(9.48)	(8.01)
Joint test: all leads zero (p-value)	0.000	0.000	/	/
HonestDiD 95% CI for:				
$\mathbb{1}\{\text{EventTime}_t = 1\} \times \mathbb{1}\{\text{Treat}_i = 1\}$	[1160.65; 1373.60]	[1192.30; 1403.38]	/	/
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat}_i = 1\}$	[1637.90; 1916.52]	[1691.30; 1968.51]	/	/
Observations	1,206,159	1,248,264	1,179,265	1,266,732
Households	35,003	35,003	41,590	41,590

Note: This table estimates the effects of electrification (electric vehicle and heat pump adoption) on households' monthly peaks (in watts) over the period January 2022 - December 2022 in a difference-in-differences framework. For each, two specifications are used to estimate the model. Columns (1) and (3) uses TWFE-DID with additional control variables. Control variables include solar inverter capacity (kVA), battery storage size (kWh) and the dummy variables for the any other low-carbon technology on top of the treatment of interest (e.g. we include a dummy variable for heat pump adoption when estimating the effect of electric vehicle ownership). Household fixed effects and time fixed effects are included. In columns (2) and (4), we show the results using the Callaway and Sant'Anna (2021) Doubly Robust DID estimator with never-treated as the control group. The unit of observation is household-month-of-sample. Standard errors are clustered at the household level. For the adoption of electric vehicles, we present HonestDiD 95% confidence intervals from the package by Rambachan and Roth (2023), explicitly accounting for smoothly evolving secular trends that differ between the treatment and control group. We report 95% Robust CIs for the case $\Delta^{\text{sd}}(M = 0)$, i.e. allowing for linearly evolving group-specific trends. Results are reported both for the first period after treatment and the overall treatment effect. Because of strong seasonality in heat pump usage effects, we do not estimate HonestDiD 95% confidence intervals for this treatment. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1.2 Prices and tariffs

Main results Table 3 reports the estimated treatment effects of peak demand charges and real-time pricing on monthly household-level peak demand, showing that the two pricing schemes had opposing effects on peak electricity demand. The first three columns show the effects for individual 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



(a) Electric vehicles

(b) Heat pumps

Figure 5. Estimates of the dynamic event-study specification in calendar time for electrification using data for 2022 - 2024. Each dot represents the point estimate of the monthly peak increase (in W) in event-time. Two different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects including control variables. Second, the doubly-robust CS-DID estimator Callaway and Sant'Anna (2021). Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

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 (common support and balancing) for the weighting procedures in Supplemental Appendix C.2.

Our results are relatively stable across specifications. While the point estimates increase in size from -51 watts to -118 watts monthly peak reduction, all carry the same sign and all are statistically significant at the one percent level. As we reject the null hypothesis that *all* pre-treatment coefficients are jointly zero, we further report HonestDiD 95% confidence intervals for the first post-treatment period and the average treatment effect (Rambachan and Roth, 2023). To assess the sensitivity of our results to potential violations of the parallel trends assumption, we estimate the HonestDiD 95% confidence interval allowing for group-specific linear trends. The results indicate that potential trend differences between treated and control households cannot account for the significant reduction in peak demand observed in the first post-treatment period. In contrast, the HonestDiD 95% confidence interval for the ATT becomes statistically insignificant. This is consistent with Figure 6, which shows that the treatment effect dissipates over time. Consequently, in later periods, the remaining effect is no longer distinguishable from plausible differential trends between treated and control households.

The magnitude of our baseline effects corresponds to an approximate reduction of between 1 to 3 percent of the average pre-treatment household monthly peak of 4,142 watts. As a comparison, Enrich et al. (2024) observe reductions of peak-hour electricity consumption up to 9% after the introduction of a time-of-use tariff. In response to a critical peak pricing experiment, Garnache et al. (2025) observe reductions of consumption up to 12.5% during critical peak hours, while

van Montfoort et al. (2026) find peak reductions up to 10% in response to an exceedance tariff. Our results indicate 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, Supplemental Appendix C.3 presents two robustness checks, where we either exclude all households that adopt new technologies (Table C.2) or omit control variables for technology adoption altogether (Table C.3). Both robustness checks deliver results similar to our main specification, confirming the negative treatment effect of peak demand charges on monthly peak demand.

Columns four and five of Table 3 present the estimated effect of real-time pricing. Column four employs the TWFE-DID estimator, which should be interpreted with caution as it does not address the staggered adoption of real-time pricing. In contrast, column five implements the estimator proposed by Callaway and Sant'Anna (2021), which accommodates staggered treatment timing. Our results suggest that, for adopters, real-time pricing leads to a statistically significant increase in monthly peak demand, with an effect size comparable to that of peak demand charges. Moreover, effects are around twice as large for households with low-carbon technologies, as shown in Supplemental Appendix Table C.6. These findings offer a new perspective on the implications of real-time pricing: while Fabra et al. (2021) report an overall insignificant price elasticity in Spain, our evidence indicates that real-time pricing may nonetheless contribute to higher household *peak* electricity consumption. Self-selection into real-time pricing in our sample might also explain part of the effect: as confirmed in Appendix Table B.4, households switching voluntarily to real-time pricing have higher electric vehicle and battery storage ownership, mechanically increasing the expected benefits and flexibility potential for the switching households.

Event study: peak demand charges Beyond average effects, we now explore the dynamics of treatment effects over time using event studies. We estimate a dynamic version of our DID models. Figure 6 presents the event-study results for the TWFE-DID estimator with control variables, the IPW-DID estimator with stabilized weights, and the Doubly Robust DID estimator (Sant'Anna and Zhao, 2020). Across all specifications, pre-treatment coefficients are statistically insignificant in most, but not all, months. Stronger divergence between the two groups emerges only after the policy's implementation, with treated households immediately reducing peak demand relative to the control group. As confirmed by the HonestDiD 95% confidence intervals in Table 3, this immediate discontinuity cannot be explained by plausible differential trends.

Figure 6 also illustrates the dynamic treatment effect of the peak demand charges, showing a clear pattern of decay over time. In the early months of 2023, treated households significantly reduce their monthly peak demand, but this reduction diminishes gradually in subsequent months. The decline is robust across the various model specifications. 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 use automated systems, continuously altering consumption patterns may become increasingly difficult. We confirm this finding in Figure 7a, which shows the treatment effects over time for households without any low-carbon technology. This pattern of response fatigue in electricity consumption is consistent with the evidence in Hofmann and Lindberg (2024), who document declining attention to electricity prices in a randomized controlled trial.

Table 3: Effect of peak demand charges and real-time prices on households' monthly peaks (W)

	Individual peak demand charges			**Real-time pricing**	
	(1)	(2)	(3)	(4)	(5)
	TWFE-DID	IPW-DID	DR-DID	TWFE-DID	CS-DID
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat PDC}_i = 1\}$	-51.40***	-95.67***	-118.47***		
	(-3.79)	(-3.11)	(-3.87)		
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat RTP}_i = 1\}$				56.10***	75.67***
				(4.79)	(2.92)
Joint test: all leads zero (p-value)	0.0031	0.0543	0.0096	0.001	0.5191
HonestDiD 95% CI for:					
$\mathbb{1}\{\text{EventTime}_t = 1\} \times \mathbb{1}\{\text{Treat}_i = 1\}$	[-177.92; -93.06]	[-177.98; -81.66]	[-168.61; -70.91]	[2.51; 62.20]	[-3.13; 85.96]
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat}_i = 1\}$	[-216.79; -78.11]	[-135.51; 30.44]	[-151.75; 11.85]	[-5.48; 93.91]	[-42.84; 186.37]
Observations	1,514,772	1,514,772	1,514,772	1,272,899	1,272,899
Households	42,077	42,077	42,077	58,274	58,274

Note: This table estimates the effects of peak demand charges and real-time prices on households' monthly peaks (in watts) over the period January 2022 - December 2024 in a difference-in-differences framework. Columns (1) to (3) show the results for peak demand charges. The introduction of the individual peak demand charge 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 inverter capacity (kVA), 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 stabilized weights, weighting based on grid withdrawals (kWh), solar inverter capacity (kVA), 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-treated as the control group, respectively. The unit of observation is household-month-of-sample. For the real-time pricing analysis, we extend the main sample of 42,077 households by including an additional 16,197 households that adopted real-time pricing during 2023–2024. The number of treated and control households varies per month-of-sample, as treatment follows staggered adoption. Note that accounting for fixed effects is implicit in IPW-DID, DR-DID and CS-DID. Standard errors are clustered at the household level. *t*-statistics in parentheses. For all estimators, we present HonestDiD 95% confidence intervals from the package by Rambachan and Roth (2023), explicitly accounting for smoothly evolving secular trends that differ between the treatment and control group. We report 95% Robust CIs for the case $\Delta^{\text{sd}}(M = 0)$, i.e. allowing for linearly evolving group-specific trends. Results are reported both for the first period after treatment and the overall treatment effect. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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, 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, reductions in monthly peak demand below 2.5 kW do not lower electricity bills and therefore generate no marginal financial incentive to further reduce peak consumption. Furthermore, even when they do attempt to reduce their peak consumption, it might be more difficult to achieve substantial reductions when pre-treatment peaks are already low.

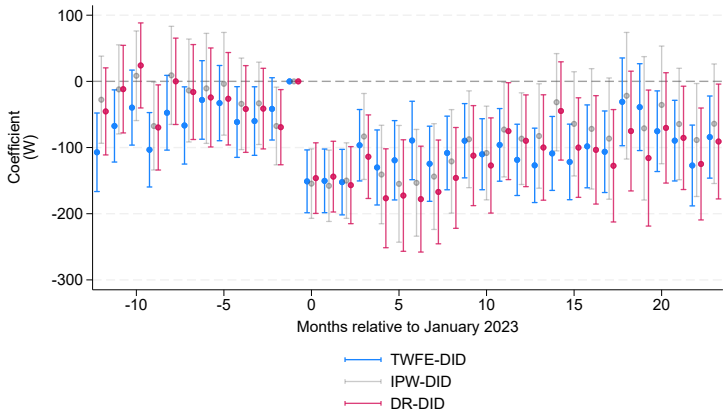
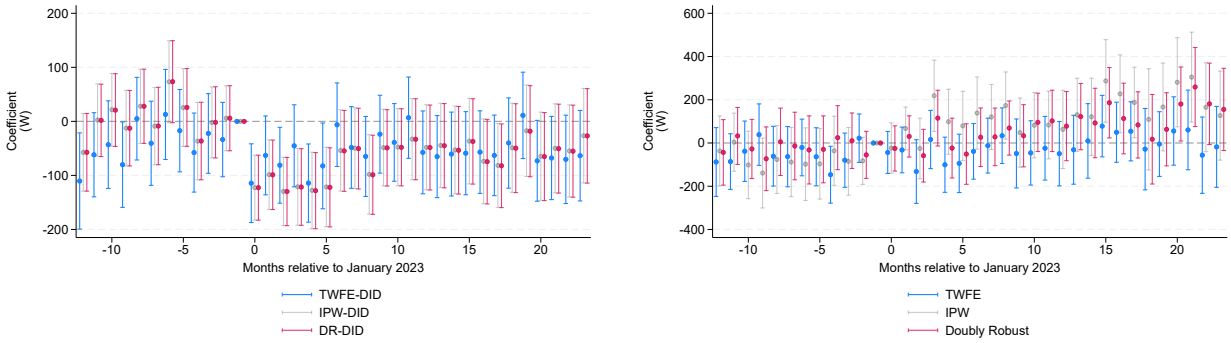


Figure 6. Estimates of the dynamic specification for the effect of peak demand charges on the households' monthly peak (watts) in the full sample using difference-in-differences. Three different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects including control variables. Second, the IPW-DID estimator with stabilized 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. Estimates of the dynamic specification for the effect of peak demand charges on the households' monthly peak (watts) in subsamples of small consumers using difference-in-differences. 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 stabilized 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.

Event study: real-time pricing We now turn our attention to the event-study effects of real-time pricing. Figure 8 shows an event-study plot for the 12 months before and after voluntary adoption, with statistically significant increases in peak demand among households that voluntarily adopt real-time pricing on top of the compulsory peak demand charge. We present event-study plots with alternative control groups in Supplemental Appendix Figure C.8. 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). In our setting, the increased peak from switching to real-time prices is low, but might be larger in settings without a peak demand charge in place. In addition, as the number of negative price hours is increasing, and expected to increase in the future (IEA, 2025), the significance of this finding is expected to increase further.

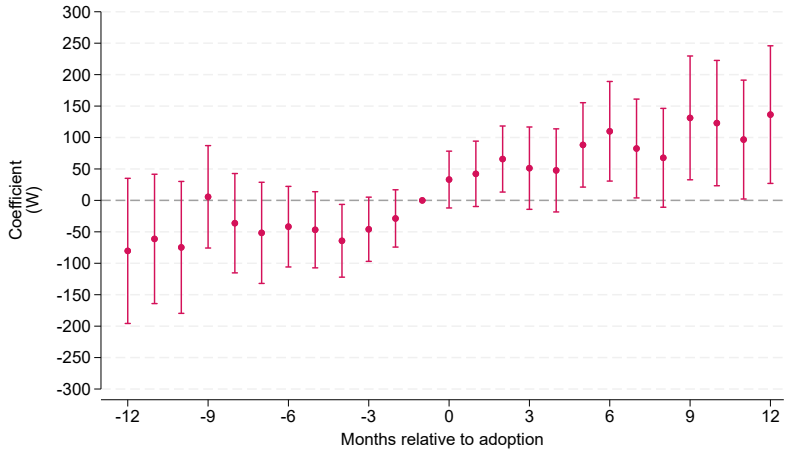


Figure 8. Estimates of the dynamic specification for real-time prices in the full sample, showing coefficients in event-time (months relative to adoption), from 12 months before to 12 months after adoption. Each dot represents the point estimate of the monthly peak change (in W) in event time. The Callaway and Sant'Anna (2021) Doubly Robust DID estimator with never-treated as the control group is used to estimate the causal effect. Group-time treatment effects are then aggregated to event time. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

5.1.3 Prices and tariffs: 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 introduction of the peak demand charge scheme. Categories are not mutually exclusive and include households without any low-carbon technology, and those with at least an electric vehicle, heat pump, or battery energy storage. Second, we estimate Equation 4 separately by subgroup to identify heterogeneous effects.

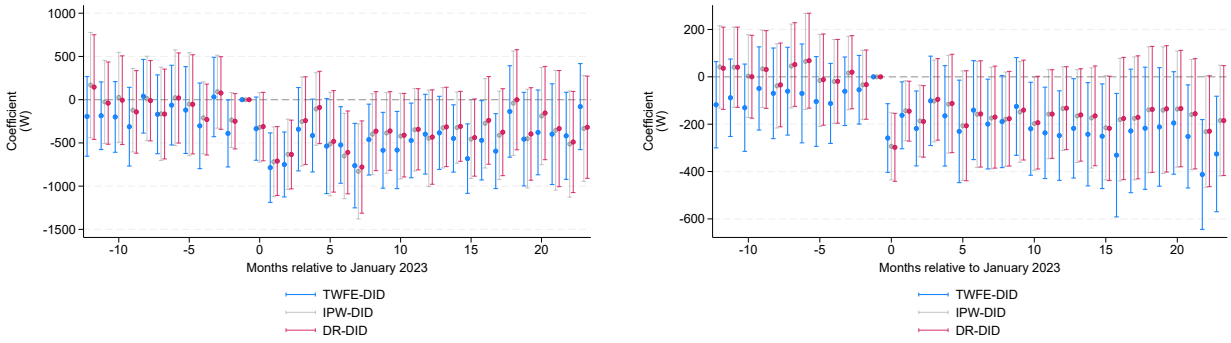
Table 4 reports treatment effect estimates for the effect of peak demand charges on monthly peak demand across household subsamples. All specifications use the TWFE-DID estimator and control for household and month-of-sample fixed effects. In addition, we include household-level control variables for grid withdrawals and grid injection and include dummy variables for adoption of new low-carbon technologies. The results reveal considerable heterogeneity in treatment effects. Peak demand reductions are smaller among households with heat pumps or without low-carbon technologies than in the full sample. Battery-owning households reduce their peaks somewhat more. The most notable finding concerns electric vehicle owning households. These households reduce their monthly peak demand by an average of 319 watts following the reform, a reduction that is both economically and statistically significant. Relative to their 2022 pre-treatment baseline of 6,331 W monthly peak demand, 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. This result is robust to the use of alternative estimators (IPW-DID and DR-DID), as shown in Supplemental Appendix Table C.5: the estimated treatment effects are consistently the largest for electric vehicle and battery storage owning households.

Figures 9a and 9b present the event-study estimates of the response of monthly peak demand to the introduction of peak demand charges for households with electric vehicle and those with battery storage. These figures show a sharp reduction in peak demand in the months immediately following the reform for both groups, an effect persistent over time. This treatment effect is consistent with the adoption of automated energy-management systems, such as smart electric vehicle chargers, as well as applications provided by electric vehicle manufacturers allowing to set charging speeds, both of which can incorporate the incentive from peak demand charges into the charging schedule to help limit peak demand. By deferring electric vehicle charging to off-peak periods and reducing charging speeds, 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, Supplemental Appendix Figure C.7 displays event-study estimates for all subgroups of low-carbon technologies. These results again confirm that households with electric vehicles exhibit the most stable and persistent reductions in peak demand over time.

Table 4: Effect of peak demand charge on monthly peak (W) for households with different low-carbon technologies.

	(1) Full sample	(2) Electric vehicle	(3) Heat pump (main)	(4) Heat pump (additional)	(5) Battery storage	(6) No LCTs
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat PDC}_i = 1\}$	-51.40***	-319.47***	-29.37	-88.70	-147.55***	-18.44
	(-3.79)	(-2.41)	(-0.45)	(-1.41)	(-2.61)	(-1.13)
Mean dep. var.: Monthly Peak$_{it}$ 2022	4142.44	6331.26	5083.59	4966.90	3861.69	3706.10
Joint test: all leads zero (p-value)	0.0031	0.4099	0.0172	0.7097	0.9750	0.1080
Observations	1,514,772	57,636	102,168	79,308	245,088	290,844
Households	42,077	1,600	2,838	2,203	6,808	8,079

Note: This table estimates the effects of peak demand charges on households' monthly peaks (in watts) for households with different low-carbon technologies over the period January 2022 - December 2024 in a difference-in-differences framework. The introduction of the individual peak demand charges on January 1st, 2023 indicates the post period and protected households on the social tariff serve as control group. Results are shown by low-carbon technology adoption group, with group membership being non-exclusive. Results are presented for the TWFE-DID estimator with additional control variables. Control variables include grid withdrawals (kWh), solar capacity (kVA), solar injection (kWh), battery storage size (kWh) and the dummy variables for the presence of heat pumps and electric vehicles. Household fixed effects and time fixed effects are included. Households are classified based on the technologies installed prior to January 2023. 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 the effect of peak demand charges on the households' monthly peak (watts) for households with an electric vehicle or battery energy storage using difference-in-differences. 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 stabilized weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. All coefficients are estimated relative to December 2022, the month immediately preceding treatment. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

Peak demand charge level Table 5 presents estimates from an extended specification that examines heterogeneity in treatment effects by the *level* of the peak demand charge. 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.

In Table 5, column (1) replicates our average treatment effect estimated with the TWFE-DID specification. Columns (2) through (4) explore heterogeneity by interacting the treatment indicator with household-level deviations from the average peak demand charge rate. The overall interaction term is not statistically significant in column (2), and the year-specific analysis in columns (3) and (4) reveals that the effect of the rate deviation is small and only becomes marginally significant at the 10% level in 2024. Specifically, in that year, a one-euro/kW-year increase in the deviation from the average rate is associated with a 2.75 watts additional reduction in peak demand. These results suggest that unlike for the *existence* of peak demand charges, we find no detectable evidence that the *level* of the peak demand charge has a meaningful significant effect on the change of the peak, as in Prest (2020).

Table 5: Effect of peak demand charge rate on households' monthly peaks (W)

	Main	**Deviations**		
	(1)	(2)	(3)	(4)
	All	All	2023	2024
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat PDC}_i = 1\}$	-51.40***	-53.06***	-58.08***	-46.00***
	(-3.79)	(-3.90)	(-4.60)	(-2.66)
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat PDC}_i = 1\} \times \widetilde{\text{Rate}}_{it}$		-1.311	-0.0921	-2.754*
		(-1.34)	(-0.10)	(-1.75)
Households	42,077	42,077	42,077	42,077

Note: This table estimates the effects of the peak demand charge rate on households' monthly peaks (in watts) over the period January 2022 - December 2024 in a difference-in-differences framework. The introduction of the individual peak demand charges January 1st, 2023 indicates the post period and protected households on the social tariff serve as control group. Each specification uses the TWFE-DID estimator. Column (1) estimates the treatment effect for the full sample, and columns (2), (3) and (4) model add the deviation from the average peak demand charge rate as a covariate. Column (3) pools the years 2022 and 2023, while column (4) pools the years 2022 and 2024. All specifications include control variables: grid withdrawals (kWh), solar inverter capacity (kVA), solar injection (kWh), battery storage size (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 electrification, peak demand charges, and real-time pricing thus far leverage data at the individual household-level. However, local distribution grids are sized to ensure meeting peaks in coincident system peak demand, not peaks in individual demand (Joskow and Tirole, 2005; Fell et al., 2021; Schittekatte et al., 2023). Grid tariffs 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 to enhance overall system efficiency. This issue is becoming increasingly salient with the growing adoption of electric vehicles, as simultaneous charging events can generate substantially higher load peaks than conventional household appliances (Bailey et al., 2025b; Becker et al., 2025; Li and Jenn, 2024; Powell et al., 2022).

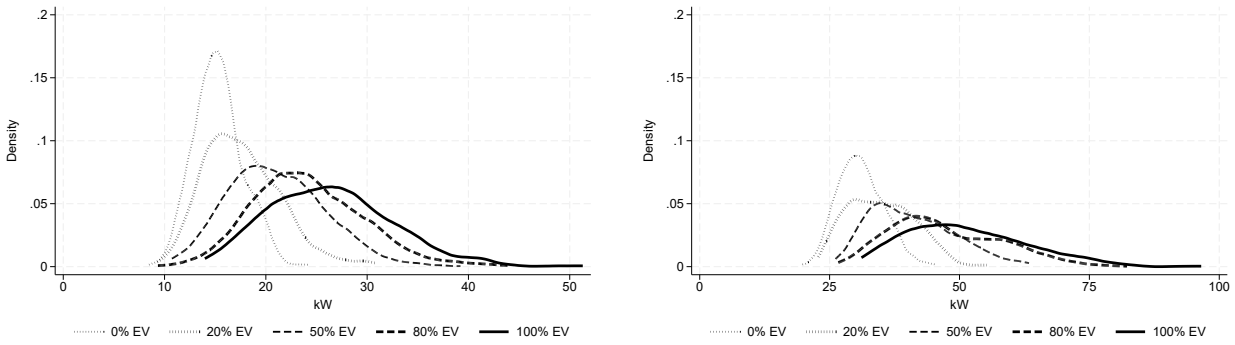
For this reason, this section leverages the granularity of our dataset to assess how the individual household-level effects of electrification, peak demand charges, and real-time prices scale to the level of the distribution grid. Our approach proceeds in two steps. First, we generate synthetic distribution circuit-level data through a procedure similar to Bailey et al. (2025b). Second, we estimate local distribution grid effects of electrification, peak demand charges, and real-time pricing through regression analysis. The circuit peak is a deterministic aggregation of the household peaks whose causal response we identify in Section 5.1 using protected customers as controls. The grid-level regressions do not exploit separate identifying variation, but they quantify how the identified household responses aggregate to the level that drives distribution investment.

5.2.1 Electric vehicles and distribution grids

To simulate the effect of electric vehicle adoption on the distribution grid, we randomly assigned households to distribution circuits comprising either 10 or 25 households. Within each distribution circuit, we vary the level of electric vehicle adoption ranging between 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 categories, we observe that monthly peak electricity demand increases consistently with the percentage of households that has adopted an electric vehicle in the circuit. At the monthly level, distribution circuits of 10 households with 0% electric vehicle adoption, peak on average at 15.32 kW (31.01 kW for circuits with 25 households), while distribution circuits with 100% electric vehicle adoption peak on average at 26.41 kW (51.34 kW for circuits with 25 households). We provide further descriptive statistics in Supplemental Appendix Tables D.1 and D.2. The coincidence factor, the ratio of the coincident circuit peak to the sum of individual household peaks, stays roughly constant at about 0.41 across electric vehicle adoption levels. Because this ratio does not fall as adoption rises, the larger individual peaks under high electric vehicle adoption pass through into proportionally larger coincident peaks at the circuit level.

We quantify the relationship through a panel fixed effects regression model with the coincident grid-level peak as the outcome variable, and a set of dummy variables indicating the share of electric vehicle adoption in the distribution feeder as the main explanatory variables. The model is estimated using data from 2022 only, when no households were subject to peak demand charges.



(a) 10 households aggregated

(b) 25 households aggregated

Figure 10. Kernel densities of coincident monthly peak demand (kW) at the circuit level in synthetic distribution grids with 10 or 25 households per circuit. For each circuit, we vary electric vehicle adoption and compute the maximum coincident monthly peak (the maximum 15-minute aggregate load within each month). There are 550 unique circuits with 10 households, and 225 unique circuits with 25 households. The densities summarize the distribution of these peaks across simulated circuits.

The results from this estimation are shown in Table 6. Relative to circuits with 0% electric vehicle adoption, circuits with 100% adoption exhibit monthly coincident peak loads that are 12.41 kW higher for circuits with 10 households and 16.02 kW higher for circuits with 25 households, corresponding to a coincident peak increase of approximately 81%.

Table 6: Effect of electric vehicle adoption on synthetic distribution grid peaks

	Percentage of households with EV				
	0%	20%	50%	80%	100%
	PANEL A: 10 households				
Peak (kW)					
Monthly	Ref.	2.619***	6.336***	9.915***	12.409***
		(7.37)	(9.71)	(10.19)	(10.41)
Monthly mean dep. var.	15.32	17.64	21.04	24.15	26.41
	PANEL B: 25 households				
Peak (kW)					
Monthly	Ref.	3.200***	7.659***	12.800***	16.016***
		(3.78)	(4.63)	(4.81)	(4.70)
Monthly mean dep. var.	31.01	34.98	40.81	47.24	51.34

Note: This table estimates the effects of electric vehicle adoption on synthetic distribution grid monthly peaks (in kilowatts) over the period January 2022 - December 2022 in a panel fixed effects model. The distribution grid level coincident monthly peak is aggregated over 10 households in Panel A or 25 households in Panel B. There are 550 unique circuits with 10 households, and 225 unique circuits with 25 households. The introduction percentage of households with an electric vehicle indicates the treatment variable. We employ a TWFE model without control group, but with additional control variables. Control variables include grid-level aggregate distributed solar production (kWh), aggregate solar capacity installed (kVA), aggregate battery energy storage size installed (kWh), temperature, and variables for the aggregate number of heat pumps in the distribution circuit. Fixed effects include 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 Electric vehicles and peak demand charges

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 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, electric vehicles, aggregate solar PV and battery energy storage capacity installed, aggregate residential electricity production, and temperature. Fixed effects include month-of-year and circuit fixed-effects.

The results from this exercise are shown in Table 7. The results indicate a statistically significant reduction in coincident peaks in local distribution circuits following the introduction of peak demand charges. Peak demand charges become more effective as electric vehicle adoption increases. Moving from circuits with 0% to 100% electric vehicle adoption raises the estimated reduction in the monthly coincident peak from 0.45 kW to 1.81 kW, implying an additional 1.36 kW reduction in highly electrified circuits. Expressed in levels, the 1.8 kW monthly peak reduction in 100% electrified circuits represents a decline of approximately 6.8% relative to the pre-treatment average monthly peak of 26.41 kW (see Supplemental Appendix Table D.1). The effect scales with the size of the circuit: in circuits with 100% electric vehicle adoption and 25 connected households, the coincident peak declines by 3.09 kW, or 6.0% of the pre-treatment average.

We translate these circuit-level reductions into avoided grid investment under a forward-looking scenario of 50% electric vehicle adoption, well above the 5% penetration in our current sample. Applied to projected grid reinforcement investments, the coincident-peak reduction corresponds to approximately €48.7 million in avoided annual expenditure, or about €16.40 per household per year[8]. We emphasize that this is a scenario value at intermediate electric vehicle penetration levels[9], not a benefit realized at current adoption levels, and that it assumes the peak reduction maps proportionally into investment savings. Distribution investment is lumpy and local, so the realized relationship between coincident-peak reductions and avoided capital expenditures will depend on which feeders are near their capacity limits.

In Supplemental Appendices D.3 and D.4 we provide similar analysis, now for circuits with in-

[8] This result is based on investment projections in Fluvius (2025), who estimate overall grid reinforcement investments for the period 2026-2035, amounting to €1 billion per year. Based on our estimates, peak demand charges at intermediate levels of 50% electric vehicle adoption lead to an overall circuit-level peak reduction 4.87%, which we assume translates directly to a reduction in required overall investments of 4.87%. These assumptions result in €48.7 million of avoided investments per year, which we then divide equally across the 2.973 million households in Flanders (Statistiek Vlaanderen, 2025)

[9] Fluvius (2025) projects 2 million electric vehicles in Flanders by 2035 under a low-adoption scenario, 2.45 million under a medium-adoption scenario, and 3.45 million under a high-adoption scenario. In all scenarios, electric vehicles account for over 50% of total mobility by 2035. In the high-adoption scenario of 1.9 million electric vehicles by 2030, electric vehicles account for close to 50% of total mobility by 2030 already.

Table 7: Effect of peak demand charges on synthetic distribution grid peaks by electric vehicle adoption level

	Percentage of households with electric vehicle				
	0%	20%	50%	80%	100%
	PANEL A: 10 households				
Peak (kW)					
Monthly	-0.453***	-0.824***	-1.511***	-1.847***	-1.810***
	(-4.58)	(-4.97)	(-6.20)	(-6.60)	(-5.24)
Monthly mean dep. var.	15.32	17.64	21.04	24.15	26.41
	PANEL B: 25 households				
Peak (kW)					
Monthly	-0.508**	-0.798**	-1.988***	-1.861**	-3.093***
	(-2.10)	(-2.14)	(-3.59)	(-2.32)	(-3.23)
Monthly mean dep. var.	31.01	34.98	40.81	47.24	51.34

Note: This table estimates the effects of peak demand charges on synthetic distribution grid monthly peaks (in kilowatts) by electric vehicle adoption level over the period January 2022 - December 2024 in a panel fixed effects model. The distribution grid level coincident monthly peak is aggregated over 10 households in Panel A or 25 households in Panel B. The introduction of individual peak demand charges 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 withdrawals (kWh), aggregate solar capacity installed (kVA), aggregate battery energy storage size installed (kWh), temperature, and variables for the aggregate 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, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

creased 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. However, additionally introducing peak demand charges does not further reduce monthly peak demand in these circuits.

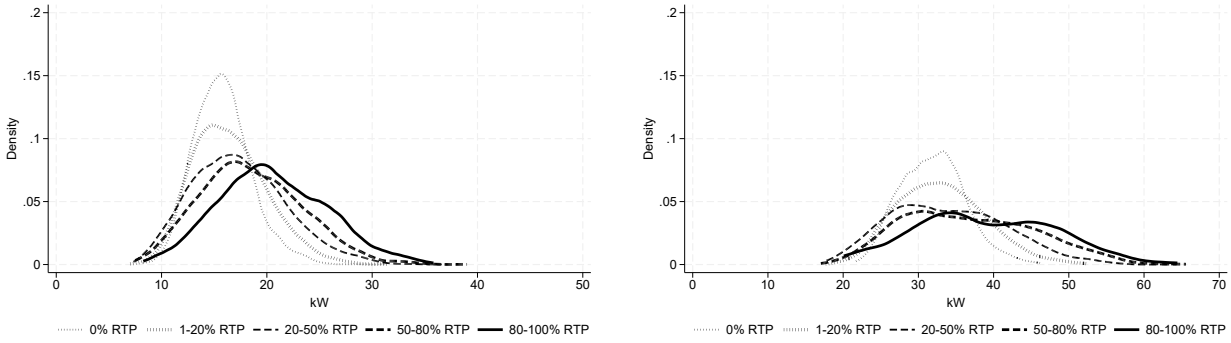
5.2.3 Real-time pricing

In Figure 11, we examine how the introduction of real-time pricing affects coincident monthly peak demand at the circuit 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, technology adoption 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, Figure 11 shows a modest increase in coincident monthly peaks at the

distribution level, although the effect is markedly less pronounced than that observed for electric vehicle adoption. Specifically, in circuits where none of the 10 connected households has adopted real-time pricing, the average monthly coincident peak is 18.92 kW. This rises to 24.17 kW in circuits where all connected households have adopted real-time pricing. Additional summary statistics are provided in Supplemental Appendix Tables D.3 and D.4.

We next examine how real-time pricing adoption affects coincident peak demand in a regression framework, controlling for adoption of low-carbon technologies, temperature and aggregate solar PV production and including month-of-year fixed effects. We thus exploit variation between circuits and within the same circuit over time. Table 8 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. We include data from January 2023 to December 2024, meaning that throughout, all real-time pricing adoption households are also subject to peak demand charges. Across both circuit sizes, we find limited evidence that real-time pricing also increases peak demand at the grid level. While the monthly peak demand increases modestly at higher adoption levels, the effects are small and are mostly not statistically significant. These findings suggest that, after controlling for technology adoption, the impact of real-time pricing in our setting with peak demand charges in place is currently modest.



(a) 10 households aggregated

(b) 25 households aggregated

Figure 11. Kernel densities of coincident monthly peak demand (kW) at the circuit level in synthetic distribution grids with 10 or 25 households per circuit. For each circuit, we vary real-time pricing participation rates and compute the maximum coincident monthly peak (the maximum 15-minute aggregate load within each month). There are 550 unique circuits with 10 households, and 225 unique circuits with 25 households. The densities summarize the distribution of these peaks across simulated circuits.

5.3 Daily load profile

After documenting treatment effects on monthly peak demand at both the household and distribution-circuit levels, we turn to the underlying behavioral responses using full daily load profiles. This section examines how households adjust consumption patterns in ways that trans-

Table 8: Effect of real-time pricing adoption on synthetic distribution grids

	Percentage of households with active real-time pricing contract				
	0%	1-20%	20-50%	50-80%	80-100%
	PANEL A: 10 households				
Peak (kW)					
Monthly	Ref.	0.138	0.353*	0.667***	1.049***
		(1.02)	(1.87)	(2.69)	(3.28)
Monthly mean dep. var.	15.79	16.49	17.35	18.55	20.60
	PANEL B: 25 households				
Peak (kW)					
Monthly	Ref.	0.267	0.359	0.811	1.039
		(0.81)	(0.83)	(1.55)	(1.59)
Monthly mean dep. var	31.96	33.07	33.96	36.77	38.95

Note: This table estimates the effects of real-time pricing adoption on synthetic distribution grid monthly peaks (in kilowatts) over the period January 2023 - December 2024 in a panel fixed effects model. The distribution grid level coincident monthly peak is aggregated over 10 households in Panel A or 25 households in Panel B. There are 550 unique circuits with 10 households, and 225 unique circuits with 25 households. We employ a TWFE model with additional control variables. Control variables include grid-level aggregate distributed solar production (kWh), aggregate grid withdrawals (kWh), aggregate solar capacity installed (kVA), aggregate battery energy storage size installed (kWh), temperature, and variables for the aggregate number of heat pumps and electric vehicles in the distribution circuit. Fixed effects include month-of-year fixed effects. Standard errors are clustered at the circuit level, t-statistics in parenthesis, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

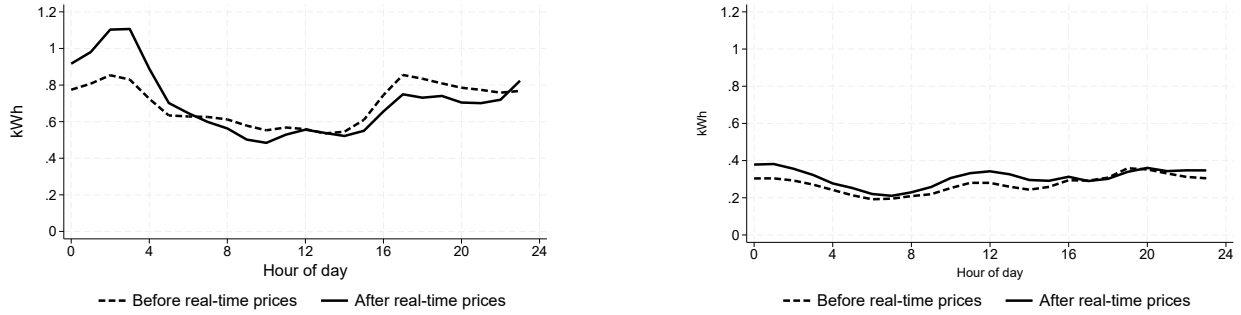
late into monthly peaks, with particular attention to key enablers of demand response such as automation and access to information (Jessoe and Rapson, 2014; Bollinger and Hartmann, 2020; Blonz et al., 2025). We focus on two groups that face strong financial incentives under peak demand charges. We begin with households that voluntarily adopted real-time pricing, and then analyze the responses of electric vehicle owners to peak demand charges.

5.3.1 Real-time pricing and peak demand

When discussing the effect of real-time pricing on peaks, we documented an increase in monthly peak electricity demand for households on real-time pricing. Supplemental Appendix Figure B.1 presents average month-by-hour day-ahead prices in Belgium for 2023 and 2024. These form the basis for residential real-time pricing contracts. We observe systematically higher prices in winter. Further, there is pronounced intraday variation: prices are lowest during summer daytime hours, consistent with solar PV generation, and peak in the early evening, typically between 17:00 and 20:00, when system demand is highest. For households on real-time pricing, these fluctuations map directly into electricity costs. The average maximum intraday spread is 90.13 €/MWh in 2023 and 91.79 €/MWh in 2024.

Figures 12a and 12b report average hourly household electricity demand (grid withdrawals, in kWh/hour) for adopters of real-time pricing. The load profiles are consistent with intraday load-shifting in response to real-time prices. Following adoption, households reduce demand during evening peak hours and increase withdrawals during nighttime hours, especially in winter months, indicating a shift of load toward lower-priced periods. In summer months, the observed

shift is less pronounced. We formalize these findings by estimating Equation 7, estimating the change in electricity demand after the uptake of a real-time pricing contract. Table 9 reports the coefficient estimates. The first row considers total daily electricity demand for grid withdrawals and shows no statistically meaningful effect of real-time pricing on aggregate daily demand. The remaining rows decompose demand into predefined time blocks. For example, the fourth row aggregates peak hour demand and indicates an average peak hour demand reduction of 0.125 kWh per day following adoption, while demand during night hours increases sharply with 0.576 kWh per day. In winter, the peak hour demand reduction is more pronounced and adds up to 0.519 kWh. In total, during winter months, there is a shift of around 1 kWh from the morning and evening peak to nighttime hours.



(a) Winter months (December - February)

(b) Summer months (June - August)

Figure 12. Average hourly demand for electricity grid withdrawals (in kWh) for households adopting real-time pricing, comparing demand before and after adoption. *Note*: the figure is based on an unbalanced sample of 1,061 households that adopted a real-time pricing contract during the sample period. Households switched to real-time pricing at different dates.

5.3.2 Electric vehicles, solar panels and peak demand charges

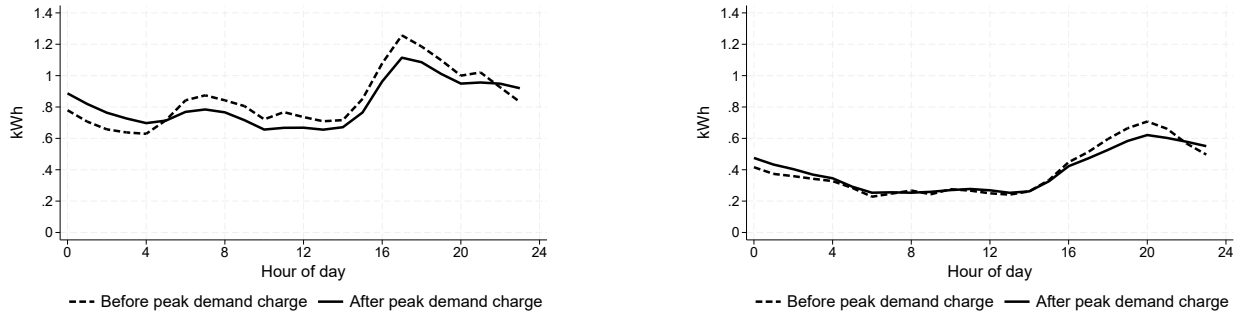
In this section, we present evidence showing the load shifting dynamics in response to the introduction of peak demand charges for electric vehicle-owning households. Figures 13a and 13b present descriptive load profiles, showing households again increase nighttime demand for grid withdrawals after the introduction of the peak demand charges scheme, while peak hour electricity demand reduces. In Table 10, we formalize the effect estimation using only households that already owned an electric vehicle before January 2023. There is no evidence of a reduction in total daily electricity use following the introduction of the peak demand charge. Instead, the response is characterized by reallocation across hours of the day. Specifically, in winter months, electric vehicle owning households reduce grid withdrawals by 0.4 kWh in the morning and 0.256 kWh in the evening peak, alongside additional reductions during morning and afternoon hours. An offsetting effect is observed at night. The overall shift of load amounts to roughly 0.75 kWh per day. In summer months, we do not find statistically significant evidence of systematic load shifting, likely driven by self-production with residential solar PV.

Replacing demand for grid withdrawals with demand for total consumption (withdrawals plus self-production minus injections) yields similar patterns, as shown in Supplemental Appendix E.2.

Table 9: Load shifting in response to switching to real-time pricing

	(1) All	(2) Winter	(3) Summer
Total grid withdrawals:			
All hours	0.405	0.0739	0.661
	(1.45)	(0.10)	(1.21)
Morning hours (06.00 - 12.00)	-0.127**	-0.438**	0.0771
	(-2.15)	(-2.22)	(0.61)
Afternoon hours (12.00 - 17.00)	0.0662	-0.318	0.304**
	(1.02)	(-1.64)	(2.12)
Peak hours (17.00 - 20.00)	-0.125**	-0.519***	-0.0538
	(-2.48)	(-3.77)	(-0.44)
Night hours (22.00 - 06.00)	0.576***	1.442***	0.341
	(3.73)	(3.61)	(1.21)
Households	1,061	1,061	1,061

Note: The 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 regression is based on a sample of 1,061 households that adopt real-time pricing throughout the sample period. 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 daily variables for temperature, dummy variables for the presence of heat pumps interacted with month-of-year indicators, dummy variables for the presence electric vehicles interacted with month-of-year indicators, and continuous solar capacity (kVA), solar production (kWh), storage capacity (kWh) variables, interacted with month-of-year indicators. Fixed effects include month-of-sample, household × month-of-year and household × day-of-week fixed effects. Standard errors are clustered at the household level. *t*-statistics in parentheses. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$



(a) Winter months (December - February)

(b) Summer months (June - August)

Figure 13. Average hourly demand for electricity grid withdrawals (in kWh) for electric vehicle adopters before and after the introduction of peak demand charges. *Note*: the figure is based on a balanced sample of 175 households that adopted an electric vehicle before January 1, 2022. Consequently, all households in the sample owned an electric vehicle throughout 2022 (the pre-reform period) and the post-reform period following the introduction of peak demand charges.

Table 10: Load shifting for electric vehicle owners in response to individual peak demand charges

	(1) All	(2) Winter	(3) Summer
Total grid withdrawals:			
All hours	0.365	-0.421	0.807
	(0.87)	(-0.58)	(1.54)
Morning hours (06.00 - 12.00)	-0.0152	-0.400***	0.203
	(-0.15)	(-2.61)	(1.44)
Afternoon hours (12.00 - 17.00)	0.000467	-0.353	0.157
	(0.00)	(-1.64)	(1.39)
Peak hours (17.00 - 20.00)	-0.0501	-0.256*	0.0843
	(-0.57)	(-1.91)	(0.68)
Night hours (22.00 - 06.00)	0.464**	0.750*	0.292
	(2.16)	(1.68)	(1.34)
Households	2,021	2,021	2,021

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) regression. The regression is based on a balanced sample of 2,021 households, who adopted their electric vehicle before January 1st, 2023. The introduction of individual peak demand charges 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 daily variables for temperature, dummy variables for the presence of heat pumps interacted with month-of-year indicators, dummy variables for the presence electric vehicles two-way interacted with month-of-year and treatment indicators, and continuous solar capacity (kVA), solar production (kWh), storage capacity (kWh) variables, interacted with month-of-year indicators. Fixed effects include month-of-sample, household $\times$ month-of-year and household $\times$ day-of-week fixed effects. Standard errors are clustered at the household level. *t*-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 the Netherlands (van Montfoort et al., 2026), and price incentive programs in Australia (La Nauze et al., 2024). Second, we find that this nighttime charging effect diminishes during the summer months. 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 grid charge reform (Liang et al., 2022; La Nauze et al., 2024).

Finally, we emphasize the following. In our main analysis, we show that peak demand charges reduce monthly peak demand, particularly among electric vehicle-owning households. By contrast, real-time pricing increases peak electricity demand. Despite this difference, both treatments induce load shifting toward night hours. This pattern is not contradictory (see Supplemental Ap-

pendix Figure E.7). Electric vehicle-owning households subject to peak demand charges exhibit substantially higher baseline peaks than the average household adopting real-time pricing. Although the electric vehicle-owning households shift average load to the night, the resulting nighttime peak demand does not increase above the original household-peak. Hence, overall peak load declines because off-peak usage rises. In contrast, households switching to real-time pricing begin with relatively flat peak profiles. For these households, shifting demand toward low-price periods, both night and afternoon hours, can raise overall peak demand.

6 Conclusion

The transition to a zero-carbon energy system is changing how electricity is priced and consumed. Real-time pricing promotes 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). We emphasize a second, increasingly important constraint: local distribution network capacity. Rising residential electrification is 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.

Using high-frequency consumption data of over 42,000 low-voltage consumers in Flanders, we find that electrification through electric vehicle adoption increases peak electricity demand by around 2 kW. Heat pump adoption leads to a more limited average increase of 0.15 kW, rising to 0.4 to 0.6 kW in winter months. Real-time pricing increases monthly peaks by around 0.075 kW, with effects roughly twice as large for households with low-carbon technologies. To address these peaks, individual peak demand charges are effective at reducing coincident monthly peaks at both the household and distribution-grid level. Their average effect at the household level is 51 to 118 watts, 1 to 3 percent of the pre-treatment average, driven by a sharp reduction in the first post-treatment months that is robust to plausible differential trends. The averaged effect dissipates over time but is persistent for households with electric vehicles.

Households with an electric vehicle show the most pronounced peak reduction of 320 watts, or 5 percent of their average pre-treatment monthly peak, an effect that remains stable 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 translate to lower local grid peaks, especially when more of the connected households own electric vehicles. The impact of real-time prices remains relatively limited at the grid level.

Rather than generating conflicting incentives, we argue that 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 becomes increasingly important for demand-side flexibility that does not violate local grid constraints.

While we argue that peak demand charges are justified as a means of containing future grid investments, their role in cost recovery for distribution and transmission system operators has long been debated. Under the standard assumption that fixed system costs are sunk and tariffs serve to recover them, Borenstein (2016) and Schittekatte et al. (2018) argue that peak demand charges are inefficient. More recently, with the increasing adoption of electric vehicles, this premise might no longer hold, as future grid expansions depend inherently on demand flexibility (Baldick, 2018). In this context, flat volumetric tariffs are not cost-reflective: by raising the marginal price uniformly across all hours and locations—often even beyond the marginal social cost of producing electricity (Borenstein and Bushnell, 2022)—they distort consumption decisions without addressing the specific times and places where capacity is scarce (Pérez-Arriaga et al., 2017). By contrast, locational marginal pricing (LMP) directly incorporates the marginal cost of congestion at each node at the transmission level, and thus provides efficient incentives for demand flexibility and investment (Kolesar, 2023), but no comparable nodal price exists at the distribution level, where the capacity constraints we study bind. In practice, many utilities rely on time-of-use tariffs, which shift demand into predefined off-peak periods. These schedules often fail to align with actual system conditions and, under widespread electric vehicle adoption, can even exacerbate simultaneity in charging demand (Bailey et al., 2025b; Turk et al., 2025). Against this background, Turk et al. (2025) show that ex-post peak demand charges offer a promising alternative, as these charges strike a balance: they limit the cost of charging electric vehicles, while also mitigating the need for costly grid expansion and thus lowering costs for households without electric vehicles. We extend this insight by noting that peak demand charges can coexist with production-cost based signals, such as real-time pricing, ensuring that consumers face incentives consistent with both generation and network constraints. Nevertheless, Turk et al. (2025) argue that capacity subscription charges, where consumers choose an ex-ante kW limit, further reduce cognitive burden and protect households against bill volatility compared to ex-post peak demand charges.

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. 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 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.

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. doi:10.1093/jeea/jvac045.

Bailey, M., Brown, D.P., Shaffer, B., Wolak, F.A., 2025a. Take the load off: effort and technology as determinants of the electricity demand response. NBER doi:10.3386/w33836.

Bailey, M.R., Brown, D.P., Myers, E., Shaffer, B., Wolak, F.A., 2025b. Electric vehicles and the energy transition: Unintended consequences of time-of-use pricing. American Economic Review: Insights 7, 550–66. doi:10.1257/aeri.20240476.

Bailey, M.R., Brown, D.P., Shaffer, B., Wolak, F.A., 2025c. Show me the money! a field experiment on electric vehicle charge timing. American Economic Journal: Economic Policy 17, 259–84. doi:10.1257/pol.20230653.

Baldick, R., 2018. Incentive properties of coincident peak pricing. J. Regul. Econ. 54, 165–194. doi:10.1007/s11149-018-9367-9.

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.

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 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. doi:10.5547/ISSN0195-6574-EJ-Vol26-No3-5.

Borenstein, S., 2016. The economics of fixed cost recovery by utilities. The Electricity Journal 29, 5–12. doi:10.1016/j.tej.2016.07.013.

Borenstein, S., Bushnell, J.B., 2022. Do two electricity pricing wrongs make a right? cost recovery, externalities, and efficiency. American Economic Journal: Economic Policy 14, 80–110.

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.T., Kopalle, P.K., 2023. Field experimental evidence on the effect of pricing on residential electricity conservation. Management Science 69, 7784–7798. doi:10.1287/mnsc.2020.02074.

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.

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.

Fluvius, 2025. Investeringsplan 2026-2035. Technical Report. Fluvius. URL: https://over.fluvius.be/nl/publicatie/investeringsplan-2026-2035-versie-goedgekeurd-vlaamse-nutsregulator.

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.

Gonzales, L.E., Ito, K., Reguant, M., 2023. The investment effects of market integration: Evidence from renewable energy expansion in chile. Econometrica 91, 1659–1693. doi:10.3982/ECTA20769.

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.21928.

Hausman, C., 2025. Power flows: Transmission lines, allocative efficiency, and corporate profits. American Economic Review 115, 2574–2615. doi:10.1257/aer.20240276.

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., Ida, T., Tanaka, M., 2023. Selection on welfare gains: Experimental evidence from electricity plan choice. American Economic Review 113, 2937–73. doi:10.1257/aer.20210150.

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 doi:10.1257/pol.20230613.

Jessoe, K., Rapson, D., 2014. Knowledge is (Less) Power : Experimental Evidence from Residential Energy Use. American Economic Review 104, 1417–1438. doi:10.1257/aer.104.4.1417.

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.

Kolesar, M., 2023. Chapter 15 - rethinking, repackaging and repricing the grid and retail electricity, in: Sioshansi, F. (Ed.), The Future of Decentralized Electricity Distribution Networks. Elsevier, pp. 333–353. doi:10.1016/B978-0-443-15591-8.00021-8.

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.

Li, Y., Jenn, A., 2024. Impact of electric vehicle charging demand on power distribution grid congestion. Proceedings of the National Academy of Sciences 121, e2317599121. doi:10.1073/pnas.2317599121.

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.

Metcalfe, R.D., Schein, A., Simpson, C.R., Sun, Y., 2026. AI in Charge: Large-Scale Experimental Evidence on Electric Vehicle Charging Demand. Working Paper 34709. National Bureau of Economic Research. doi:10.3386/w34709.

van Montfoort, F., Dijkstra, P.T., Mulder, M., Kopányi, D., 2026. Reducing peak load from electric vehicles through grid tariffs: Evidence from a randomized field experiment. Journal of Environmental Economics and Management 139, 103354. doi:10.1016/j.jeem.2026.103354.

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.

Prest, B.C., 2020. Peaking interest: How awareness drives the effectiveness of time-of-use electricity pricing. Journal of the Association of Environmental and Resource Economists 7, 103–143. doi:10.1086/705798.

Pérez-Arriaga, I.J., Jenkins, J.D., Batlle, C., 2017. A regulatory framework for an evolving electricity sector: Highlights of the MIT utility of the future study. Econ. Energy Environ. Pol. 6.

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.

Rambachan, A., Roth, J., 2023. A more credible approach to parallel trends. The Review of Economic Studies 90, 2555–2591. doi:10.1093/restud/rdad018.

Rapson, D., Shaffer, B., 2025. Smooth operator? managing electric vehicle integration in constrained distribution networks. Working Paper 2025.

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.

Schittekatte, T., Momber, I., Meeus, L., 2018. Future-proof tariff design: Recovering sunk grid costs in a world where consumers are pushing back. Energy Economics 70, 484–498. doi:10.1016/j.eneco.2018.01.028.

Shaffer, B., 2020. Misunderstanding nonlinear prices: Evidence from a natural experiment on residential electricity demand. American Economic Journal: Economic Policy 12, 433–461. doi:10.1257/pol.20180061.

Statistiek Vlaanderen, 2025. Huishoudtypes. https://www.vlaanderen.be/statistiek-vlaanderen/bevolking/huishoudtypes. [Accessed 04-06-2026].

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 doi:10.1177/01956574251365616.

Vickrey, W., 1969. Congestion theory and transport investment. American Economic Review 59, 251–60. URL: https://EconPapers.repec.org/RePEc:aea:aecrev:v:59:y:1969:i:2:p:251-60.

Vlaanderen, 2025. Sociaal tarief voor energie (elektriciteit, aardgas, warmte). https://www.vlaanderen.be/sociaal-tarief-voor-energie-elektriciteit-aardgas-warmte. [Accessed 04-06-2026].

Williamson, O.E., 1966. Peak-load pricing and optimal capacity under indivisibility constraints. American Economic Review 56, 810–827.

Supplemental Appendix

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

A Supplementary Derivations: Conceptual Framework **2**

A.1 Baseline scenario . . . 2

A.2 Coincident peak demand charges . . . 4

B Supplementary Descriptives **6**

B.1 Real-time prices . . . 6

B.2 Sample composition - Individual peak demand charges . . . 9

B.3 Sample composition - Individual peak demand charges - Electric Vehicles . . . 12

B.4 Sample composition - Real-Time Pricing . . . 13

B.5 Consumer survey data . . . 14

C Supplementary Results: Monthly peak **17**

C.1 Electrification: Specification Tests . . . 17

C.2 Individual peak demand charges: Specification Tests . . . 18

C.3 Individual peak demand charges: Robustness Checks . . . 19

C.4 Individual peak demand charges: Heterogeneity . . . 22

C.5 Real-time pricing: Specification Tests . . . 24

C.6 Real-time pricing: Heterogeneity . . . 25

D Supplementary Results: Grid-Level Effects **27**

D.1 Electric vehicles . . . 27

D.2 Real-time pricing . . . 29

D.3 Heat pumps . . . 31

D.4 Battery energy storage . . . 32

E Supplementary Results: Load Profile **33**

E.1 Real-time pricing . . . 33

E.2 Electric vehicles . . . 34

E.3 Heat pumps . . . 35

E.4 Battery energy storage . . . 37

E.5 Load shifting and peaks . . . 39

A Supplementary Derivations: Conceptual Framework

A.1 Baseline scenario

Setup Assume demand Q_D and supply Q_S for electricity are given by:

$$\begin{aligned} Q_d &= D(P) + e, & D'(P) < 0, \\ Q_s &= S(P) + q_{renewable}, & S'(P) > 0, \end{aligned}$$

where demand is a decreasing function of the market price P and can shift with the level of residential electrification, e, modelled as an additive demand shock. Electricity supply consists of renewable generation, which has zero marginal cost $q_{renewable}$ and fossil generation, which has a positive marginal cost, and increases with P. Market equilibrium is defined by $Q^* = Q_d = Q_s$ or equivalently,

$$D(P^*) + e = S(P^*) + q_{renewable}. \tag{A.1}$$

Comparative statics We can rewrite the equilibrium condition implicitly by defining $F(P^*, e, q_{renewable}) \equiv D(P^*) + e - S(P^*) - q_{renewable} = 0$. We examine the comparative statics for an outward shift of the demand curve through electrification and an outward shift of the supply curve through increased generation of renewables. Totally differentiating $F(P^*, e, q_{renewable}) = 0$ yields

$$\frac{\partial F}{\partial P} dP^* + \frac{\partial F}{\partial e} de + \frac{\partial F}{\partial q_{renewable}} dq_{renewable} = 0,$$

which implies

$$\left[D'(P^*) - S'(P^*)\right] dP^* + de - dq_{renewable} = 0.$$

Solving for the effect of the supply and the demand shock on the equilibrium price using the implicit function theorem gives

$$\frac{dP^*}{dq_{renewable}} = -\frac{\partial F/\partial q_{renewable}}{\partial F/\partial P^*} = \frac{-(-1)}{D'(P^*) - S'(P^*)} = \frac{1}{D'(P^*) - S'(P^*)}, \tag{A.2}$$

$$\frac{dP^*}{de} = -\frac{\partial F/\partial e}{\partial F/\partial P^*} = \frac{-1}{D'(P^*) - S'(P^*)}. \tag{A.3}$$

From the supply function it follows that the equilibrium quantity changes according to

$$\frac{dQ^*}{dq_{renewable}} = S'(P^*)\frac{dP^*}{dq_{renewable}} + 1 = \frac{S'(P^*)}{D'(P^*) - S'(P^*)} + 1 = \frac{D'(P^*)}{D'(P^*) - S'(P^*)}, \tag{A.4}$$

$$\frac{dQ^*}{de} = S'(P^*)\frac{dP^*}{de} = -\frac{S'(P^*)}{D'(P^*) - S'(P^*)}. \tag{A.5}$$

Since $D'(P^*) < 0$ and $S'(P^*) > 0$, the denominator is negative, implying the signs of the shocks:

- $dP^*/dq_{renewable} < 0$ and $dQ^*/dq_{renewable} > 0$,
- $dP^*/de > 0$ and $dQ^*/de > 0$.

Link with elasticities Define the (absolute value of the) price elasticity of demand and the price elasticity of supply as

$$|\varepsilon_d| = -D'(P^*)\frac{P^*}{Q^*} \Leftrightarrow \qquad D'(P^*) = -|\varepsilon_d|\frac{Q^*}{P^*},$$
$$S'(P^*) = \varepsilon_s\frac{Q^*}{P^*} \Leftrightarrow \qquad S'(P^*) = \varepsilon_s\frac{Q^*}{P^*}.$$

Substituting gives

$$\frac{dP^*}{dq_{renewable}} = -\frac{P^*}{Q^*}\frac{1}{|\varepsilon_d| + \varepsilon_s}, \tag{A.6}$$
$$\frac{dQ^*}{dq_{renewable}} = \frac{|\varepsilon_d|}{|\varepsilon_d| + \varepsilon_s}, \tag{A.7}$$
$$\frac{dP^*}{de} = \frac{P^*}{Q^*}\frac{1}{|\varepsilon_d| + \varepsilon_s}, \tag{A.8}$$
$$\frac{dQ^*}{de} = \frac{\varepsilon_s}{|\varepsilon_d| + \varepsilon_s}. \tag{A.9}$$

Linear supply and demand Assume now linear supply and demand. The general demand and supply functions then reduce to

$$Q_d = D(P) + e = e - \beta P,$$
$$Q_s = S(P) + q_{renewable} = q_{renewable} + b_{fossil}P.$$

Then $D'(P^*) = -\beta$ and $S'(P^*) = b_{fossil}$, and the comparative static conditions reduce to

$$\frac{dP^*}{dq_{renewable}} = \frac{1}{-\beta - b_{fossil}} = -\frac{1}{\beta + b_{fossil}},$$
$$\frac{dQ^*}{dq_{renewable}} = \frac{-\beta}{-\beta - b_{fossil}} = \frac{\beta}{\beta + b_{fossil}},$$
$$\frac{dP^*}{de} = \frac{-1}{-\beta - b_{fossil}} = \frac{1}{\beta + b_{fossil}},$$
$$\frac{dQ^*}{de} = \frac{b_{fossil}}{\beta + b_{fossil}}.$$

A.2 Coincident peak demand charges

Setup Assume demand Q_D and supply Q_S for electricity are given by:

$$\begin{aligned} Q_d &= D(P, cQ) + e, & D_P < 0, \quad D_{cQ} < 0, \\ Q_s &= S(P) + q_{renewable}, & S'(P) > 0, \end{aligned}$$

where demand is a decreasing function of the market price P and of the total consumption Q (due to a coincident peak demand charge) with $c \geq 0$, and e is an additive demand shock. Electricity supply consists of renewable generation, which has zero marginal cost $q_{renewable}$, and fossil generation, which has positive marginal cost and increases with P. For the demand function, we now define explicitly two partial derivatives: $D_P \equiv \partial D/\partial P < 0$ and $D_{cQ} \equiv \partial D/\partial(cQ) < 0$, with the latter representing the demand response to the coincident peak demand charge. Market equilibrium is defined by $Q^* = Q_d = Q_s$ or equivalently,

$$D(P^*, cQ^*) + e = S(P^*) + q_{renewable}. \tag{A.10}$$

Comparative statics In analogy with before, we can rewrite the equilibrium condition implicitly by defining:

$$G(P^*, q_{renewable}, e) \equiv D(P^*, cQ^*) + e - S(P^*) - q_{renewable} = 0, \quad Q^* = S(P^*) + q_{renewable}.$$

After substitution of the equilibrium quantity from the supply side into the demand function, the implicit equilibrium condition becomes:

$$G(P^*, q_{renewable}, e) \equiv D(P^*, c \cdot (S(P^*) + q_{renewable})) + e - S(P^*) - q_{renewable} = 0.$$

This is analogous to before, but now additionally reflecting the feedback effect from equilibrium quantity into demand. Totally differentiating $G(P^*, q_{renewable}, e) = 0$ gives

$$\frac{\partial G}{\partial P^*} dP^* + \frac{\partial G}{\partial q_{renewable}} dq_{renewable} + \frac{\partial G}{\partial e} de = 0.$$

Before applying the implicit function theorem, we first explicitly compute the partial derivatives. These are non-trivial, because they depend on a chain rule, reflecting exactly the feedback effect from equilibrium quantity on demand.

$$\begin{aligned}
\frac{\partial G}{\partial P^*} &= D_P + \underbrace{D_{cQ}}_{\text{Outer derivative}} \cdot \underbrace{c \cdot S'(P^*)}_{\text{Inner derivative}} - S'(P^*), \\
\frac{\partial G}{\partial q_{renewable}} &= \underbrace{D_{cQ}}_{\text{Outer derivative}} \cdot \underbrace{c}_{\text{Inner derivative}} - 1, \\
\frac{\partial G}{\partial e} &= 1,
\end{aligned}$$

Solving for the effect of the supply and the demand shock on the equilibrium price using the implicit function theorem gives

$$\frac{dP^*}{dq_{renewable}} = -\frac{\partial G/\partial q_{renewable}}{\partial G/\partial P^*} = \frac{1 - cD_Q}{D_P + cD_Q S' - S'}, \tag{A.11}$$

$$\frac{dP^*}{de} = -\frac{\partial G/\partial e}{\partial G/\partial P^*} = -\frac{1}{D_P + cD_Q S' - S'}. \tag{A.12}$$

From the supply function it follows that the equilibrium quantity changes according to

$$\frac{dQ^*}{dq_{renewable}} = S'\frac{dP^*}{dq_{renewable}} + 1 = \frac{S'(1 - c \cdot D_{cQ})}{D_P + c \cdot D_{cQ} \cdot S' - S'} + 1 = \frac{D_P}{D_P + c \cdot D_{cQ} \cdot S' - S'}, \tag{A.13}$$

$$\frac{dQ^*}{de} = S'\frac{dP^*}{de} = -\frac{S'}{D_P + c \cdot D_{cQ} \cdot S' - S'}. \tag{A.14}$$

Linear supply and demand example Assume linear supply and demand with a coincident peak demand charge. Demand and supply equations reduce to:

$$\begin{aligned}
D(P, cQ) + e &= e - \beta P - \gamma c Q, \\
S(P) &= q_{renewable} + b_{fossil} P.
\end{aligned}$$

Then $D_P = -\beta$, $D_{cQ} = -\gamma$, $S' = b_{fossil}$, and the comparative statics reduce to:

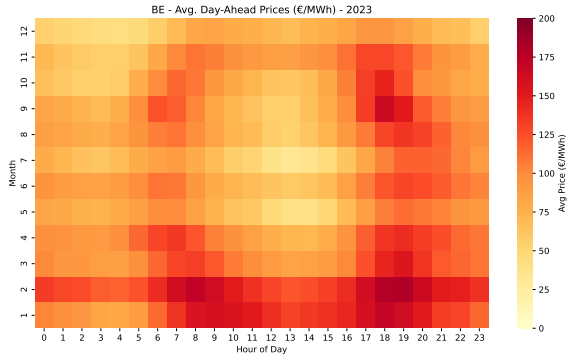
$$\begin{aligned}
\frac{dP^*}{dq_{renewable}} &= -\frac{1 + \gamma c}{\beta + b_{fossil} + \gamma c b_{fossil}}, \\
\frac{dQ^*}{dq_{renewable}} &= \frac{\beta}{\beta + b_{fossil} + \gamma c b_{fossil}}, \\
\frac{dP^*}{de} &= \frac{1}{\beta + b_{fossil} + \gamma c b_{fossil}}, \\
\frac{dQ^*}{de} &= \frac{b_{fossil}}{\beta + b_{fossil} + \gamma c b_{fossil}}.
\end{aligned}$$

B Supplementary Descriptives

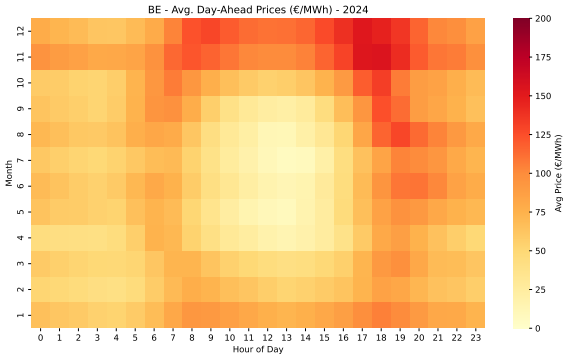
B.1 Real-time prices

Figure B.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.

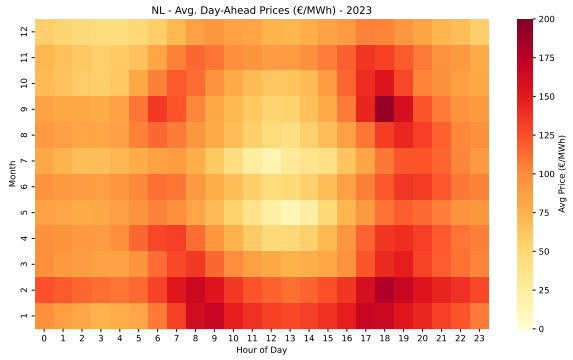
Figure B.2 shows correlation matrices for pairwise correlation between day-ahead electricity prices (€/MWh) for four European bidding zones. Correlations are high, ranging from between 0.7 to 0.97. Finally, Figure B.3 plots correlation matrices between day-ahead electricity prices, total load and total renewables generation. Prices correlate negatively with renewables generation, but positively with total load.



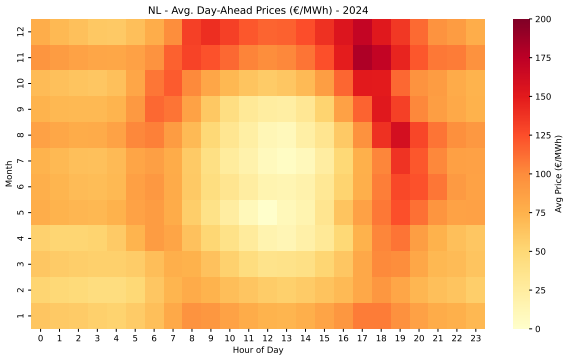
(a) Bidding Zone Belgium, 2023



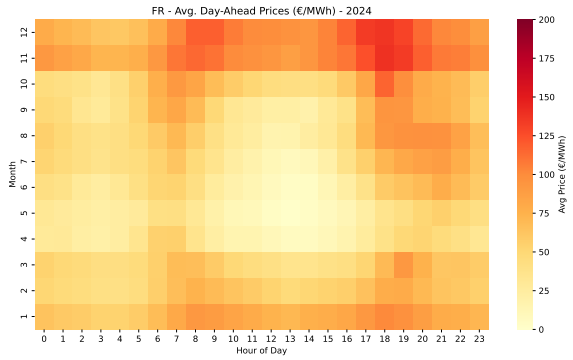
(b) Bidding Zone Belgium, 2024



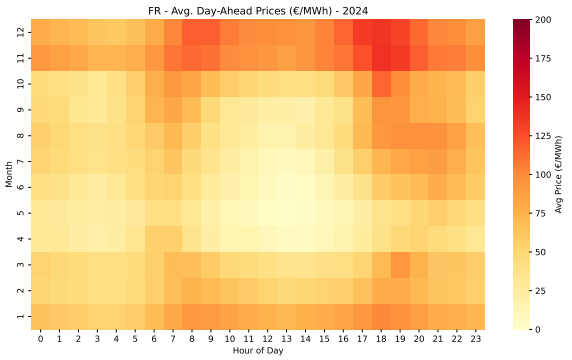
(c) Bidding Zone Netherlands, 2023



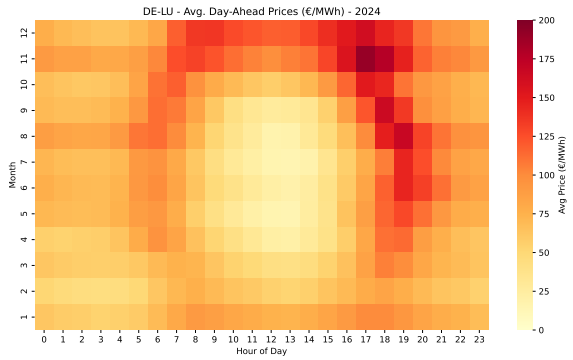
(d) Bidding Zone Netherlands, 2024



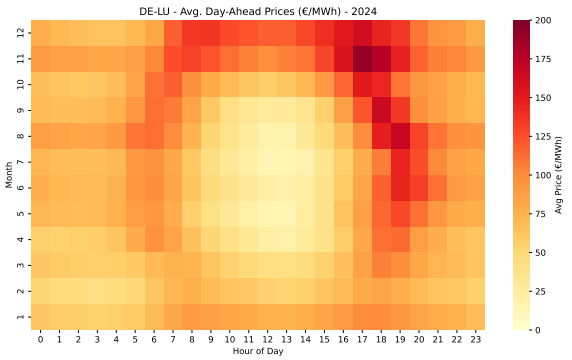
(e) Bidding Zone France, 2023



(f) Bidding Zone France, 2024

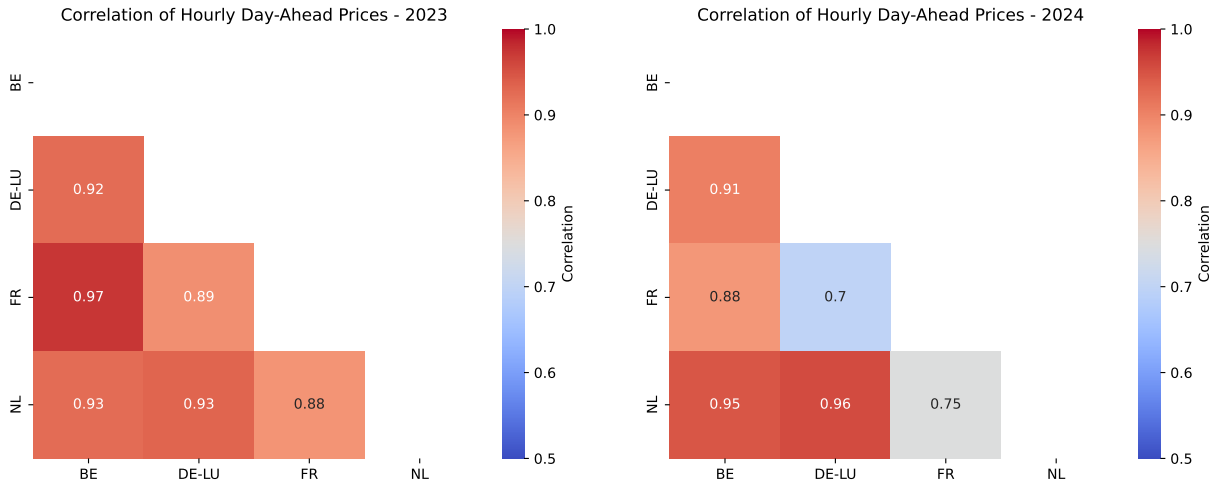


(g) Bidding Zone Germany-Luxembourg, 2023



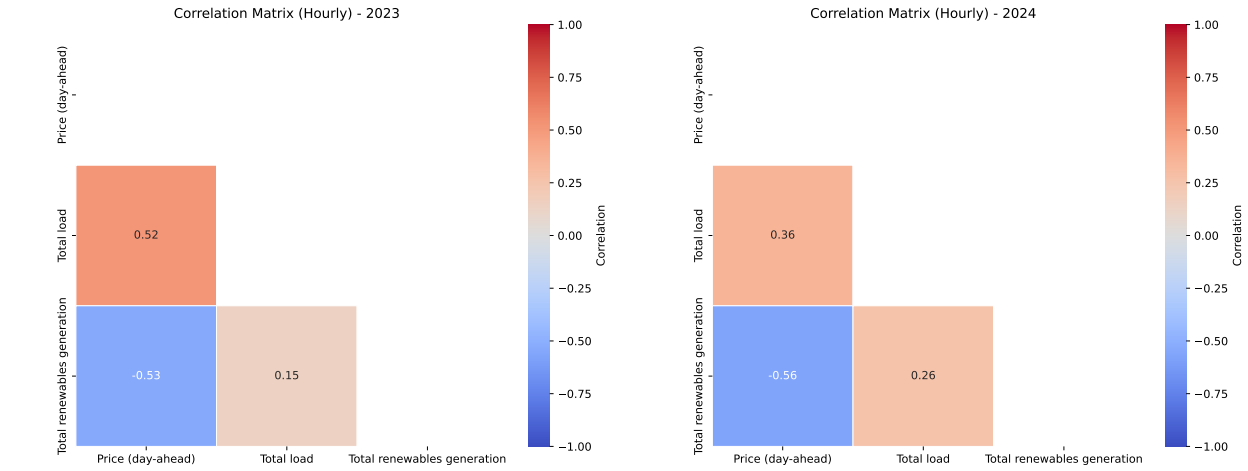
(h) Bidding Zone Germany-Luxembourg, 2024

Figure B.1. Heatmaps for hour-by-month average day-ahead electricity prices (€/MWh). Source: ENTSO-E Transparency Platform



(a) 2023 (b) 2024

Figure B.2. Correlation matrix for pairwise correlation between day-ahead electricity prices (€/MWh) for four European bidding zones (BE, DE-LU, FR, NL). Source: ENTSO-E Transparency Platform



(a) 2023 (b) 2024

Figure B.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). Source: ENTSO-E Transparency Platform

B.2 Sample composition - Individual peak demand charges

Table B.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 B.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 B.1: Descriptive statistics: smart meter data

Treated	Mean	Std	25%	50%	75%
Monthly peak withdrawal [W]	4,152	1,821	2,990	3,886	4,963
Monthly peak withdrawal (2022) [W]	4,148	1,752	3,040	3,924	4,952
Monthly peak withdrawal (2023) [W]	4,051	1,753	2,926	3,801	4,854
Monthly peak withdrawal (2024) [W]	4,257	1,944	3,005	3,934	5,087
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]	4,016	1,626	2,926	3,847	4,865
Monthly peak withdrawal (2022) [W]	4,020	1,557	2,984	3,884	4,860
Monthly peak withdrawal (2023) [W]	3,968	1,590	2,892	3,798	4,804
Monthly peak withdrawal (2024) [W]	4,059	1,726	2,905	3,856	4,931
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 1,514,772 observations for 42,077 households, 40,630 treated households and 1,717 control households.

Table B.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	26,613	25,774	839	63.2%	63.9%	48.9%
	HP	615	601	14	1.4%	1.5%	0.8%
	Battery	3,845	3,722	123	9.1%	9.2%	7.1%
	Total	42,077	40,360	1,717			
1-1-2023							
	EV	2,023	1,957	66	4.8%	4.8%	3.8%
	PV	29,199	28,287	912	67.2%	72.3%	53.1%
	HP	7,257	6,990	267	17.2%	17.3%	15.5%
	Battery	6,859	6,636	223	16.3%	16.4%	12.9%
	Total	42,077	40,360	1,717			
All	**Total**	42,077	40,360	1,717			

Note: Characteristics of the households studied. This table reports household-level statistics. There are 42,077 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.

B.3 Sample composition - Individual peak demand charges - Electric Vehicles

Table B.3: Descriptive statistics for electric vehicle owning households

	Mean	Std	25%	50%	75%
Monthly peak withdrawal [W]	6,090	2,485	4,384	5,740	7,410
Monthly peak withdrawal (2022) [W]	6,153	2,655	4,320	5,704	7,536
Monthly peak withdrawal (2023) [W]	5,980	2,368	4,361	5,678	7,277
Monthly peak withdrawal (2024) [W]	6,137	2,419	4,476	5,847	7,448
Grid withdrawals per month [kWh]	425	267	226	379	577
Grid withdrawals per month (2022) [kWh]	398	260	208	350	536
Grid withdrawals per month (2023) [kWh]	425	262	228	382	580
Grid withdrawals per month (2024) [kWh]	451	275	243	405	614
Grid injection per month [kWh]	210	225	20	137	337
Grid injection per month (2022) [kWh]	238	244	22	169	389
Grid injection per month (2023) [kWh]	206	225	18	132	329
Grid injection per month (2024) [kWh]	186	200	19	117	298
Solar PV (01-01-2023)	0.84	0.37	1.00	1.00	1.00
Battery storage (01-01-2023)	0.21	0.41	0.00	0.00	0.00
Electric vehicle (01-01-2023)	1.00	0.00	1.00	1.00	1.00
Heat pump (01-01-2023)	0.53	0.50	0.00	1.00	1.00
Average solar capacity (2023) [kVA]	4.96	1.85	3.68	5.00	5.60
Average battery size (2023) [kWh]	9.88	3.45	8.80	10.00	10.60
Average battery power (2023) [kW]	4.98	1.93	3.00	5.00	5.00

Note: Descriptive statistics for the smart meter data and sample composition for the households owning an electric vehicle before January 1st, 2023, prior to the introduction of peak demand charges. This table reports household-month statistics.

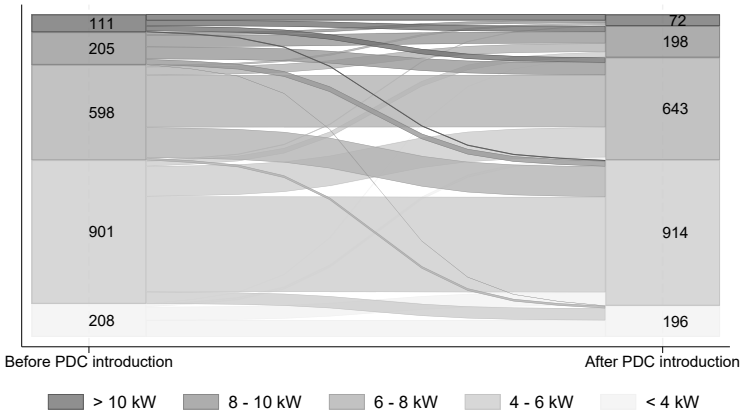


Figure B.4. Sankey plot for electric vehicle-owning households. This figure presents a Sankey diagram for all households owning an electric vehicle before January 1st, 2023, prior to the introduction of peak demand charges. Monthly peaks are binned into five consecutive categories: [> 2kW], [4kW, 6kW], [6kW, 8kW], [8kW, 10kW], [> 10kW]. Following the implementation of the peak demand charges, electric vehicle-owning households tend to shift toward bins with lower peak electricity demand.

B.4 Sample composition - Real-Time Pricing

Table B.4 summarizes the characteristics of the 16,197 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. We also present information on the adoption of low-carbon technologies, reflecting the status as of January 1, 2024. In addition, in Figure B.5 we show the distribution of real-time pricing start months in the sample.

Table B.4: Descriptive statistics: smart meter data and sample composition for real-time pricing households

	Mean	Std	25%	50%	75%
Monthly peak withdrawal [W]	4,259	2,152	2,880	3,888	5,168
Monthly peak withdrawal (2023) [W]	4,212	1,929	3,004	3,916	5,020
Monthly peak withdrawal (2024) [W]	4,277	2,232	2,828	3,872	5,236
Grid withdrawals month [kWh]	266	221	115	207	352
Grid withdrawals month (2023) [kWh]	263	201	133	216	342
Grid withdrawals month (2024) [kWh]	267	228	110	203	356
Grid injection month [kWh]	135	203	0	22	215
Grid injection month (2023) [kWh]	124	194	0	8	197
Grid injection month (2024) [kWh]	139	207	0	27	222
Solar 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
Electric vehicle (01-01-2024)	0.08	0.27	0.00	0.00	0.00
Heat pump (01-01-2024)	0.10	0.30	0.00	0.00	0.00
Average solar capacity (2024) [kVA]	4.94	2.05	3.68	5.00	5.00
Average battery size (2024) [kWh]	9.23	3.30	7.00	10.00	10.00
Average battery power (2024) [kW]	4.98	1.82	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 16,197 households on a real-time pricing contract in 2023 or 2024, for which there are 263,398 observations. For this group, not the full three year period spanning 2022-2024 is available.

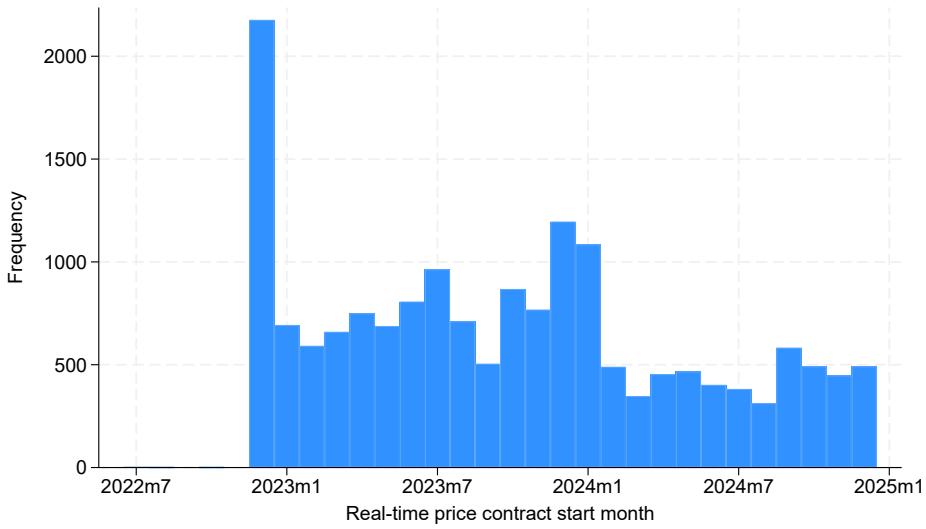


Figure B.5. Distribution of real-time pricing start months for the 16,307 households included in the analysis for real-time pricing.

B.5 Consumer survey data

This Appendix provides survey data adapted from survey questions by the Vlaamse Nutsregulator (2024). Each year, the Vlaamse Nutsregulator surveys a representative sample of 1000 households about their residential electricity consumption. Tables B.5, B.6 and B.7 present results for survey questions relating to familiarity with peak demand charges, the ability to correctly define how a peak demand charges works, and the estimated bill impact of peak demand charges.

In a subsequent study (Vlaamse Nutsregulator, 2025), the share of respondents reporting familiarity with peak demand charges has declined slightly, whereas the share providing a correct definition has remained stable over time. When subsequently asked how they reduce their monthly peak demand, respondents most frequently cite spreading the use of household appliances, followed by reducing overall consumption, aligning usage with solar generation, employing "smart" technologies, lowering electric vehicle charging speeds, and using battery energy storage.

Table B.5: Familiarity with peak demand charges

		Do you know the "peak demand charge"?		
		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 Vlaamse Nutsregulator (2024). Differences between categories are statistically significant, Pearson $\chi^2 = 40.35$, p-value = 0.00.

Table B.6: Correct definition of peak demand charges

		Give correct definition of "peak demand charge"		
		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 Vlaamse Nutsregulator (2024). Differences between categories are statistically significant, Pearson $\chi^2 = 13.07$, p-value = 0.00.

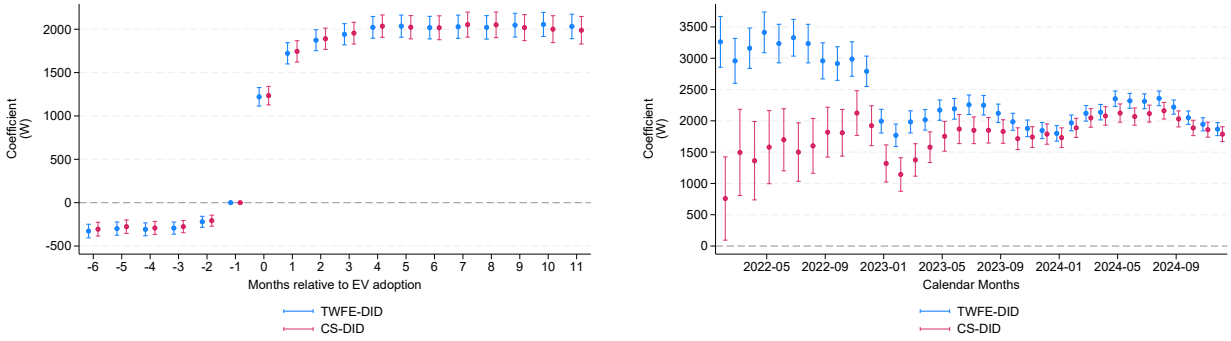
Table B.7: Financial impact of peak demand charges

		What impact has the "peak demand charge" had on overall bill?					
		Remarkable decrease	Slight decrease	No change	Slight increase	Remarkable increase	Total
	Yes	6	15	43	17	19	100
		(6.00%)	(15.00%)	(43.00%)	(17.00%)	(19.00%)	(100%)
Is the price you pay	No	42	53	258	188	95	636
for electricity the social		(6.60%)	(8.33%)	(40.57%)	(29.56%)	(14.94%)	(100%)
maximum price, also referred	Do not know	1	3	15	8	4	31
to as the social tariff?		(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 Vlaamse Nutsregulator (2024). Differences between categories are not statistically significant, Pearson $\chi^2 = 11.25$, p-value = 0.19.

C Supplementary Results: Monthly peak

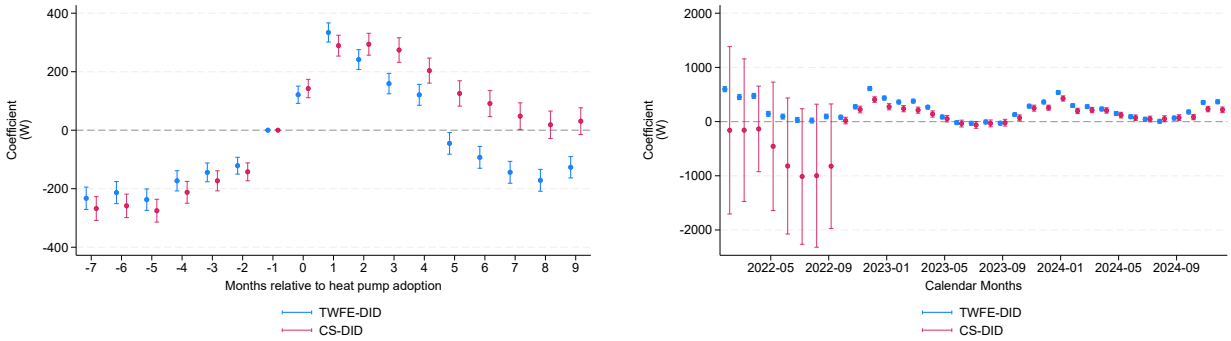
C.1 Electrification: Specification Tests



(a) Event time

(b) Calendar time

Figure C.1. Electric vehicles: estimates of the dynamic event-study specification in event time and calendar time for electrification through electric vehicle adoption using data for 2022 - 2024. Each dot represents the point estimate of the monthly peak increase (in W) in event-time. Two different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects including control variables. Second, the doubly-robust CS-DID estimator Callaway and Sant'Anna (2021). Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.



(a) Event time

(b) Calendar time

Figure C.2. Heat pumps: estimates of the dynamic event-study specification in event time and calendar time for electrification through heat pump adoption using data for 2022 - 2024. Each dot represents the point estimate of the monthly peak increase (in W) in event-time. Two different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects including control variables. Second, the doubly-robust CS-DID estimator Callaway and Sant'Anna (2021). Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

C.2 Individual peak demand charges: Specification Tests

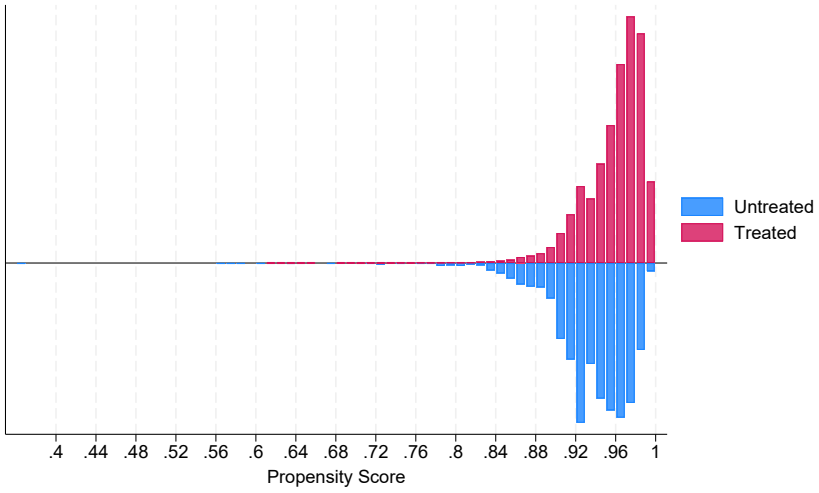


Figure C.3. Common support graph. This figure plots the distribution of estimated propensity scores for the Doubly Robust DiD model (Sant'Anna and Zhao, 2020) estimated for the full sample of 42,077 households.

Table C.1: Balancing Table

Variable	Matched	Treated	Control	Bias (%)	Bias reduction (%)	t	p
Solar capacity (kVA)	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	19.76	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).

C.3 Individual peak demand charges: Robustness Checks

Table C.2: Effect of peak demand charges on households' monthly peaks (W), excluding all households that adopt new low-carbon technologies

	(1) TWFE-DID	(2) IPW-DID	(3) DR-DID
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat PDC}_i = 1\}$	-10.03	-68.26***	-83.20**
	(-0.83)	(-2.81)	(-2.99)
Observations	734,688	734,688	734,688
Households	20,408	20,408	20,408

Note: This table estimates the effects of peak demand charges on households' monthly peaks (in watts) over the period January 2022 - December 2024 in a difference-in-differences framework, exclusing all households that adopt any new low-carbon technology throughout. The introduction of individual peak demand charges 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 (kVA), 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 stabilized weights, weighting based on grid withdrawals (kWh), solar capacity (kVA), 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

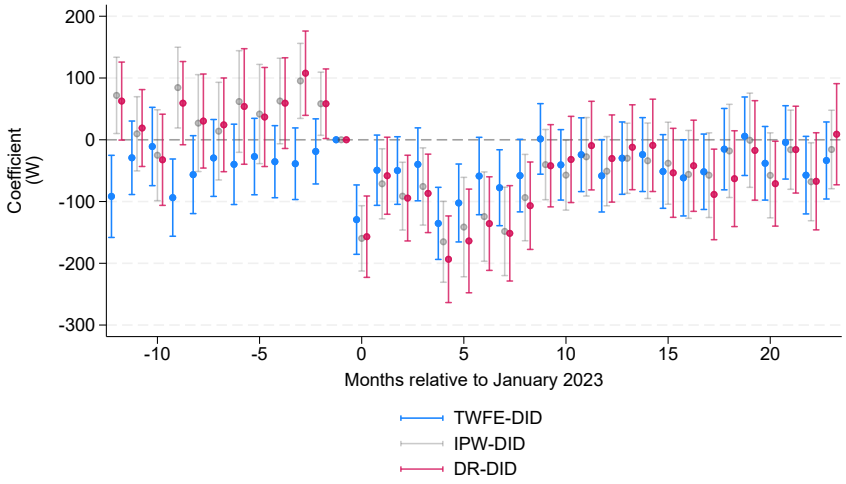


Figure C.4. Estimates of the dynamic specification for individual peak demand charges in the sample of households that does not adopt any new low carbon technology throughout the period 2022-2024. Each dot represents the point estimate of the monthly peak reduction (in W) for a given month-of-sample 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 stabilized weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. All coefficients are estimated relative to December 2022, the month immediately preceding treatment. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

Table C.3: Effect of peak demand charges on households' monthly peaks (W), without explicit control variables for low-carbon technology adoption

	(1) TWFE-DID	(2) IPW-DID	(3) DR-DID
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat PDC}_i = 1\}$	-32.91***	-85.96***	-106.81***
	(-2.61)	(-3.43)	(-4.39)
Observations	2,012,724	2,012,724	2,012,724
Households	55,909	55,909	55,909

Note: This table estimates the effects of peak demand charges on households' monthly peaks (in watts) over the period January 2022 - December 2024 in a difference-in-differences framework, without explicit control variables for low-carbon technology adoption. The introduction of individual peak demand charges 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 electric vehicle or heat pump 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 (kVA), 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 stabilized weights, weighting based on grid withdrawals (kWh), solar capacity (kVA), 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

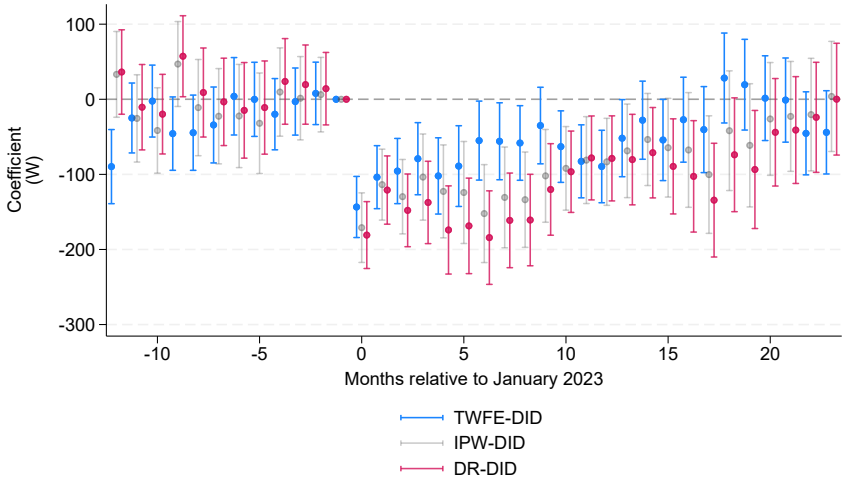


Figure C.5. Estimates of the dynamic specification for peak demand charges in the full sample, without controls for new low carbon technologies. Each dot represents the point estimate of the monthly peak reduction (in W) for a given month-of-sample t. Three different estimators are used. First, the TWFE-DID estimator with individual and month-of-sample fixed effects, excluding control variables for low-carbon technology adoption. Second, the IPW-DID estimator with stabilized weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. All coefficients are estimated relative to December 2022, the month immediately preceding treatment. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

Table C.4: Effect of peak demand charges on households' monthly grid withdrawals (kWh)

	(1) TWFE-DID	(2) IPW-DID	(3) DR-DID
$\mathbb{1}\{\text{Post}_t = 1\} \times \mathbb{1}\{\text{Treat PDC}_i = 1\}$	3.27**	9.14***	6.63**
	(2.12)	(2.28)	(1.98)
Households	42,077	42,077	42,077

Note: This table estimates the effects of peak demand charges on households' monthly peaks (in watts) over the period January 2022 - December 2024 in a difference-in-differences framework, without explicit control variables for low-carbon technology adoption. The introduction of individual peak demand charges 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 electric vehicle or heat pump 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 (kVA), 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 stabilized weights, weighting based on grid withdrawals (kWh), solar capacity (kVA), 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

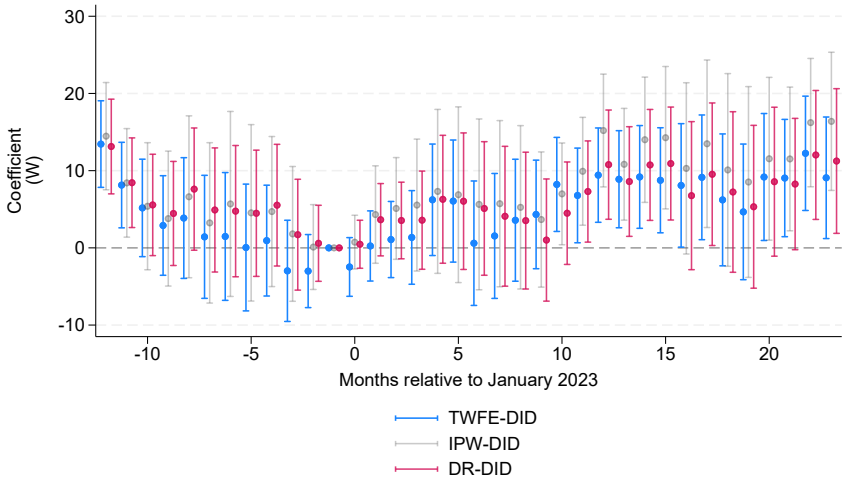


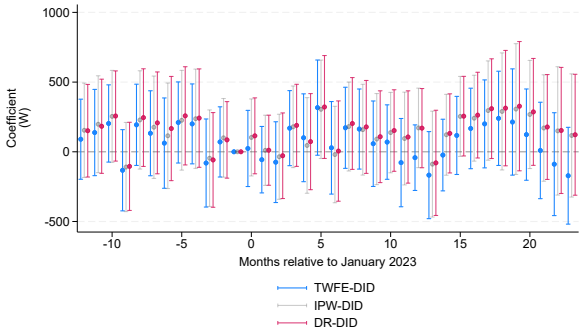
Figure C.6. Estimates of the dynamic specification for the effect of peak demand charges on households' monthly grid withdrawals (kWh) in the full sample. Each dot represents the point estimate of the grid withdrawals change (in kWh) for a given month-of-sample t. Three different estimators are used. 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 stabilized weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. All coefficients are estimated relative to December 2022, the month immediately preceding treatment. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

C.4 Individual peak demand charges: Heterogeneity

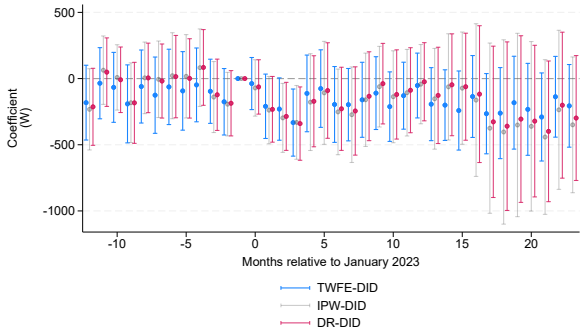
Table C.5: Effect of peak demand charge on monthly peak (W) for households with different low-carbon technologies.

	(1) Full sample	(2) Electric vehicle	(3) Heat pump (main)	(4) Heat pump (additional)	(5) Battery storage	(6) No low-carbon technology
TWFE-DID	-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**	-68.76**
	(-3.11)	(-2.05)	(1.10)	(-1.44)	(-2.09)	(-2.29)
DR-DID	-122.22***	-380.89**	161.01	-192.72	-168.33**	-69.30**
	(-3.99)	(-2.02)	(1.21)	(-1.35)	(-2.63)	(-2.31)
Observations	1,514,772	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

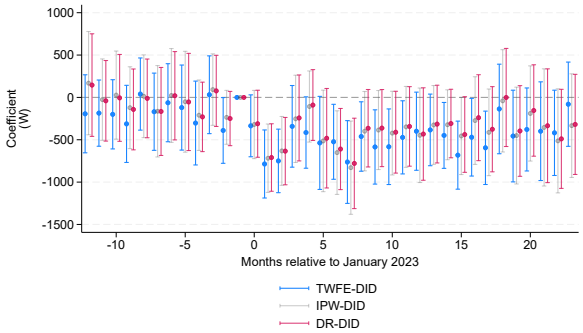
Note: This table estimates the effects of peak demand charges and real-time prices on households' monthly peaks (in watts) for households with different low-carbon technologies over the period January 2022 - December 2024 in a difference-in-differences framework. The introduction of the peak demand charge 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. Results are shown by low-carbon technology adoption group, with group membership being non-exclusive. Row (1) uses TWFE-DID with additional control variables. Control variables include grid withdrawals (kWh), solar capacity (kVA), solar injection (kWh) and battery storage size (kWh) and dummy variables for the adoption of electric vehicles and heat pumps. Household fixed effects and time fixed effects are included. In row (2), we apply the IPW-DID estimator with stabilized weights, weighting based on grid withdrawals (kWh), solar capacity (kVA), solar injection (kWh) and battery storage size (kWh). This specification does not explicitly weigh observations by heat pump and electric vehicle adoption cohort, because of smaller sample size in the heterogeneity analysis. Finally, row (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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



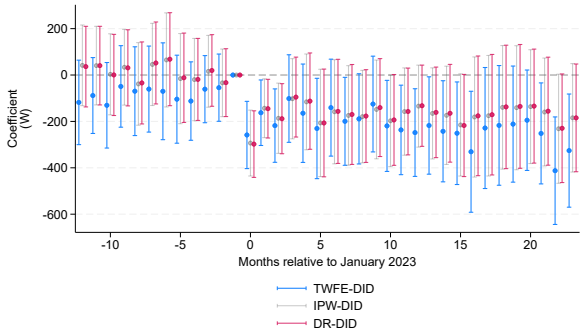
(a) Heat pump as main heating



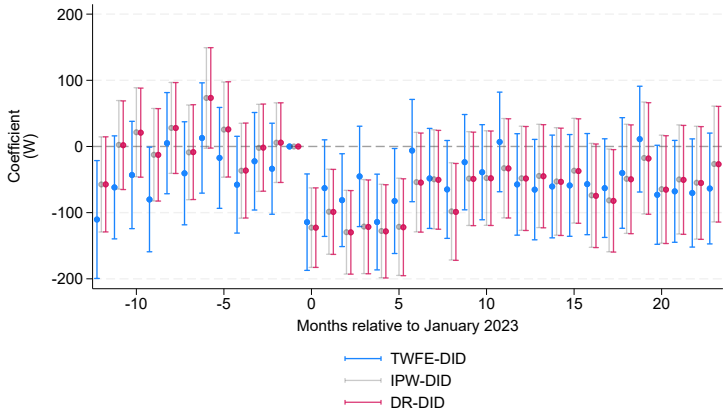
(b) Heat pump as additional heating



(c) Electric vehicle



(d) Battery energy storage

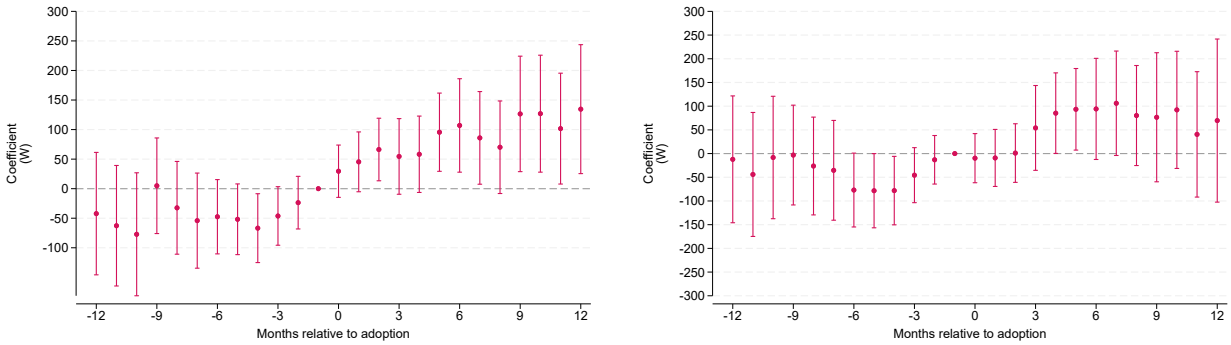


(e) No low-carbon technologies

Figure C.7. 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 as in Appendix C.5. Second, the IPW-DID estimator with stabilized weights. Third, the Sant'Anna and Zhao (2020) Doubly Robust DID estimator. All specifications are estimated using control variables as in Table C.5. All coefficients are estimated relative to December 2022, the month immediately preceding treatment. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

C.5 Real-time pricing: Specification Tests

In this Appendix we show pre-trends for the Callaway and Sant'Anna (2021) Doubly-Robust DiD estimator using alternative control groups, estimating the effect of real-time pricing on monthly peak electricity demand. While adoption of real-time prices is staggered over time, most adoption takes place throughout 2023 and 2024, as shown in Figure B.5. In Figure C.8 we alternatively use the not-yet treated plus never treated, or not-yet treated only as a control group.



(a) Never treated and not-yet treated

(b) Not-yet treated only

Figure C.8. Estimates of the dynamic specification for real-time prices in the full sample, showing coefficients in event-time (months relative to adoption) using alternative control group definitions. Each dot represents the point estimate of the monthly peak change (in W) for a given month relative to adoption. The Callaway and Sant'Anna (2021) Doubly Robust DID estimator is used to estimate the causal effect. Group $\times$ period treatment effects are then aggregated to event time. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

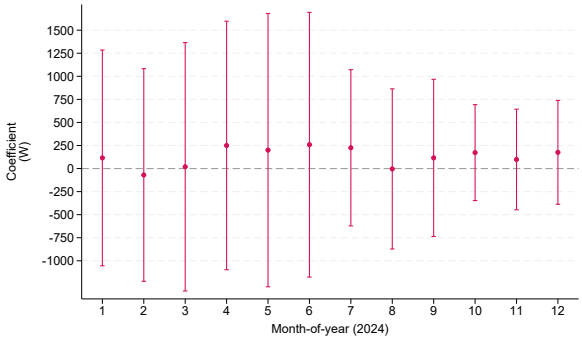
C.6 Real-time pricing: Heterogeneity

This Appendix provides heterogeneity analysis for the main results on real-time prices. In Table C.6 we present results for the conditional average treatment effect using the TWFE-DID and Callaway and Sant'Anna (2021) Doubly-Robust DiD estimators. Then, Figure C.9 provides dynamic results in calendar time for the year 2024, estimated using the Callaway and Sant'Anna (2021) Doubly-Robust DiD estimator.

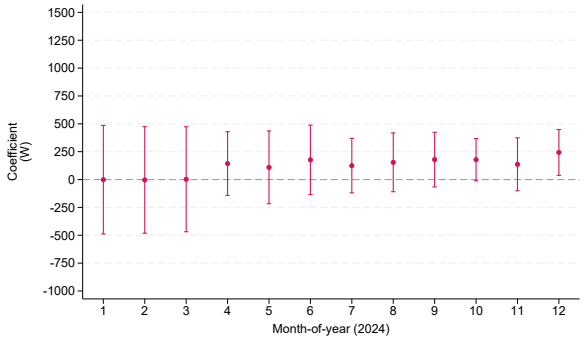
Table C.6: Effect of real-time pricing on monthly peak (W) for households with different low-carbon technologies.

	(1)	(2)	(3)	(4)	(5)
	Full sample	Electric vehicle	Heat pump	Battery storage	EV, BES or HP
TWFE-DID	56.09***	122.7	88.09	155.6***	169.9***
	(4.79)	(0.41)	(0.78)	(4.98)	(5.51)
CS-DID	76.66***	126.90	135.92	134.35*	132.41***
	(3.06)	(0.30)	(1.23)	(1.95)	(2.78)
Households	58,274	2,060	7,374	9,460	16,205

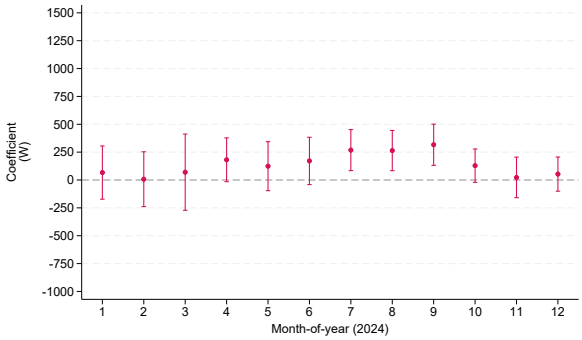
Note: This table estimates the effect of real-time pricing on monthly peak (in watts) over the period January 2023 - December 2024 for households with different low-carbon technologies. The enrollment into real-time pricing serves as the treatment variable. We use two specifications to estimate the treatment effect. First, we show results using the TWFE-DID estimator with additional control variables. Control variables include grid withdrawals (kWh), solar inverter capacity (kVA), solar injection (kWh), battery storage size (kWh) and dummy variables for adoption of low-carbon technologies. Household fixed effects and time fixed effects are included. Second, we use the Callaway and Sant'Anna (2021) Doubly Robust DID estimator with never treated as the control group. The unit of observation is household-month-of-sample. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



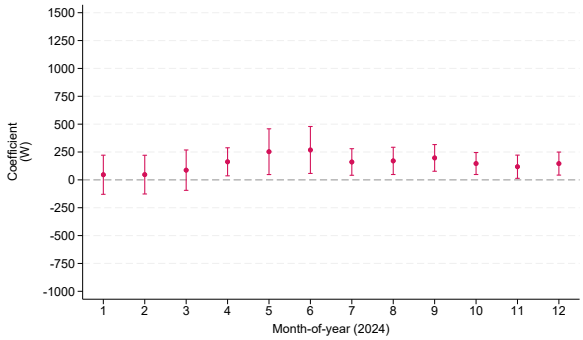
(a) Electric vehicle



(b) Heat pump



(c) Battery storage



(d) Electric vehicle, heat pump or battery storage

Figure C.9. Estimates of the dynamic specification for real-time prices in three subsamples. Each dot represents the point estimate of the monthly peak change (in W) for a given month-of-year in 2024. The Callaway and Sant'Anna (2021) Doubly Robust DID estimator is used to estimate the causal effects. Group $\times$ period treatment effects are then aggregated to calendar time. Standard errors are clustered at the household level and vertical bars show 95% confidence intervals.

D Supplementary Results: Grid-Level Effects

D.1 Electric vehicles

Table D.1: Synthetic distribution grid descriptive statistics by electric vehicle 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)
Half-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)
Half-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)
Half-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, using data from July 2022 - December 2022, i.e. before the introduction of peak demand charges. The columns 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 D.2: Synthetic distribution level descriptive statistics by electric vehicle 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)
Half-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)
Half-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)
Half-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, using data from July 2022 - December 2022, i.e. before the introduction of peak demand charges. The columns 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.

D.2 Real-time pricing

Table D.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	10.89	11.12	11.49	12.13	13.57
	(2.67)	(3.25)	(4.00)	(4.43)	(4.77)
Monthly	15.79	16.49	17.35	18.55	20.60
	(2.73)	(3.53)	(4.44)	(4.83)	(5.06)
Grid withdrawals (kWh)					
Daily	81.45	85.71	90.44	96.80	112.92
	(17.75)	(25.74)	(36.24)	(43.73)	(49.35)
Monthly	2478.31	2607.22	2755.37	2958.66	3460.88
	(432.46)	(651.27)	(952.09)	(1163.26)	(1341.55)
Coincidence factor					
Daily	0.54	0.53	0.53	0.54	0.54
	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
Monthly	0.41	0.41	0.41	0.41	0.42
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)

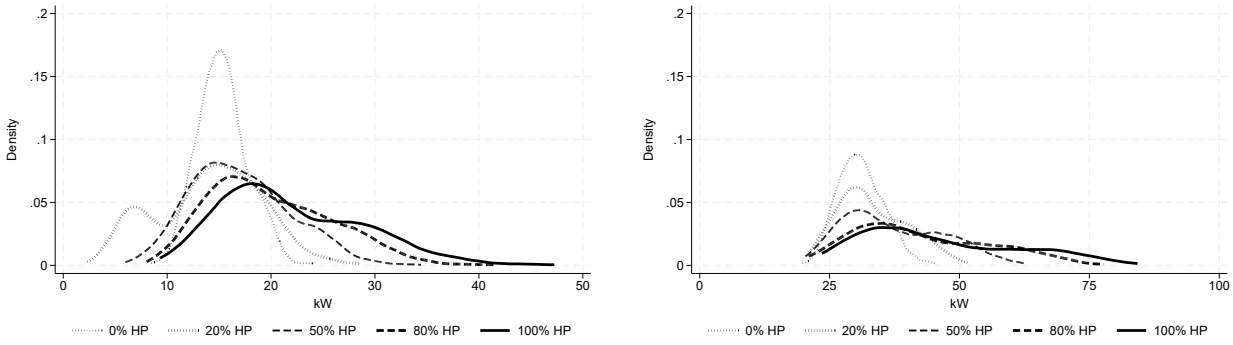
Note: Synthetic distribution grid descriptive statistics based on an aggregation of 10 households using data from January 2023 - December 2024. The columns indicate the percentage of households with an active real-time pricing contract. Other households in the synthetic distribution grid are never-treated, households that will not adopt real-time pricing, or not-yet treated, 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 D.4: Synthetic distribution level descriptive statistics by real-time pricing adoption level. 25 households

	Percentage of households with real-time pricing				
	0%	1-20%	20-50%	50-80%	80-100%
Peak (kW)					
Daily	24.17	24.58	24.35	26.36	27.94
	(4.55)	(5.63)	(7.36)	(8.44)	(9.04)
Monthly	31.96	33.07	33.96	36.77	38.95
	(4.21)	(5.76)	(7.65)	(8.70)	(9.17)
Grid withdrawals (kWh)					
Daily	203.08	211.52	219.68	245.88	271.35
	(29.51)	(46.84)	(73.56)	(95.29)	(110.73)
Monthly	6178.44	6434.64	6689.13	7486.10	8374.58
	(688.99)	(1212.59)	(1963.51)	(2605.63)	(3116.46)
Coincidence factor					
Daily	0.48	0.47	0.46	0.46	0.46
	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)
Monthly	0.33	0.33	0.32	0.32	0.33
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)

Note: Synthetic distribution grid descriptive statistics based on an aggregation of 25 households using data from January 2023 - December 2024. The columns indicate the percentage of households with an active real-time pricing contract. Other households in the synthetic distribution grid are never-treated, households that will not adopt real-time pricing, or not-yet treated, 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.

D.3 Heat pumps



(a) 10 households aggregated

(b) 25 households aggregated

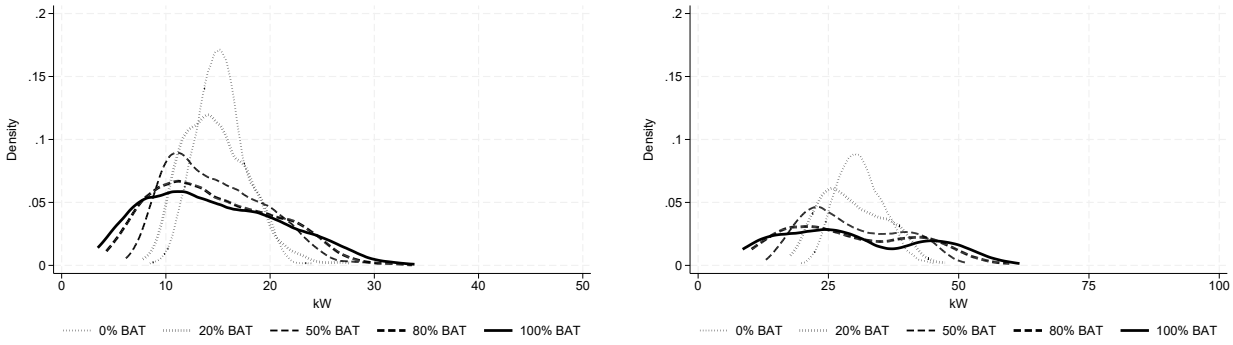
Figure D.1. Kernel density for the distribution of monthly peaks in the distribution grid for circuits with 10 or 25 households connected, and varying levels of heat pump adoption

Table D.5: Effect of peak demand charges on synthetic distribution grid peaks 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**	-0.120**	-0.161***	-0.176**	-0.242***
	(-3.37)	(-3.16)	(-3.36)	(-3.01)	(-3.49)
Monthly	-0.453***	-0.328**	-0.397*	-0.542**	-0.464
	(-4.58)	(-3.11)	(-2.44)	(-2.67)	(-1.90)
	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 individual peak demand charges 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 solar capacity installed (kW), aggregate battery energy storage size installed (kWh), temperature, and variables for the aggregate 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, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.4 Battery energy storage



(a) 10 households aggregated

(b) 25 households aggregated

Figure D.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

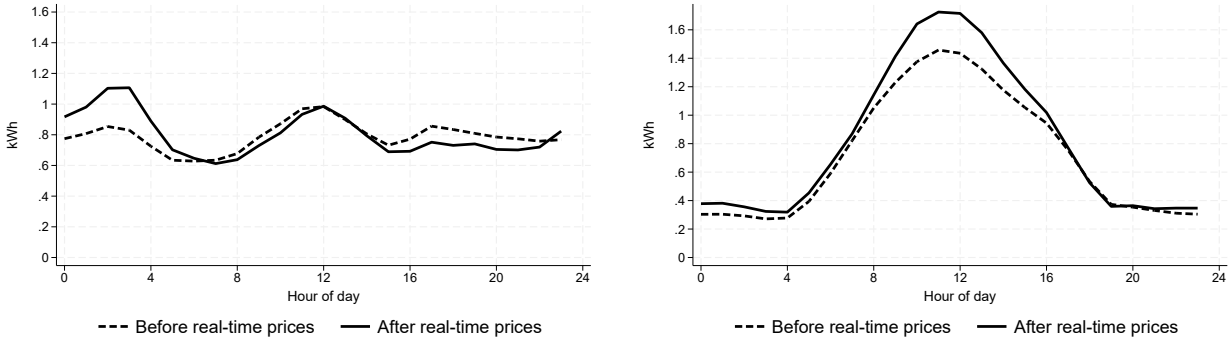
Table D.6: Effect of peak demand charges on synthetic distribution grid peaks by battery energy storage adoption level

	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 individual peak demand charges 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 solar capacity installed (kW), aggregate battery energy storage size installed (kWh), temperature, and variables for the aggregate 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, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E Supplementary Results: Load Profile

E.1 Real-time pricing



(a) Winter months (December - February)

(b) Summer months (June - August)

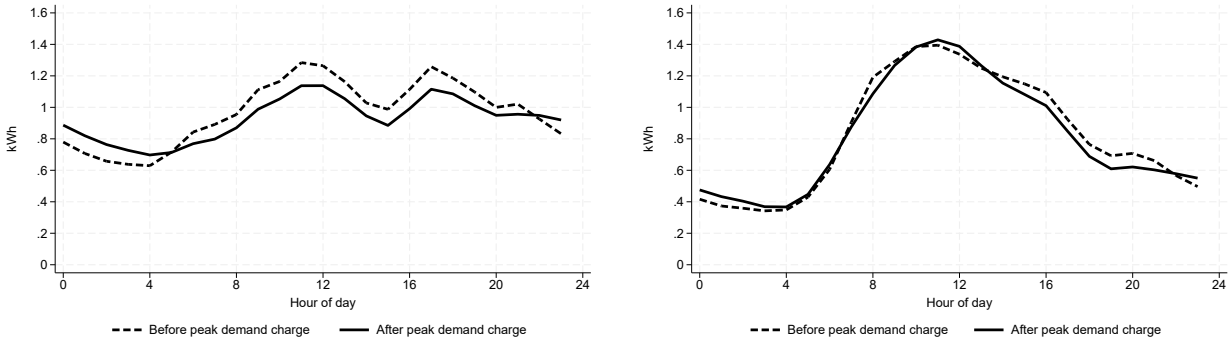
Figure E.1. Average kWh hourly electricity consumption for real-time pricing adopters before and after adoption

Table E.1: Load shifting total consumption in response to switching to real-time pricing

	(1) All	(2) Winter	(3) Summer
Total electricity consumption:			
All hours	0.273	-0.0459	0.244
	(0.82)	(-0.06)	(0.25)
Morning hours (06.00 - 12.00)	0.108	-0.529**	0.101
	(0.73)	(-2.40)	(0.25)
Afternoon hours (12.00 - 17.00)	-0.163	-0.391*	0.0391
	(-0.93)	(-1.93)	(0.06)
Peak hours (17.00 - 20.00)	-0.240***	-0.520***	-0.174
	(-3.93)	(-3.79)	(-0.92)
Night hours (22.00 - 06.00)	0.548***	1.444***	0.288
	(3.48)	(3.61)	(0.88)
Households	1,061	1,061	1,061

Note: The 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 daily variables for temperature, dummy variables for the presence of heat pumps interacted with month-of-year indicators, dummy variables for the presence electric vehicles two-way interacted with month-of-year and treatment indicators, and continuous solar capacity (kVA), solar production (kWh), storage capacity (kWh) variables, interacted with month-of-year indicators. Fixed effects include month-of-sample, household $\times$ month-of-year and household $\times$ day-of-week fixed effects. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E.2 Electric vehicles



(a) Winter months (December - February)

(b) Summer months (June - August)

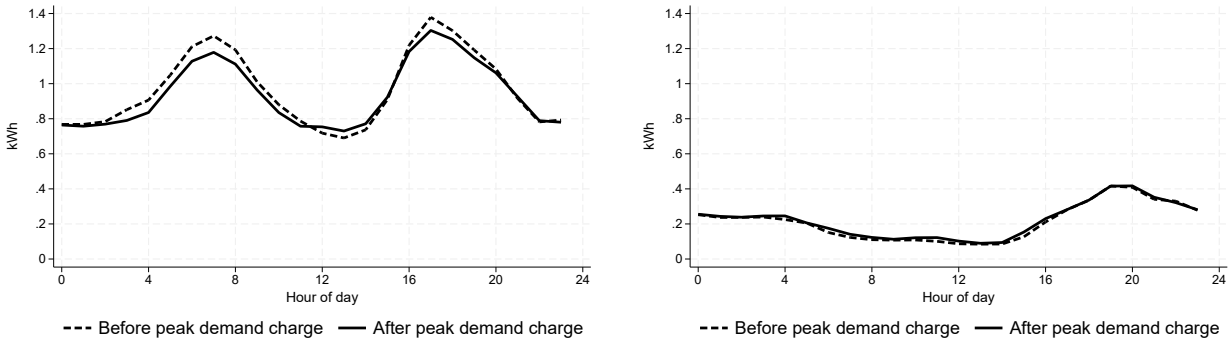
Figure E.2. Average kWh hourly electricity consumption for electric vehicle adopters in response to individual peak demand charges. *Note*: the figure is based on a balanced sample of 175 households that adopted an electric vehicle before January 1, 2022. Consequently, all households in the sample owned an electric vehicle throughout 2022 (the pre-reform period) and the post-reform period following the introduction of peak demand charges.

Table E.2: Load shifting for electric vehicle owners in response to individual peak demand charges

	(1) All	(2) Winter	(3) Summer
Total electricity consumption:			
All hours	0.474	-0.363	1.046*
	(1.16)	(-0.47)	(1.82)
Morning hours (06.00 - 12.00)	0.00353	-0.351*	0.280
	(0.02)	(-1.91)	(1.12)
Afternoon hours (12.00 - 17.00)	0.0968	-0.346	0.349
	(0.76)	(-1.34)	(1.61)
Peak hours (17.00 - 20.00)	-0.0536	-0.254*	0.0790
	(-0.58)	(-1.88)	(0.59)
Night hours (22.00 - 06.00)	0.461**	0.750*	0.266
	(2.13)	(1.68)	(1.21)
Households	2,021	2,021	2,021

Note: The electricity consumption (kWh) in a block of hours over the day over the period January 2022 - December 2024 is regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of the individual peak demand charges 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 daily variables for temperature, dummy variables for the presence of heat pumps interacted with month-of-year indicators, dummy variables for the presence electric vehicles two-way interacted with month-of-year and treatment indicators, and continuous solar capacity (kVA), solar production (kWh), storage capacity (kWh) variables, interacted with month-of-year indicators. Fixed effects include month-of-sample, household $\times$ month-of-year and household $\times$ day-of-week fixed effects. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E.3 Heat pumps



(a) Winter months (December - February)

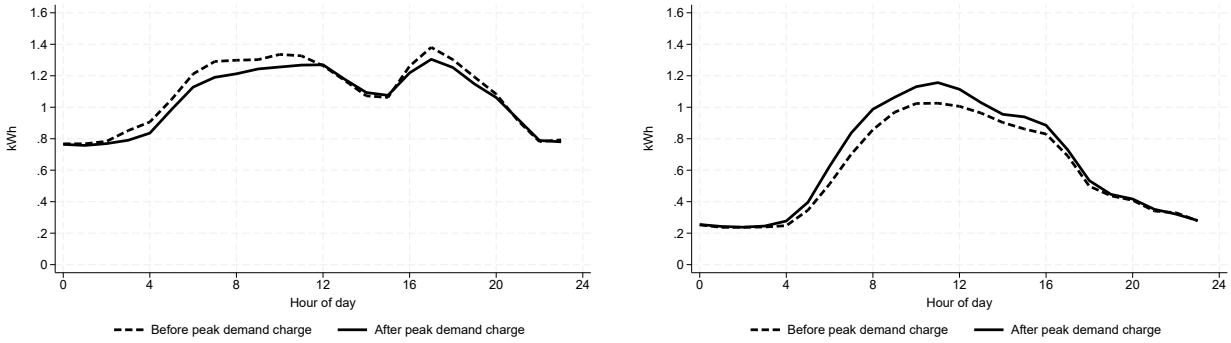
(b) Summer months (June - August)

Figure E.3. Average kWh hourly electricity grid withdrawals for heat pump adopters before and after the introduction of individual peak demand charges. *Note*: the figure is based on a balanced sample of 116 households that adopted a heat pump before January 1, 2022. Consequently, all households in the sample owned a heat pump throughout 2022 (the pre-reform period) and the post-reform period following the introduction of peak demand charges.

Table E.3: Load shifting for heat pump owners in response to individual peak demand charges

	(1) All	(2) Winter	(3) Summer
Total grid withdrawals:			
All hours	0.472**	0.773**	0.331
	(2.02)	(2.20)	(1.24)
Morning hours (06.00 - 12.00)	-0.0108	-0.0775	0.0570
	(-0.18)	(-0.73)	(0.91)
Afternoon hours (12.00 - 17.00)	0.00363	0.0322	0.00405
	(0.07)	(0.34)	(0.08)
Peak hours (17.00 - 20.00)	0.0733*	0.125*	0.0146
	(1.67)	(1.73)	(0.31)
Night hours (22.00 - 06.00)	0.350***	0.646***	0.209
	(2.85)	(3.12)	(1.60)
Households	1,123	1,123	1,123

Note: The 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 individual peak demand charges 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 daily variables for temperature, dummy variables for the presence of heat pumps interacted with month-of-year indicators, dummy variables for the presence electric vehicles two-way interacted with month-of-year and treatment indicators, and continuous solar capacity (kVA), solar production (kWh), storage capacity (kWh) variables, interacted with month-of-year indicators. Fixed effects include month-of-sample, household $\times$ month-of-year and household $\times$ day-of-week fixed effects. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a) Winter months (December - February)

(b) Summer months (June - August)

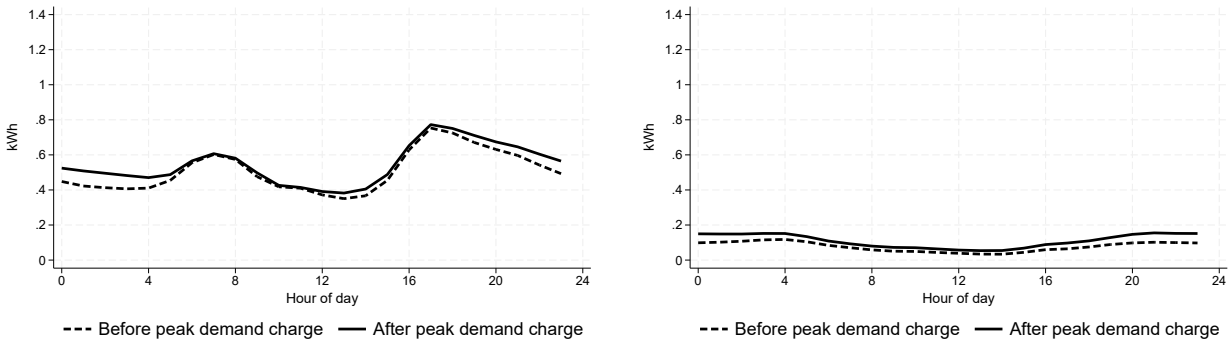
Figure E.4. Average kWh hourly electricity consumption for heat pump adopters before and after the introduction of individual peak demand charges. *Note*: the figure is based on a balanced sample of 116 households that adopted a heat pump before January 1, 2022. Consequently, all households in the sample owned a heat pump throughout 2022 (the pre-reform period) and the post-reform period following the introduction of peak demand charges.

Table E.4: Load shifting for heat pump owners in response to individual peak demand charges

	(1)	(2)	(3)
	All	Winter	Summer
Total electricity consumption:			
All hours	0.553**	0.772**	0.465
	(2.10)	(2.16)	(1.30)
Morning hours (06.00 - 12.00)	-0.0101	-0.0765	0.101
	(-0.10)	(-0.69)	(0.65)
Afternoon hours (12.00 - 17.00)	0.105	0.0298	0.137
	(1.00)	(0.27)	(0.92)
Peak hours (17.00 - 20.00)	0.0759*	0.125*	0.0245
	(1.68)	(1.73)	(0.38)
Night hours (22.00 - 06.00)	0.327***	0.646***	0.157
	(2.67)	(3.12)	(1.25)
Households	1,123	1,123	1,123

Note: The electricity consumption (kWh) in a block of hours over the day over the period January 2022 - December 2024 is regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of individual peak demand charges 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 daily variables for temperature, dummy variables for the presence of heat pumps interacted with month-of-year indicators, dummy variables for the presence electric vehicles two-way interacted with month-of-year and treatment indicators, and continuous solar capacity (kVA), solar production (kWh), storage capacity (kWh) variables, interacted with month-of-year indicators. Fixed effects include month-of-sample, household $\times$ month-of-year and household $\times$ day-of-week fixed effects. Standard errors are clustered at the household level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E.4 Battery energy storage



(a) Winter months (December - February)

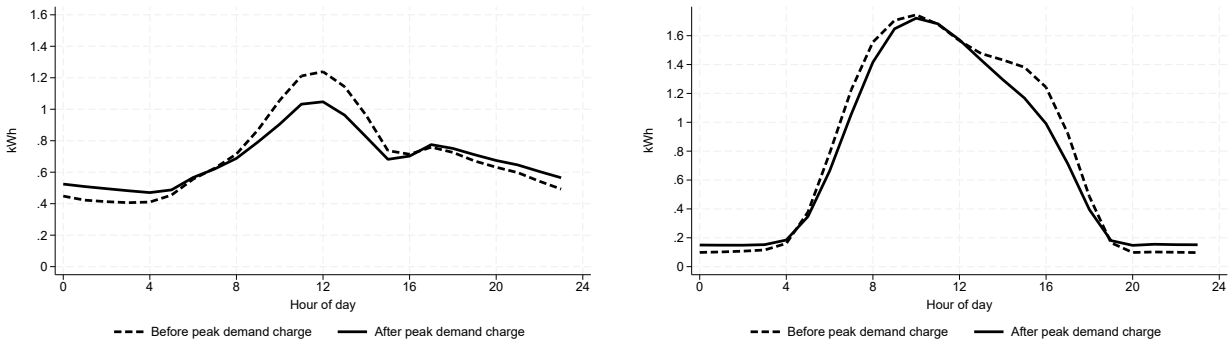
(b) Summer months (June - August)

Figure E.5. Average kWh hourly electricity grid withdrawals for battery energy storage adopters before and after the introduction of individual peak demand charges. *Note*: the figure is based on a balanced sample of 2000 households that adopted battery energy storage before January 1, 2022. Consequently, all households in the sample owned battery energy storage throughout 2022 (the pre-reform period) and the post-reform period following the introduction of peak demand charges.

Table E.5: Load shifting for battery energy storage owners in response to individual peak demand charges

	(1)	(2)	(3)
	All	Winter	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)
Households	2,000	2,000	2,000

Note: The 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 individual peak demand charges 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 daily variables for temperature, dummy variables for the presence of heat pumps interacted with month-of-year indicators, dummy variables for the presence electric vehicles two-way interacted with month-of-year and treatment indicators, and continuous solar capacity (kVA), solar production (kWh), storage capacity (kWh) variables, interacted with month-of-year indicators. Fixed effects include month-of-sample, household $\times$ month-of-year and household $\times$ day-of-week fixed effects. Standard errors are clustered at the household level. *t*-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a) Winter months (December - February)

(b) Summer months (June - August)

Figure E.6. Average kWh hourly electricity consumption for battery energy storage adopters before and after the introduction of individual peak demand charges. *Note:* the figure is based on a balanced sample of 2000 households that adopted battery energy storage before January 1, 2022. Consequently, all households in the sample owned battery energy storage throughout 2022 (the pre-reform period) and the post-reform period following the introduction of peak demand charges.

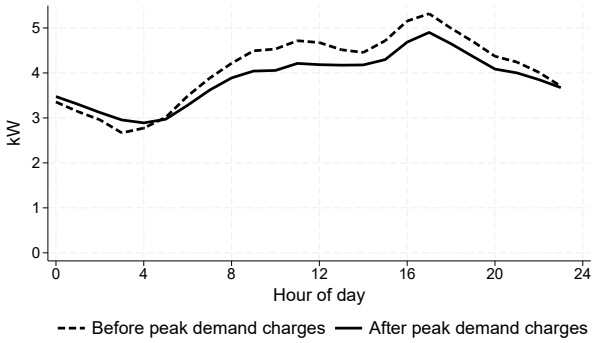
Table E.6: Load shifting for battery energy storage owners in response to individual peak demand charges

	(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)
Households	1,123	1,123	1,123

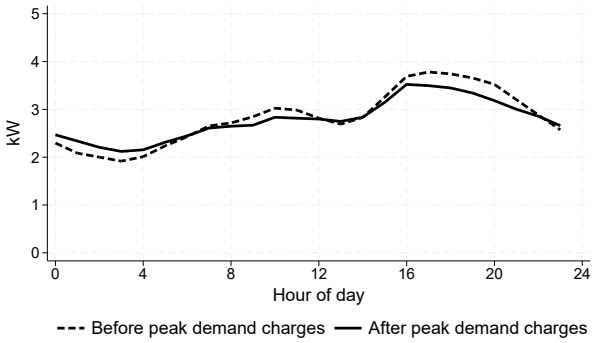
Note: The electricity consumption (kWh) in a block of hours over the day over the period January 2022 - December 2024 is regressed in a multi-way fixed effects difference-in-difference (MWFE-DID). The introduction of individual peak demand charges on January 1st, 2023 indicates the post period and protected 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 daily variables for temperature, dummy variables for the presence of heat pumps interacted with month-of-year indicators, dummy variables for the presence electric vehicles two-way interacted with month-of-year and treatment indicators, and continuous solar capacity (kVA), solar production (kWh), storage capacity (kWh) variables, interacted with month-of-year indicators. Fixed effects include month-of-sample, household $\times$ month-of-year and household $\times$ day-of-week fixed effects. Standard errors are clustered at the household level. *t*-statistics in parentheses. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

E.5 Load shifting and peaks

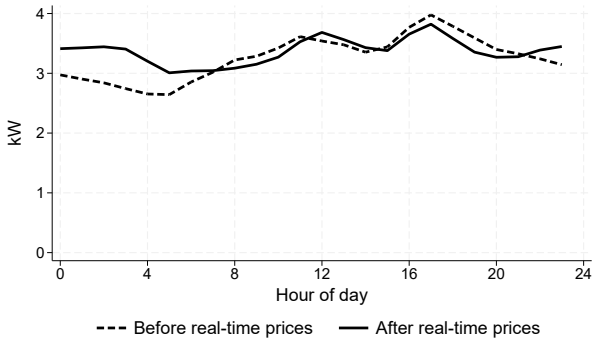
Appendix Figure E.7 shows maximum kW peak electricity grid withdrawals for households with an electric vehicle and households adopting into a real-time pricing contract. For both groups, we first compute per household-month-hour-of-day the maximum kW peak electricity grid withdrawal. We then take the average maximum grid withdrawal over all households in the sample, and present the evolution by hour-of-day separately for winter and summer months.



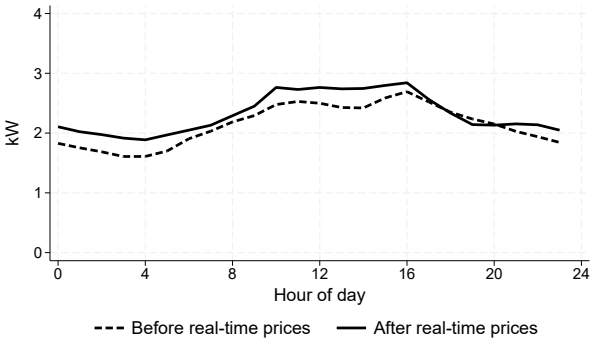
(a) Electric vehicles: winter months (December - February)



(b) Electric vehicles: summer months (June - August)



(c) Real-time pricing: winter months (December - February)



(d) Real-time pricing: summer months (June - August)

Figure E.7. Maximum kW hourly electricity grid withdrawals for electric vehicle owning households before and after introduction of individual peak demand charges (top row) and real-time pricing adopting households before and after adoption (bottom row).

References

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.

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.

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.

Vlaamse Nutsregulator, 2024. Marktmonitor 2024. Technical Report. Vlaamse Nutsregulator.

Vlaamse Nutsregulator, 2025. Marktmonitor 2025. Technical Report. Vlaamse Nutsregulator.