Decarbonizing Heat: The Impact of Heat Pumps and a Time-of-Use Heat Pump Tariff on Energy Demand*

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Abstract: Heat pumps have been proposed as the leading technology in the electrification of domestic heat and therefore could play a crucial part in the transition to low-carbon energy systems. However, there is very little causal evidence of the impact of heat pumps on energy demand and the impact of marginal prices to help optimize energy demand with heat pumps. We leverage a staggered roll-out of heat pumps from Octopus Energy Group to show that: (1) heat pumps have a large impact on energy demand, on average causing a 90% reduction in home gas use and a 61% increase in home electricity use – overall, households reduced total energy demand by 40% and carbon dioxide emissions in 2024 by 36% (increasing to 68% over the lifetime of the technology); (2) a time-of-use tariff designed for heat pumps can provide large demand flexibility benefits, halving electricity consumption during the evening peak to help balance the grid, and that load shifting is possible on the coldest days and from all building types in our sample; (3) the marginal value of public funds of the current UK heat pump subsidy is £1.24 (for every £1 spent by the Government). Overall, we find that heat pumps can meaningfully decarbonize heat and subsidies to encourage heat pumps can be welfare-enhancing.

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1 Introduction

Half of the global final energy consumption is related to heat, which accounts for 40% of global carbon emissions, almost half of which is used to heat buildings (International Energy Agency, 2019). In many industrialized countries, homes rely on gas boilers to provide heat, leading to large shares of these countries' carbon emissions. Replacing these heating appliances with heat pumps using low-carbon electricity has the potential to reduce household carbon emissions and energy costs (Billimoria et al., 2021, Gaur et al., 2021). Heat electrification has been recommended by the IEA (2021) and IPCC (2022) as fundamental to decarbonization and is critical if ambitious world climate goals are to be met by the mid-21st century. Heat pumps have been recognized as the key universal solution for this heat decarbonization (Rosenow et al., 2022), and as a result many governments around the world are subsidizing the adoption of industrial, commercial, and residential heat pumps.

Electrification of heat may cause large problems for grid operators and consumers. For instance, in the UK (like many industrialized countries), the electrification of heat will be a major determinant of the more than doubling of electricity demand expected by 2050, which will increasingly be met by variable renewable generation (National Grid ESO, 2024). It is predicted that electrified heat will have a major impact on peak demand, with the prospect of a surge in demand from millions of households on a cold day, leading to fears of power outages (Zhang et al., 2022). Electric heat demand is therefore a critical concern for the future operation of low-carbon grids as well as planning for necessary upgrades to network capacity, which face significant costs and challenges. Demand flexibility is presented as a potential solution to reduce peak heat demand and mitigate capacity constraints, incentivizing consumers to shift consumption outside of peak periods when the grid is under strain, namely through time-of-use tariffs. Such time-of-use tariffs might be very socially valuable with flexible demand technologies (Schittekatte et al., 2024), and such tariffs have productivity and investment efficiency benefits (Borenstein, 2005), as well as potentially improving environmental outcomes (Holland and Mansur, 2008).

However, there is a lack of credible causal evidence on the change in both electricity and gas demand from heat pumps, and then the change in demand from time-of-use tariffs that encourage customers to adjust how they use their heat pumps. Despite engineering estimates suggesting that heat pumps are three to four times more efficient than gas boilers at turning energy demand into heat, these estimates are mostly descriptive studies of *in-situ* performance of a handful of heat pumps (Carroll et al., 2020, Energy Systems Catapult, 2023, IEA, 2022). In particular, while there are some large model estimates of the impact on greenhouse gas emissions (Blum et al., 2010, Deetjen et al., 2021, Ruhnau et al., 2019, Thomaßen et al., 2021), the societal benefits of heat pumps might depend on the carbon content of the source of electricity (Kaufman et al., 2019, Walker et al., 2022).[1] In addition, while modeling work shows that heat pumps could increase grid flexibility (Arteconi et al., 2016, Baeten et al., 2017, Flower et al., 2020, Franken et al., 2025, Hedegaard and Münster, 2013, Quiggin and Buswell, 2016, Teng et al., 2016, Waite and Modi, 2020), we have no causal evidence on how any heat pump interventions, let alone time-of-use tariffs designed for heat pumps, affect energy demand (Schittekatte et al., 2023, Turk et al., 2024).

Accurate estimates of the causal impact of heat pumps on energy demand are crucial for energy system operators contending with electrification to expand grids in an efficient and low-cost way.[2] Furthermore, for many governments around the world considering introducing or amending a heat pump subsidy, understanding the causal change in overall energy demand is essential to estimate the optimal heat pump subsidy for society and understand payback periods of major home energy investments.[3]

In our study, we estimate the causal impact of heat pumps on energy demand (with a sample of 1,321 heat pump adopting customers)[4] and, separately, the impact of a time-of-use tariff designed for heat pump owners (with a sample of 6,631 time-of-use tariff adopting customers). In both cases, we employ a staggered difference-in-differences identification strategy, whereby everyone in our sample eventually adopts a heat pump with the utility, but they adopt a heat pump at different times of the year due to the utility being unable to treat everyone (i.e., install heat pumps) at once.[5] This natural experiment allows us to causally estimate the impact of heat pumps on electricity and gas demand using actual consumption data from Octopus Energy consumers in Great Britain. We use this same natural experiment and a similar staggered

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[1] There have been previous calls for creating a credible counterfactual (Carmichael, 2022, Rathmell et al., 2021, Rosenow and Hamels, 2023).

[2] Evidence of heat flexibility will also inform policy and business models designed to encourage this behavior in consumers, particularly as heat demand is expected to be less elastic than other demand due to temporal constraints and the primacy of consumer comfort (Franken et al., 2023, The Centre for Research in Energy Demand Solutions, 2023).

[3] Many countries around the world currently subsidize heat pump adoption (in a renovation or a new build). For instance, in 2023, the U.S. Inflation Reduction Act has a $2,000 subsidy (in New York it is $8,000 for low-income households), the UK has a £7,500 subsidy, and many other countries in Europe have similar levels of subsidy (Austria: €5,000; Belgium €6,400; Croatia: €4,250; Czech Rep: €5,700; Denmark: ¢4,500; Finland: €4,000; France: €15,000; Germany: €15,000; Ireland: €6,500; Italy: up to 85% of cost; Lithuania: €14,500; Netherlands: €5,100; Norway: €1,000; Poland: €10,750; Portugal: €2,500; Slovakia: €11,400; Spain: €13,500; Sweden: €5,000; Switzerland: €15,200) (European Heat Pump Association and others, 2023). This list goes to shows that most industrialized countries are spending a great deal of public money by subsidizing heat pumps despite no credible causal evidence that they reduce energy demand and carbon dioxide emissions (which are needed to estimate the policy-relevant optimal subsidy).

[4] In our data, we know the exact weeks in which the heat pump was installed, which contrasts with much of the previous literature using self-reported survey responses.

[5] In October 2023, the UK Government increased the size of the heat pump subsidy, and this raised the demand for heat pumps. The demand for Octopus Energy heat pumps outstripped supply, which caused an average delay of 28 weeks between agreeing to buy the heat pump and installation of the heat pump.

difference-in-differences estimator to identify the impact of Octopus Energy's new heat pump time-of-use tariff on energy demand. We address the weaknesses of the two way fixed effects (TWFE) difference-in-differences estimator highlighted by the recent literature (Baker et al., 2022, Callaway and Sant'Anna, 2021, Goodman-Bacon, 2021) by using Callaway and Sant'Anna (2021) (CS) dynamic estimators (in addition to Borusyak et al. (2024)).

1.1 Primary Findings

We have three main sets of results. First, we find that the adoption of heat pumps causes a substantial change in energy demand. For gas, on average we find a 90% decrease in demand per year – a 9,351 kilowatt-hour (kWh) reduction, from a baseline of 10,336 kWh per year.[6] For electricity, we find a 61% increase in demand per year – a 3,080 kWh increase, from a baseline of 5,062 kWh per year. Altogether, we find that households substantially reduce their total energy (electricity plus gas) demand – the gas reduction is greater in absolute terms than the electricity increase. In other words, heat pumps replace gas demand with electricity using only about 30% of the energy. This is broadly in line with engineering estimates of heat pumps having approximately 300% efficiency of a gas boiler. In our preferred empirical specification, households reduced energy use by approximately 40%[7] by replacing their gas boiler[8] with a heat pump. In today's terms, that is equivalent to a 1.16 tonne reduction in CO_2eq emissions per household per year – we calculate that this is a 36% reduction on their pre-heat-pump adoption CO_2eq footprint from annual energy consumption of 3.23 tonnes.[9] By the end of an assumed 20-year heat pump lifespan (i.e., in 2043), emissions savings rise to 1.86 tonnes per year as the electricity grid decarbonizes. Overall, this indicates that heat pumps can reduce a household's $\mathrm{CO_2}$ equivalent emissions by 68% throughout their operational lifespan.[10]

We also estimate how heat pump adoption affects demand over different seasons, temperatures, times of the day, and types of homes – all potential moderators for different treatment effects. Our analysis measures long-term impacts: on average, we have over five months of

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[6] This is largely a mechanical result of households no longer needing any gas and thus stop all gas contracts, but some households do continue using gas for cooking.

[7] We refer here to end-use demand. Electricity generation may be greater than end-use demand due to upstream efficiency losses. When we calculate $\mathrm{CO_2}$eq impacts of demand, we use emissions factors that account for these upstream efficiency losses.

[8] In the UK, the majority of households heat their homes with gas boilers that heat up water and distribute through the home via radiators, what is commonly as a "wet" heating system.

[9] We use UK Government (2024*a*) and Department for Energy Security and Net Zero (2023*b*) estimates of $\mathrm{CO_2}$eq per kWh of electricity and gas consumption. In 2024, electricity marginal carbon intensity is 0.226 kg CO_2eq per kWh, whereas gas carbon intensity is 0.20226 0.226 kg CO_2eq per kWh.

[10] This figure is based on the assumption that the impact of heat pumps and pre-heat pump energy consumption remain constant over time, with the only variable being the decreasing carbon intensity of electricity as it becomes cleaner.

post-heat-pump-adoption consumption data for our sample, and many of the customers in our analysis sample have heat pumps for two winters (18 months). We find that most of the increase in electricity consumption is concentrated during the winter months, with virtually no increases in demand past 15°C. We find that heat pumps alone do not drastically change the shape of electricity demand during the day, suggesting that heat pumps alone do not provide demand flexibility. We find no clear evidence that properties with worse energy performance certificate ratings or in areas with higher incomes (based on middle layer super output area or based on individual property value) increase their electricity consumption more than other properties. However, we find that floor area (a proxy for heat loss) shows a correlation with the increase in electricity consumption due to heat pump installation.

We assess the external validity of our results to a broader population sample. While our sample is not fully representative of the entire population, we explore the generalizability of the estimated effects by re-weighting our data to match the covariate distribution of Octopus Energy smart meter customers in terms of annual electricity consumption, property value, energy performance rating, and floor area. After applying this re-weighting, the treatment effects remain consistent, indicating that our findings may be generalizable to the national population. This result reinforces the notion that the observed effects of heat pumps are largely mechanical — though they do not significantly change energy usage patterns in homes, they are more efficient from a kWh perspective.

Second, we investigate heat flexibility by estimating the causal impact of Octopus Energy's heat pump time-of-use tariff on energy demand. The tariff, named *Cosy Octopus*, was introduced at the end of December 2022. As heat becomes the main source of electricity demand, a time-of-use tariff for heat pump owners is designed to shift electricity consumption away from times of grid constraints and higher marginal prices – this is especially important as the grid is supplied by more renewable generation. For most of the time in our analysis frame, the tariff includes two three-hour "*Cosy*" periods (4-7am and 1-4pm) with a 40% reduction in the marginal price, and a three-hour peak period (4-7pm) with a 60% increase in the marginal price. All other hours are billed at the customers' typical standard marginal price.[11] We analyze consumption impacts from December 2022 through June 2024. The identification strategy here is the same as for heat pump adoption – we use the staggered enrolment into the time-of-use tariff over time and estimate the impact against everyone who eventually becomes treated (in other words, all customers in our sample eventually "opt in" to treatment). The identification strategy comes from the increase in the UK heat pump subsidy which drew a great deal of attention from consumers.[12]

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[11] (This *Cosy* tariff is priced closer to the wholesale price of energy than the standard tariff, whose price does not change by hour of the day.

[12] This identification strategy of using a change in attention – an "advertising effect" – to examine tariff switching and inertia is related to analyses by Dressler and Weiergraeber (2023), Hastings et al. (2017), Ho et al. (2017), Honka et al. (2017), Hortaçsu et al. (2017).

Again, our analysis measures relatively long-term consumption impacts, covering customers' consumption for an average of seven months after *Cosy* adoption. Over 500 customers in our sample have two winters of data on *Cosy*. We observe stable and persistent treatment effects over time, where adopting *Cosy* causes a decrease in peak rate electricity consumption and simultaneous increase in consumption during the two cheaper off-peak time periods. Based on yearly averages, we find that switching to *Cosy* causes: (i) a more than doubling of consumption in the morning *Cosy* off-peak period (4-7am); (ii) a nearly doubling of consumption in the afternoon *Cosy* off-peak period (1-4pm); (iii) a halving of peak consumption (4-7pm); and (iv) a ≈28% consumption reduction during all other times (the other 15 hours of the day). In summary, in the off-peak periods, prices drop by 40% and electricity demand increases by 100%. In the peak period, prices increase by 60% and electricity demand decreases by 50%.[13] These implied own-price and cross-price elasticities are large. Cosy adopters save £318 – ≈18% on their energy costs from switching to *Cosy* – compared to if they are on Octopus Energy's standard tariff. Of this £318 in savings, £78 is "structural" winnings, while £240 comes from demand shifting.[14]

We also analyze the impact of the time-of-use tariff on different moderators (e.g., seasons, outdoor temperatures, and households). We find that households' load shifting towards off-peak times is twice as high during the winter, while peak avoidance persists during non-winter months, but with a much smaller magnitude of reduction. We find greater peak reduction and off-peak increase on colder days, among larger homes (measured by floor area), and among homes that Octopus Energy predicts have high heat loss (based on data from the homes' energy performance certificate). We also find larger absolute shifts in demand from higher-income households, but all income levels shift consumption and benefit equally as a fraction of their bill from the time-of-use tariff.[15] We believe that these findings are linked. We see greater impact of time-of-use tariffs where heat pumps have higher energy consumption due to higher heat loss – whether this higher heat loss is due to external conditions such as cold weather, or to property-specific characteristics such as higher floor area or heating needs. In a survey we ran with these customers, a majority of respondents say they automate their heat pumps through smart thermostats.[16] We also find that when we re-weight the estimates to have the identical covariate distribution as Octopus Energy smart meter customers on annual electricity consumption, property value, energy performance rating, and floor area, the treatment effects are somewhat smaller in absolute terms given the slightly above-average size of the homes in

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[13] During our sample time period, there were no secondary effects on causing local distribution peaks, which has been recently noted for EV time-of-use tariffs (Bailey, Brown, Myers, Shaffer and Wolak, 2024).

[14] This means that, on average, customers benefit on this tariff even without shifting their consumption. However, consumers who are more elastic with their heating benefit more form the tariff (Borenstein, 2007).

[15] This result is consistent with other research suggesting that dynamic pricing benefits all households (Borenstein, 2013, Burger et al., 2020, Leslie et al., 2021), but in contrast to the research suggesting an income gradient (Cahana et al., 2022, Horowitz and Lave, 2014).

[16] This finding echoes the results from Jessoe and Rapson (2014) and Bollinger and Hartmann (2020) that households need the correct technology in order to respond to time-varying prices.

our *Cosy* sample.

Third, given our demand estimates from heat pumps and the time-of-use tariff, we calculate the welfare changes of policies to encourage heat pump adoption. We compute the marginal value of public funds (MVPF) (Hahn et al., 2024, Hendren and Sprung-Keyser, 2020) for the heat pump subsidy in the UK (the Boiler Upgrade Scheme) to understand its efficiency. We also estimate the resource, government, and social cost per tonne for the heat pump subsidy. The subsidy was introduced in May 2022, with a £5,000 subsidy for air-source heat pumps, which increased to £7,500 per air-source heat pump from 23 October 2023.[17] Using data on the predictions of the grid over the next 20 years, the change in the social cost of carbon (SCC) over the next 20 years,[18] and assuming that half of the new adopters from the subsidy are marginal and the rest are inframarginal (which is similar to other large residential energy efficiency elasticities – see Hahn et al. (2024)), we find that the average MVPF of the current heat pump subsidy administered in 2023 is 1.24. This means that the heat pump subsidy generates £1.24 in societal benefits for the £1 in net government cost. The 1.24 MVPF calculated in our study for the heat pump subsidy is favorable to other subsidies to reduce CO_2 (Hahn et al., 2024).[19] The MVPF increases to 1.90 if we include the learning by doing benefits of the subsidy wherein greater production reduces costs. Given learning rates for heat pumps are not well established in the literature, this estimate assumes a similar rate as for gas boilers; it should therefore be treated with caution.

We also find that resource and social costs per tonne of CO_2 are both £125 and £122, respectively, while the government cost per tonne of CO_2 is £450. When we consider the changes in demand that result from the time-of-use heat pump tariff, the resource and social costs per tonne of CO_2 reduce to -£31 and -£35, respectively.[20] In either case, the government cost per tonne is greater than the social cost per tonne, but this ignores the benefits of the subsidies to

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[17] The subsidy has been focused on upfront costs of heat pumps (U.K. Department for Business, Energy & Industrial Strategy, 2021), as some previous evidence points to these costs being pivotal for consumers (Shen et al., 2022). Note that it also subsidizes ground-source heat pumps and biomass boilers. Our analysis focuses on air-source heat pumps.

[18] The UK government's SCC is £250 per tonne of CO_2, but it is calculated by estimating the marginal abatement cost (i.e., resource costs) per tonne of CO_2. The government estimates the amount of CO_2 that is needed to meet the UK's future CO_2 targets and walks up the marginal abatement cost curve until it hits that CO_2 target, which hits costs at £250 per tonne of CO_2. This UK government approach is in contrast to how other countries, like the US, estimate the social cost of carbon. Those other countries use the marginal damage per tonne of CO_2 from integrated assessment models (EPA, 2022).

[19] This favorability to other policies is particularly evident when analyzing the initial £1 of the subsidy, which yields a marginal value of public funds (MVPF) of 2.77, excluding the benefits from learning by doing. Additionally, as the carbon intensity of electricity generation is expected to decline over time, the reduction in CO_2 emissions from heat pumps will increase. This implies that the MVPF for a heat pump subsidy will likely rise in the future, suggesting that higher optimal subsidies for heat pumps could be justified moving forward.

[20] This negative number suggests that consumers save money by adopting a heat pump and the associated time-of-use tariff (*Cosy Octopus*).

inframarginal customers. As shown in Hahn et al. (2024), the MVPF includes the inframarginal benefits and is overall a better measure of welfare from subsidies than cost per tonne.

1.2 Relationship to Existing Literature

While our paper is focused on a change in fuel type, we can compare the impacts on energy use and CO_2 emissions to that from the general literature on energy conservation and energy efficiency. Much of this literature suggests that engineers' predictions about demand reductions from such technologies are not the same as the actual demand reductions when having a credible counterfactual (Brandon et al., 2022, Fowlie et al., 2018). Our paper is slightly in contrast to these papers since, based on a robust counterfactual, we observe demand reductions from heat pump adoption in our sample that are largely in line with engineering estimates – in that heat pumps cause a nearly total elimination of gas consumption and an increase in electricity consumption of about 30% of the magnitude (in kWh) of the gas consumption abated, in line with heat pumps having approximately 300% efficiency (Jadun et al., 2017).[21]

To the best of our knowledge, the treatment effect of heat pumps in this paper – a 40% reduction in household energy demand and a total 68% reduction in household CO_2 emissions – is the largest ever estimated for an energy demand reduction technology or intervention with a credible identification strategy. Heat pumps demonstrate a demand reduction effect that is two to three times greater than that of weatherization efforts (Allcott and Greenstone, 2017, Fowlie et al., 2018) and larger than other low carbon technologies.[22] Given the ambitious national and international CO_2 reduction targets set, policymakers need to prioritize encouraging technologies capable of significantly reducing society's CO_2 emissions. Heat pumps are one such technology, and our findings suggest they should be subsidized, as such subsidies are welfare-enhancing. Such heat pump subsidies also have a larger MVPF than other subsidies to reduce CO_2 in the residential sector, such as for more energy-efficient appliances, insulated homes (through weatherization), and electric vehicles. Moreover, pairing heat pumps with time-of-use tariffs specifically designed for this technology can make them cost-effective for households while delivering flexibility benefits to the grid.

Furthermore, our estimates of the shift in consumption from the heat pump time-of-use tariff are somewhat larger than the existing literature. Some of the existing papers in this area with similar pricing structures (Fowlie et al., 2021) show price elasticity of approximately -0.075 in the context of critical peak pricing events. We find that our *Cosy* impacts imply own-price elas-

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[21] There have been instances when the engineering estimates are in line with the energy demand changes, e.g., Berkouwer and Dean (2022). Our treatment effect of the heat pumps on demand are larger than some of the earlier studies that estimate changes over time without a clear counterfactual group and where the measurement of the adoption of heat pumps is based on self-selected survey responses (Alberini et al., 2016, Liang et al., 2022).

[22] The heat pump demand effect is towards the higher end of the range of estimates from installing solar PV on energy demand (Beppler et al., 2023, D'Agosti and Danza, 2023, Kattenberg et al., 2022, Qiu et al., 2019)

ticities of -1 to -2.[23] Our estimates of within-day shifting might be larger because the tariff was focused specifically for heat pump users who might be more elastic; or the way that consumers can respond to prices is easier, since the technology can be automated to be switched on during off-peak periods and turned off at peak and all other time periods, and time-of-use tariffs with technologies are associated with price changes have larger demand changes (Faruqui and Sergici, 2010, Faruqui et al., 2017).[24] On this last possibility, we note that, in responses to a survey we sent to customers about how they responded to *Cosy*, around 70% say they use smart thermostats or automation settings on their heat pumps to change their energy use in response to the time-of-use pricing schedule. While we cannot separate out these potential mechanisms, it seems that ease-of-shift with heat pumps is particularly important and thus future research on technology-specific tariffs has a great deal of potential value.

Our study relates to the wider literature on heat pumps. For example, heat pump adoption is related to geography, climate, and electricity prices (Anderson and Kirkpatrick, 2024, Davis, 2023*a*,*b*, Sahari, 2019), and also property prices (Shen et al., 2021). We find that the average income level of areas with heat pump customers in our sample is slightly higher than the rest of England and Wales, consistent with previous research showing that low carbon technologies and the subsidies associated with such technologies largely go to higher-income households (Borenstein, 2017, Borenstein and Davis, 2016, De Groote and Verboven, 2019, Feger et al., 2022, Metcalf, 2019), and in contrast to the pattern of heat pump adoption that Davis (2023*a*) finds in the US. The population in the areas that heat pump customers are based is also older and slightly more educated.

Our research also contributes to the literature on tariff design and switching. Many studies suggest a high degree of inertia in energy tariff markets, often due to significant switching costs (Gravert, 2024, Hortaçsu et al., 2017). However, in our case, we examine a technology-specific tariff that consumers can easily benefit from through simple forms of automation. No previous empirical study has explored switching in the context of such a technology-specific tariff.[25] As heat pumps and smart thermostats become more prevalent across energy markets, and as demand for these tariffs increases, we believe that future switching studies should focus on the benefits and costs associated with adopting these types of tariffs.

The rest of the paper is structured as follows. First, we present the set-up and identification strategy in Section 2. Next, we show the main results for the impact of heat pump installation

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[23] We acknowledge here that we have three different time periods, where prices are changing simultaneously in peak and off-peak, but remaining static for all other times in comparison to the counterfactual tariff. This makes comparisons in price elasticities more nuanced.

[24] It has been previously noted that heat pumps might provide excellent flexibility for time-varying prices (Arteconi et al., 2013, Fitzpatrick et al., 2020, Lyden et al., 2024, Pallonetto et al., 2016, Rodríguez et al., 2018, Schibuola et al., 2015, Sweetnam et al., 2019).

[25] The closest work has focused on understanding whether changing incentives for night-time EV charging affect demand (Bailey, Brown, Shaffer and Wolak, 2024, Qiu et al., 2022).

on energy use and subsequent adoption of heat pump specific time-of-use tariff in Section 3. We discuss welfare implications in Section 4. Finally, we summarize the main results in the conclusion Section 5.

2 Set-up and Identification Strategy

In this section, we outline our approach to identifying the causal impacts of two key interventions on energy consumption: the installation of heat pumps and the adoption of a specific time-of-use tariff tailored for heat pump users.[26] In our set-up, we first isolate the causal impact of heat pumps on energy demand, and then isolate the causal impact of a heat pump tariff on energy demand.

2.1 Heat Pump Installation

Our primary goal is to identify the causal impact of heat pumps on consumer energy demand. Estimating this causal impact by comparing those who adopt a heat pump versus those who do not may be plagued by various sources of bias. Those that adopt heat pumps may differ systematically from other customers in a multitude of unobservable ways that correlate with their potential outcomes.

To address this concern, we use the staggering of heat pump adoption around Great Britain among customers purchasing their heat pumps from Octopus Energy to create a counterfactual control group who adopted a heat pump but were delayed in doing so. Octopus Energy has been installing heat pumps since February 2022 and was taking orders as of December 2021. In Figure 1, we show how Octopus Energy's rollout of heat pumps progressed over time. We plot both *installations* and their corresponding *deals*. Deals are defined as the customer paying a refundable deposit to obtain their heat pump (they have skin in the game). We see a natural delay between customers making a deal for the heat pump and installation, due to installation constraints. This delay provides us with a natural experiment to understand the impact of heat pumps on energy demand for all those who want a heat pump. We see evidence that deals increased markedly in September 2023, when the Government announced its plan to increase the level of the main subsidy for heat pumps (the Boiler Upgrade Scheme), from £5,000 to £7,500 per air-source heat pump. However, because of the delay between deal and order, we see a slower and steadier increase in heat pump *installations* both before and after September 2023.

We use the whole universe of Octopus Energy retail customers that adopted a heat pump with Octopus Energy as their heat pump installer. There are 1,321 such customers who adopted

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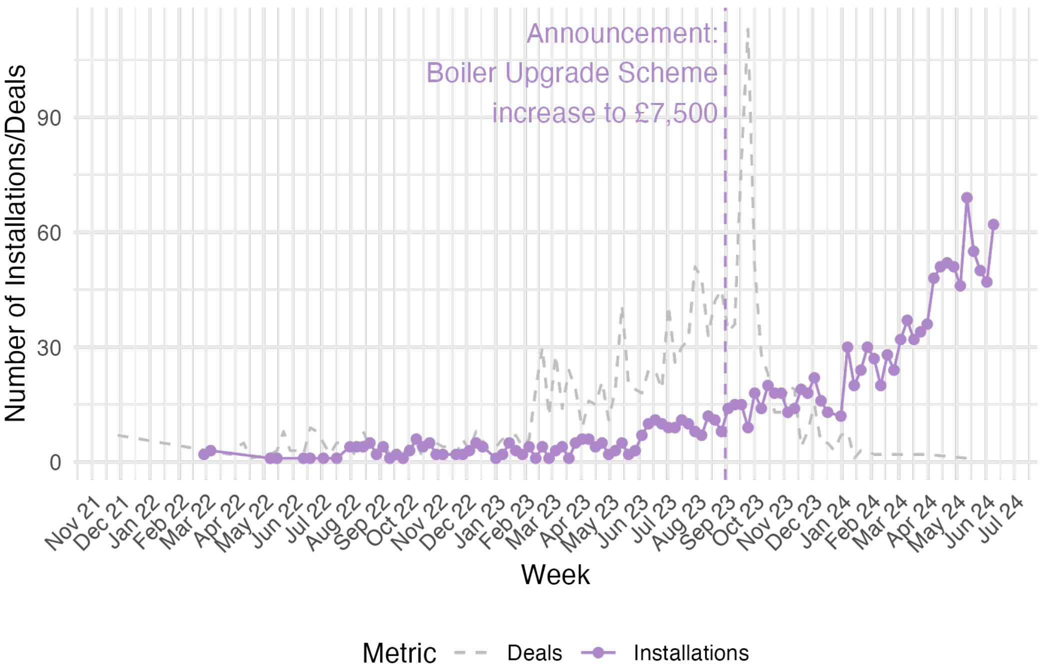
[26] The tariff included every unit of energy used in the household but was designed to be more friendly for heat pump users.

Figure 1: Weekly deals and installations



Note: We show weekly heat pump adoptions in solid purple – these adoptions, together, comprise our sample of 1,321 heat pump adopters. We also show in hashed gray the *deals* for these 1,321 adoptions. The drop-off in the deals line is not reflective of broader trends in heat pump adoption by Octopus Energy customers – it is driven by the fact that we only show deals for the customers whose installation was complete by 15 June 2024 (customers who are in our analytical sample, i.e., the solid purple line). The Boiler Upgrade Scheme was increased from £5,000 to £7,500 in October 2023, with the announcement of this change coming in September 2023.

a heat pump as early as 28 February 2022 or as late as 15 June 2024, and who have sufficient consumption data for analysis. Customers who have a deal but no installation as of 15 June 2024 are akin to never treated in our sample; we exclude these 514 customers from our main analysis but include them in a robustness check we present in Table A.2. We examine consumption from 13 December 2021 through 15 June 2024.[27]

Heat pumps in our sample have an average size of 8kW, which is quite representative of the average heat pump sold. Almost all customers in our sample took advantage of the Boiler Upgrade Scheme subsidy. On average, it was worth £6,800 to the customers in our sample – this

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[27] Smart meter data availability in the sample is contingent upon customers having an active contract with Octopus Energy during the time period (December 2021 to June 2024), a functioning smart meter, and granting permission to share half-hourly data. This results in limitations, as we cannot access prior installation data for customers who acquired a heat pump with Octopus Energy but were not existing customers at the time. Similarly, data gaps exist for customers who joined and then switched to another provider. The situation is even more complex with gas data. Despite the popularity of dual tariffs in the UK, some customers have different suppliers for gas and electricity. Consequently, although 82% of customers who installed heat pumps also used gas, we can only observe a fraction of this subset. For a visualization of these dynamics, see Figure A.1.

is a weighted average of the £5,000 subsidy level and the later, more generous, £7,500 level.[28]

Our quasi-experimental design presents some econometric challenges. In particular, staggered difference-in-differences models may produce biased estimates if treatment effects are heterogeneous across units and over time (Callaway and Sant'Anna, 2021, Goodman-Bacon, 2021). This might happen in our setup because: (a) households may get better at using their heat pump over time; and (b) households could also adopt more low carbon technologies to complement their heat pump usage. With this in mind, we calculate Callaway and Sant'Anna (2021) (CS) difference-in-differences estimators. We do this by aggregating the data at weekly level. Our cohorts are divided by their week of heat pump adoption, and the unit of observation is the average consumption for household i in the cohort g in week t.

The CS model is estimated as follows. We start by calculating the group-time Average Treatment Effect on the Treated (ATTs) for all our treated cohorts and weeks, and then aggregate these group-time ATTs across different groups or time periods to obtain summary measures of treatment effects relevant to our analysis. We examine three ways of using CS to aggregate and understand HP impacts. First, dynamic effects: this captures how the treatment effect evolves over time since adoption. Second, calendar-time effects: this assesses the impact of treatment across different points in the calendar, accounting for when the treatment occurred, which is particularly important as heat pump impacts are seasonal. Third, overall treatment effect: for an overall measure, the ATT is averaged across all groups and time periods.

Our outcome Y_{it} is the energy consumption (gas, electricity or gas + electricity consumption, which we call "total energy") for household i in week t. We define G as the first week the heat pump was fully installed. We do not observe if customers change heating systems later, but we consider it unlikely. $Y_{it}(0)$ is household i's potential energy use at time t if they remain untreated. $Y_{it}(g)$ is the potential energy use for household i at time t if they were first treated in week g. G_{ig} is a dummy variable equal to one if a household i had a heat pump installed in week g, and zero otherwise. For simplicity, we will consider that some customers get a heat pump in week 2 (in reality, we observe more weeks before treatment). Thus, $g = 2, \ldots, \tau$.

The observed and potential outcomes for each household i can be written as:

$$Y_{it} = Y_{it}(0) + \sum_{g=2}^{\tau}(Y_{it}(g) - Y_{it}(0)) \cdot G_{ig} \tag{1}$$

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[28] For commercial sensitivity reasons, we are not able to share the cost to households in our sample after the Boiler Upgrade Scheme subsidy. However, we note that the average cost of heat pump installation since the Boiler Upgrade Scheme subsidy was increased to £7,500 per air-source heat pump (in October 2023), according to MCS (Microgeneration Certification Scheme (MCS), 2024), is £12,713. This is a simple average of MCS's monthly average cost for air-source heat pumps from November 2023 through June 2024. Heat pumps must be certified by MCS to be eligible for the Boiler Upgrade Scheme subsidy, so we believe that MCS data encompasses all relevant air-source heat pump installations during this period, implying an average private expenditure of £5,213 per air-source heat pump after the subsidy was applied.

We define the Average Treatment Effect on the Treated (ATT) for cohort (week of adoption) g at time t (referred to as the group-time average treatment effect in the Callaway and Sant'Anna (2021) framework) as:

$$ATT_{gt} = \mathbb{E}_{gt}\left[Y_t(g) - Y_t(0) \mid G_g = 1\right] \tag{2}$$

This group-time ATT measures the expected difference in energy consumption at time t for customers who received the heat pump in week g, compared to what their consumption would have been without the treatment.

The dynamic effects (event-style analysis) for the time e since adoption, with $e = t - g$, can be written as:

$$\theta_{es}(e) = \sum_{g \in G} \mathbf{1}\left\{g + e \leq \tau\right\} P(G = g \mid G + e \leq \tau) \cdot ATT(g, g + e) \tag{3}$$

Here, $P(G = g \mid G + e \leq \tau)$ represents the probability that a customer was first treated in week g, given that they are observed e periods after treatment. This probability acts as a weight, ensuring that the treatment effect $ATT(g, g + e)$ is appropriately scaled according to the size of the group treated in week g and their exposure duration. This aggregation averages the treatment effect for all customers who have been treated for exactly e periods. However, it should be noted that this approach introduces some compositional effects because it mixes the treatment effects across different cohorts who might have different baseline energy consumption patterns due to seasonality or other factors. Therefore, it should only be interpreted as the treatment effect for exposure e if we assume that $ATT_{g,g+e}$ does not vary across cohorts. In the case of heat pump analysis, this effect varies across cohorts as customers install their heat pumps at different times of the year.

Then, we calculate the calendar-time average treatment effect, which can be defined as:

$$\theta_c(\tilde{t}) = \sum_{g \in G} \mathbf{1}\left\{\tilde{t} \geq g\right\} P(G = g \mid G \leq \tilde{t}) \cdot ATT(g, t) \tag{4}$$

This expression captures the average treatment effect at a specific calendar time $\tilde{t}$, weighted by the probability that a customer was treated by week $\tilde{t}$. This helps in understanding the impact of heat pump installations across different points in time, accounting for when the treatment was administered.

Finally, the simple overall treatment effect can be expressed as:

$$\theta_W^O = \frac{1}{\kappa} \sum_{g \in G} \sum_{t=2}^{\tau} \mathbf{1}\left\{t \geq g\right\} ATT_{gt} \cdot P(G = g \mid G \leq \tau) \tag{5}$$

where $\kappa = \sum_{g \in G} \sum_{t=2}^{\tau} \mathbf{1}\{t \geq g\} P(G = g \mid G \leq \tau)$. This normalization ensures that the weights sum to 1. The overall treatment effect θ_W^O is a weighted average of the group-time ATTs, putting more weight on larger groups and those who have remained in treatment for longer periods. This method avoids the issues associated with traditional two-way fixed effects (TWFE) models, such as negative weighting, which can lead to biased estimates.

The validity of our identification strategy rests on several key assumptions. First, we have irreversible treatment, so once a customer installs a heat pump, they do not revert to their previous heating system, which is a very reasonable assumption. Second, we have random sampling, so selection into receiving a heat pump earlier versus receiving a heat pump later is not correlated with trends in energy use. Importantly, the average waiting time in our sample is 28 weeks (nearly half a year), due to installation constraints and not energy levels or trends. This time period between initial quote and final installation is a key natural experiment for our identification strategy, as it implies that many of the customers who do not yet have a heat pump and form our counterfactual are customers who nevertheless *want* a heat pump.

Third, we have no anticipation, so customers do not change their behavior in anticipation of heat pump installation, or if they do, this anticipation is limited to a clearly defined period. We use an anticipation period of one week to account for the 5 days it takes to remove the previous heating source and install all the necessary parts of the heat pump system in properties.[29] Last, we assume unconditional parallel trends. This assumption, based on "not-yet-treated" groups, ensures that the comparison between treated and untreated groups is valid, as the trends in outcomes would have been parallel in the absence of treatment.

For a visual inspection of pre-trends, we include event study style plots in Section 3.1.2. Due to our sample size, we have a great deal of power to reject differences in trends close to zero, addressing concerns (Freyaldenhoven et al., 2019, Roth, 2022, Roth et al., 2023) that low statistical power could undermine the validity of parallel trends tests.

Finally, note that, in addition to the CS estimators, for certain heterogeneity analyses (in particular, see Sections 3.1.5 and 3.2.5), we run TWFE models.[30] We use this TWFE model to interact treatment (heat pump installation or tariff adoption) with contextual variables or customers characteristics. However, because the comparison between earlier adopters to later

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[29] We see evidence of longer anticipation effects than one week, as can be seen in Figure A.15. Specifically, heat pump impacts increase slightly when we use longer anticipation periods. This is especially the case for the extent to which heat pumps cause a reduction in gas consumption. We hypothesize that this pattern may be due to people removing their gas meters more than one week before heat pump installation, even up to five weeks before heat pump installation. Customers might then use portable electric heaters as temporary substitutes during this period. The upshot of these possibilities is that our results could be an underestimate of the electricity increase and, especially, gas reduction, caused by heat pumps. However, we use the more conservative estimates generated by assuming one week anticipation.

[30] The TWFE model is:

$$Y_{it} = \alpha_i + \lambda_t + \delta D_{it} + \beta \mathrm{HDD}_{it} + \epsilon_{it} \tag{6}$$

adopters may bias our coefficients, we only use TWFE results to estimate the shape of the relationship between the treatment and interaction variables of interest. Overall, we find a small amount of bias in the TWFE estimates (approximately 8% for analysis of electricity consumption, but larger for analysis of gas consumption; see Table A.1). We still use the CS estimates as the model of choice for estimating the treatment effects.

2.1.1 Threats to Internal and External Validity

For internal validity, we show in Section 3.1.2 that we have parallel trends in pre-adoption energy use between the earlier and later heat pump adopters in the CS framework. There might be other threats to identification, such as the co-varying adoption of other technologies in the home. Before 08 May 2024, the Boiler Upgrade Scheme required an energy performance certificate with no recommendations for loft and cavity wall insulation. In our sample and data, we find evidence that insulation is adopted many time periods before heat pump adoption. We discuss some further technologies that might threaten internal validity in Section 3.1.4, such as electric vehicles and solar panels. These technologies together are the future of decarbonization in the residential sector; thus our analysis of their interaction with heat pumps is a beneficial feature of our sample that we exploit.

For external validity, we compare those in our sample to those who are not in our sample.[31] We compare the geographic areas in which we have heat pump adopting customers to other geographic areas in England and Wales in Table A.14. We use these ecological comparisons because we lack individual-level data on certain key variables about our sample, such as their household income. In Great Britain, the Office of National Statistics (ONS) compiles data on income and related statistics at various levels of geographic granularity. The measure we use is at the middle layer super output area (MSOA). There are 7,201 MSOAs in England and Wales, each comprising on average approximately 8,000 people.[32] We use approximately 6,000 MSOAs

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with Y_{it} being the energy consumption for household i at time t. We run different models depending on the analysis: weekly overall energy, gas and electricity consumption in kWh in week t for the heat pump analysis, and average half hourly electricity consumption by rate period in kWh in day t for the heat pump specific tariff analysis. D_{it} is a dummy variable equal to 1 if the customer has a heat pump installed for the week t, 0 otherwise for the heat pump analysis. D_{it} is a dummy variable equal to 1 if the customer has adopted the heat pump specific tariff in day t, 0 otherwise for the heat pump specific tariff analysis; HDD_{it} is the average heating degrees in week/day t and GSP Group of household i for the heat pump and heat pump specific tariff analysis respectively. We use average daily temperature measured at the GSP Group level, based on the highest-quality weather station in the GSP Group. GSP Groups are zones commonly used in the energy sector in Great Britain to divide customers geographically. There are 14 GSP Groups. These are the same regions that determine slight variations in the exact prices of *Cosy*, as shown in Section A.2.1.) $\alpha_i + \lambda_t$ are household i and week/day t fixed effects, and the standard errors are clustered at the customer households level.

[31] In Section A.3.2, we re-weight our sample to have the identical covariate distribution as Octopus Energy smart meter customers on annual electricity consumption, property value, energy performance rating, and floor area.

[32] Scotland uses a different system of aggregation; we focus this descriptive analysis on England and Wales.

that have full data from the ONS on average income, demographics and socio-economics variables used at the MSOA level.

We find that the average income level of areas with heat pump customers in our sample is slightly higher than the rest of England and Wales (household income of £49.3k in our sample versus £46.1k in all other areas). This difference is consistent with previous research showing that low carbon technologies and the subsidies associated with such technologies largely go to higher-income households (Borenstein, 2017, Borenstein and Davis, 2016, De Groote and Verboven, 2019, Feger et al., 2022, Metcalf, 2019), and in contrast to the pattern of heat pump adoption that Davis (2023*a*) finds in the US. Using the Index of Multiple Deprivation (IMD) (created by the Consumer Data Research Centre) to measures relative deprivation across each of the constituent nations of the United Kingdom, we find that areas with heat pump customers are also slightly less likely to be deprived.[33] The population in the areas that heat pump customers come from is also slightly older and slightly more likely to have achieved a Level 4 qualification (the latter being a measure of educational attainment, equivalent to a high school degree). Interestingly, the property prices in treated areas are lower than the property prices in the control areas, suggesting that there is not a consistent story that all of the early adopters have large differences in income.

Beyond observable differences between our heat pump adopter sample and other customers, we note that our sample comprises "early adopters" who may be different in unobservable ways from the general population. In addition, our heat pump adopter sample comprises reasonably well-insulated properties, given it was a funding condition for the Boiler Upgrade Scheme until 08 May 2024, as noted above.

2.2 Heat Pump Time-of-Use Tariff Adoption

We also aim to evaluate the causal impact of a specific time-of-use tariff for heat pump users, called *Cosy Octopus*, on energy demand. Octopus Energy designed this new tariff in 2022 to encourage heat pump users to shift their electricity demand in a way that would be beneficial for reducing wholesale power procurement costs; in other words, encouraging heat pump owning customers to shift their electricity consumption away from peak periods, which are most polluting for the grid. The marginal price faced by *Cosy*-adopting customers differs by hour of the day, as we show in Figure 2.

Specifically, *Cosy*'s marginal price shape has two off-peak periods and one peak period. The first off-peak period is in the morning, from 4am to 7am, and the second in the early afternoon, from 1pm to 4pm. The peak period is from 4pm to 7pm. All other hours are charged at the

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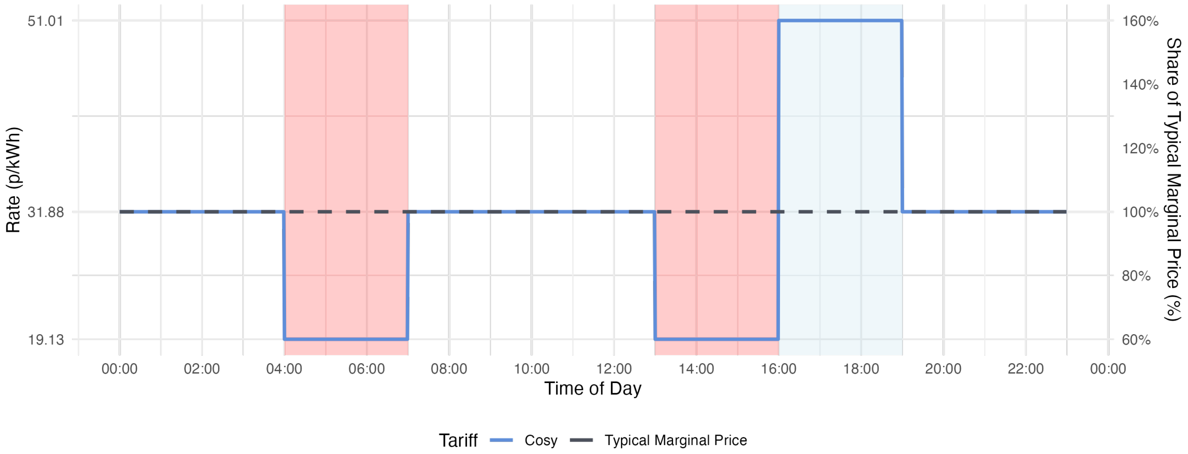
[33] The IMD datasets are small area measures of relative deprivation across each of the constituent nations of the United Kingdom. Dimensions include income, employment, education, health, crime, barriers to housing and services, and the living environment.

standard tariff's marginal price. In contrast, a standard tariff would have no hour-of-day varying marginal prices. The design of the tariff with respect to prices varying within a day is designed to broadly correlate with wholesale market prices. We show average wholesale prices across the four *Cosy* periods in 2022, 2023, and the first half of 2024 in Table A.7 based on data from LCP Delta (2024). We find that the *Cosy* tariffs' consumer-facing marginal prices *are* correlated with wholesale prices, albeit in a way that flattens within- and between-day variation in wholesale prices. However, the tariff structure is also designed with an eye toward how people use heat pumps; in particular, a sustained period of "pre-heating" in the afternoon low-price *Cosy* period might improve customers' ability to constrain their demand during the higher-priced *Cosy* peak period. This tariff can also be viewed as a way to encourage the adoption of heat pumps more generally because consumers can reduce running costs by adopting a heat pump with a specially designed tariff.

Figure 2: *Cosy* Rate by Period



Note: We show the marginal price for *Cosy* adopting customers by time of day (blue line) compared to the typical marginal price of Octopus Energy's standard tariff, on 13 December 2022, the day that *Cosy* was first available to customers. The two off-peak 40%-reduction on typical marginal price "*Cosy*" periods are shaded light red, while the peak period with 160% of the typical marginal price is shaded light blue. We use the prices for customers in the North West England, as of 15 June 2024. Marginal prices vary slightly by customers' region. There are 14 regions for tariff pricing in Great Britain. In all 14 regions, the overall structure of the marginal prices of the *Cosy* tariff is similar: 40% lower than the typical marginal rate for the *Cosy* off-peak periods, 60% higher than the typical marginal rate for the peak period, and the typical marginal rate for all other hours of the day. Prices also can change over time; but, again, the overall structure of the prices has always been as in Figure 2 during the period of our analysis, except in the final two months of our analysis period when the peak was 151% of the standard rate and off-peak was 45% lower. (See Section A.2.1 for further detail.)

We use the entire universe of Octopus Energy customers who switched to the *Cosy* tariff – 6,631 customers who adopted the *Cosy* tariff as early as 13 December 2022 or as late as 15 June 2024. Interestingly, the announcement in September 2023 of the coming increase in the heat pump subsidy made national headlines in the British media and made customers more likely to switch to the heat pump tariff. This is likely to be purely an advertising effect on the switching rates, which has been found in other studies in energy (Dressler and Weiergraeber, 2023, Hortaçsu et al., 2017), healthcare (Ho et al., 2017), social security (Hastings et al., 2017) and banking (Honka et al., 2017). Therefore, our identification strategy is that there are no differences in the pre-trends between earlier versus later *Cosy* tariff adopters, and the presence of the subsidy provides an exogenous shock on attention to the heat pump tariff offered by Octopus.

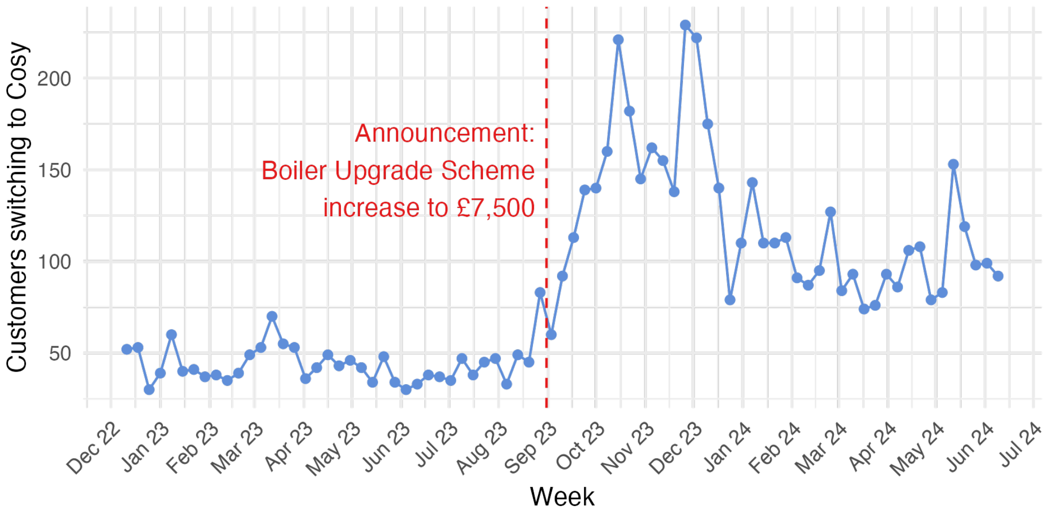
Our *Cosy* analysis covers the same time period as the heat pump adoption analysis. Therefore, we use consumption data from 13 December 2021 through to 15 June 2024. Our analysis thus measures relatively long-term consumption impacts, covering customers' consumption for on average seven months after *Cosy Octopus* adoption, not just the weeks immediately before and after adoption. Many customers in our sample have two winters of data on *Cosy Octopus*.

Similar to the heat pump analysis, we employ CS models to assess the causal impact of the *Cosy* tariff on consumption during different periods of the day. We use the same CS model as Equations (1) to (5), but where G_{ig} is an indicator for adoption of the *Cosy* tariff, and our sample is 6,631 *Cosy* adopters rather than 1,321 heat pump adopters. As with the heat pump analysis, our identification strategy relies on the assumption that the electricity consumption of customers that adopted *Cosy* earlier would have followed a parallel trend to control customers (in this case, those who adopted *Cosy* later) in the absence of adoption of the tariff. We also assume that once customers adopt the tariff, they do not leave. In reality, although the majority of customers stay on *Cosy*, some of them switch back and forth or leave completely, as discussed in Section 2.2.1. However, while earlier adopters have slightly different characteristics than later adopters, there is little heterogeneity in treatment effect, as shown in Section A.2.7. We believe that impacts are similar because mechanisms are similar; as discussed in Section 3.2.2, in a survey we sent customers, we find that the main way that customers respond to *Cosy* is through smart thermostat settings.

2.2.1 Timeline of *Cosy* Adoption

The tariff officially launched in December 2022. The rate of new adoptions per week was stable for the first year and then increased during Winter 2023-2024, as shown in Figure 3. As discussed above, we speculate that this increase was driven by the increase in the Boiler Upgrade Scheme subsidy for heat pumps, announced in September 2023, which may have heightened public interest in heat pumps and increased online discussion of the *Cosy* tariff, at the time the only tariff designed especially for heat pumps.

Figure 3: Weekly Adoption of the *Cosy* tariff



Note: We show weekly switches to *Cosy Octopus* among the 6,631 customers in our *Cosy* analysis sample. The Boiler Upgrade Scheme was increased from £5,000 to £7,500 in October 2023, with the announcement of this change coming in September 2023.

Before discussing the analysis, there are some features of the panel dataset and tariff switching to note. First, we only have smart meter data if the customer has an active contract with Octopus, a working smart meter, and has given consent to share half hourly data (required to join *Cosy*; note that 96% of Octopus Energy smart meter customers allow half-hourly data sharing). We present in Figure A.19 how our treatment and the smart meter data availability interacts. We have an imbalanced panel, with customers entering and exiting our sample due to smart meter data availability at different times. Obtaining a smart meter is a prerequisite for adopting *Cosy*, leading to a pattern in which data is more likely to be missing before *Cosy* adoption than after.

Second, we investigate from and to which tariffs customers are switching. From our sample of customers, the great majority (N=4,830) switched to *Cosy* and stayed on *Cosy*. Another 1,403 switched to *Cosy* and then switched to another tariff. Finally, 504 have multiple contracts, by which we mean a more complicated switching pattern, such as switches to, away from, and then back to *Cosy*. The majority of our *Cosy* adopters were previously enrolled on standard, non-time-of-use tariffs before switching to *Cosy*. Customers that switch to *Cosy* but then switch to another tariff are likely to adopt another "smart" tariff. Smart tariffs are time-of-use tariffs that make use of more granular readings from smart meters.[34] Overall, prior to *Cosy* adoption, 88% of adopters are on a non-smart tariff. After adopting *Cosy*, only 2% revert back to a non-smart tariff.

Among customers who purchased their heat pump from Octopus Energy from February 2022 through June 2024,[35] more than two thirds adopted a smart tariff, with *Cosy Octopus* being the third most popular of these tariffs. Intelligent Octopus Go and Agile, which precede *Cosy* in popularity, are two tariffs offering, respectively, automated cheap electric vehicle (EV) charging, and dynamic time-of-use where each half-hour of the year reflects day-ahead wholesale prices. Given that many heat pump owners also have EVs, it is reasonable to hypothesize that customers who charge their EVs at home might prefer Intelligent Octopus Go. Meanwhile, Agile is a popular tariff among the most engaged energy enthusiasts.

2.2.2 Geographic Representativeness

In this section, we present the same geographic representativeness checks as in Section 2.1.1 in Table A.15. Similar to the heat pump installation sample, *Cosy* adopters generally live in MSOAs with a higher total annual income, average age, and share of level 4 qualifications. The share of households not deprived in any dimension is higher and the average household size is lower. We examine heterogeneity in the treatment effects by these characteristics.

Finally, we present a comparison of the *Cosy* adopters, Heat pump adopters and a random sample of Octopus Energy smart meter users in Table A.16 using the DOMUS dataset. Note that the property prices presented are different from the previous tables as they do not come from the same source. This table shows that *Cosy* adopters have larger and more valuable properties than more recent heat pump adopters and the random sample of Octopus Energy smart meter customers. Recent heat pump adopters (at least, those who purchased their heat pumps installed by Octopus Energy) have better energy efficiency. Finally, property prices for both heat pump and heat pump tariff adopters are much higher than a random sample of customers.[36]

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[34] Before the widespread adoption of smart meters, some households had special electricity meters that enabled a simple time-of-use tariff by registering consumption depending on whether it fell during pre-set "peak" or "off-peak" times of day. These traditional time-of-use tariffs have existed since at least 1978 in Great Britain (Electricity Council, 1987). Smart meters allow retailers to offer a wider range of time-of-use tariffs and enable customers to switch between various tariffs without changing their meter's physical hardware.

[35] In other words, these are customers who are in both our heat pump adoption and our *Cosy* adoption analyses.

[36] In Section A.3.2, we re-weight our sample to have the identical covariate distribution as Octopus Energy smart meter customers on annual electricity consumption, property value, energy performance rating, and floor area.

3 Empirical Analysis

Our analysis is divided into two parts, each addressing distinct aspects of energy consumption related to heat pumps. First, we examine the impact of heat pump installation on overall energy consumption. Second, we investigate the effects of a time-of-use tariff designed for heat pump users. This tariff aims to incentivize users to shift their energy usage to off-peak periods, potentially reducing peak demand and overall energy costs.

3.1 Impact of Heat Pump Installation on Energy Consumption

3.1.1 Main results

We show the results of three CS models in Table 1: weekly electricity consumption (kWh) for all customers in our sample (1,321 customers grouped into 100 cohorts in Column 1); weekly gas consumption (kWh) for the 80% of the customers in our sample who have a contract with Octopus Energy to supply them with mains gas (1,079 customers grouped into 98 cohorts in Column 2); and (again only for those 80% supplied with mains gas), weekly *energy* consumption – by which we mean, the sum of weekly electricity plus gas consumption, in kWh (in Column 3). We then multiply coefficients and standard errors by 52 to show the impacts in annual consumption terms; this is solely to improve interpretability for readers accustomed to examining annual electricity and gas consumption.

In all three analyses, we start by aggregating half-hourly customer data into weekly adoption cohorts and calculating weekly consumption. The CS simple Aggregate Group-Time Average Treatment Effect (AGGTE) estimator is used to evaluate the impact of heat pump installation on electricity consumption for each weekly cohort of adopters. In this analysis, the control group comprises units that have not yet adopted heat pumps. We defined the first week of treatment as the first week where the customers are fully treated (e.g., if their "true" installation date is midweek, their first week will be the next week). We assume a one-week anticipation effect to take into account that the average installation lasts 5 days. That means that our group "effect" is effectively calculated using periods up to one week before installation. Similarly, we lose the last estimates of the event study style analysis as we effectively do not have any more untreated cohorts. The main assumption remains the same – that, in absence of treatment, the cohorts would have followed similar trends. The significance level for confidence intervals is set at 0.01, and standard errors are bootstrapped with 1000 iterations. Clustering is done at the weekly adoption cohort level. The estimation method used is doubly robust (DR), which combines

Table 1: Heat Pump Installation on Yearly Energy Consumption in kWh

Model:	Electricity (1)	Gas (2)	Overall (3)
Variable			
Is HP Installed = 1	3,080.0***	-9,350.7***	-6,119.8***
	(140.8)	(347.9)	(401.9)
Pre-treatment Average			
Yearly Consumption	5,062.1	10,335.7	15,287.2
Fit statistics			
Number of Households	1,321	1,079	1,079
Number of Cohorts	100	98	98
Number of Time Periods	127	127	127

Clustered (Household) standard-errors in parentheses
Estimation Method: Doubly Robust
Control Group: Not Yet Treated, Anticipation Periods: 1
Signif. Codes: *** 99% confidence band does not cover 0

Note: We show estimates from three CS estimates of the impact of consumption on customers' electricity consumption (column 1), gas consumption (column 2), and overall (electricity plus gas) consumption (column 3). The latter two models' are from a subset of our full sample for customers with gas consumption before their heat pump installation.

propensity score weighting and outcome regression.[37]

We find that heat pump installations have large impacts on energy consumption. They increase annual electricity consumption in our sample of 1,321 customers by 3,080 kWh. Relative to our sample's baseline average pre-heat-pump consumption of 5,062 kWh per year, this increase represents 61% of pre-installation annual electricity consumption.

Most of the customers in our sample have a gas boiler before installing their heat pump, according to administrative survey data related to their heat pump purchase. Thus, in addition to examining electricity consumption, we look at gas consumption data for 1,079 Octopus Energy customers who had their heat pumps installed between February 2022 and May 2024 (a subset of the full sample), had a gas account with Octopus Energy before heat pump installation, and have sufficient gas consumption data. Similar to the electricity consumption analysis, the data spans 13 December 2021 through 15 June 2024, providing a comprehensive view of gas usage patterns before and after heat pump installation. We lack gas consumption data for customers that were not with Octopus Energy before signing up for a heat pump or never had gas. There is also more missing data from smart meters for gas consumption than for electricity consumption. We use only the customers for whom we have at least one week of gas consumption data in the pre-installation period. We mechanically exclude customers who obtain their gas from retailers other than Octopus Energy. For these reasons, our sample is smaller for our gas and overall energy consumption analyses, even though the majority of our heat pump adopters sample have gas boilers as their previous heating source. In Table A.6, we show that the electricity consumption impacts for this smaller sample are similar to our larger sample.

The heat pump decreases customers' gas consumption by 9,351 kWh per year (column 2). Relative to the pre-installation average of 10,336 kWh, this consumption reduction corresponds to a 90% decrease in gas consumption. Octopus Energy's standard procedure to install a heat pump is to remove the previous heating source.[38] Given these aspects of the heat pump installation, one would expect heat pump adoption to cause a sharp reduction in gas consumption. Our empirical analysis confirms this expectation.

We find that the heat pump installation reduces overall *energy* (electricity plus gas) consumption by 6,119.8 kWh per year (column 3). Relative to the pre-installation average energy

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[37] The analysis uses a varying base period, and for robustness, we examine a universal base period in Figure A.14. We do not observe significant pre-trends with this method, either. Additionally, we apply an alternative estimator from Borusyak et al. (2024) in Figure A.12, which yields similarly consistent results. Finally, see Figure A.13 for a TWFE event study visualization.

[38] The installation typically lasts four days, though in the beginning of the analysis period installations could last five days. They involve removal of the previous heat source first, followed by installation of a new hot water tank. Pipe work, radiators, and the heat pump are installed in the next two days. The final one to two days are spent fully commissioning the new system and teaching the customer how to operate their new heating system. If the installation happens on cold days, Octopus Energy provides electric heaters during the process.

consumption of 15,287.2 kWh per year, this represents a 40% decrease.[39] The substantial decrease in overall energy highlights that heat pumps are more efficient than gas boilers at turning energy input into heat output–which is the overall decarbonizing heat result. Nevertheless, because electricity currently costs more per kWh than gas, in terms of ongoing marginal costs, we estimate slightly higher running costs between gas boiler heated homes and comparable homes heated via heat pumps.[40] However, the adoption of time-of-use tariffs like *Cosy* can reduce the electricity consumption costs of the heat pump. We discuss these estimates in more depth in Section 4.

3.1.2 Dynamic ATTs

Using our CS model, we show the dynamic ATT of heat pump installation on electricity consumption in Figure 5. We find that the impact of heat pump installation is effectively instantaneous: a sharp decrease in gas consumption and corresponding increase in electricity consumption. After the large effects at adoption, we see a pattern that we believe is influenced by the seasonal effects discussed in Figure 5; our cohorts are of unequal size, making the dynamic ATT sensitive to the season when the largest cohorts adopted. There is little change in electricity or gas consumption before adoption.

3.1.3 Seasonal Variation

Using our CS models of electricity and gas consumption, we show the calendar ATT of heat pump installation in Figure 5. There is a marked seasonal variation. We find that during winter, the calendar ATT increase in electricity consumption reaches over 200 kWh per week but drops to almost 0 between April to October. The decrease in gas consumption is larger in magnitude, but shows similar seasonal patterns, with very little decrease during warm months and a large decrease during the winter.

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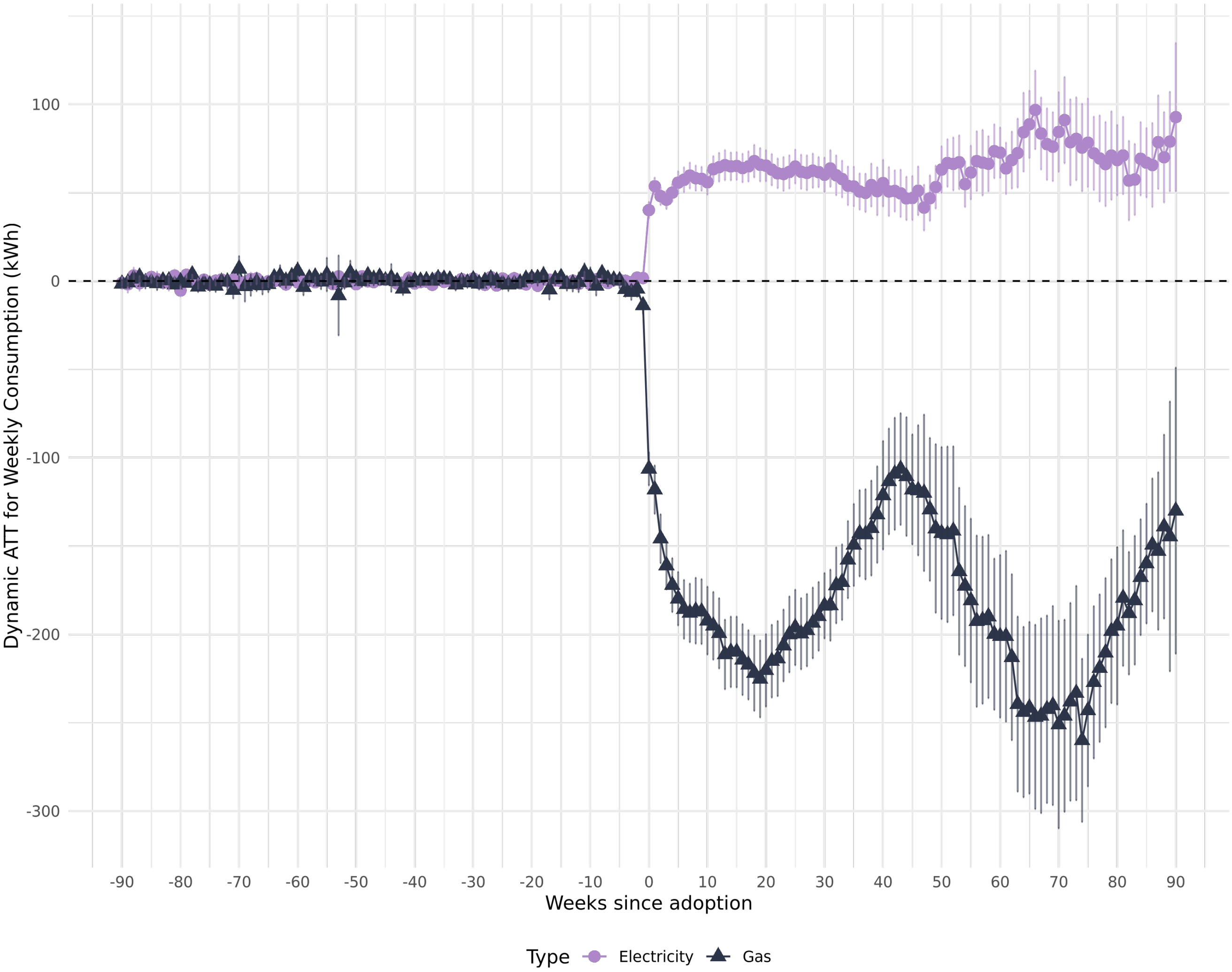
[39] These results are not exactly what one obtains by summing the coefficients from our electricity and gas consumption analyses, partly because the sample for our gas and overall energy consumption analyses, as discussed above; as we show in Table A.6, however, the electricity impacts are similar between our full sample and the smaller gas-consumption-analysis sample.

[40] As of 15 June 2024, the average electricity unit rate for Octopus Energy customers was £0.2450 versus a gas unit rate of £0.0604 (Octopus Energy, 2024). 3,080.0 * £0.2450 -9,350.7 * £0.0604 comes to £190 higher running costs per year from heat pump compared with gas boiler, by this calculation; though note that insofar as customers may disconnect from the gas grid entirely, they can save approximately £100 per year, bringing the running costs difference to only £83/year. UK Government (2024*a*) retail price estimates show similar differences in fuel prices, although electricity and gas rates are both higher than Octopus Energy's unit rates. We use these latter UK Government (2024*a*) prices to forecast running costs from 2024 through 2043 in Section 4, as they provide retail price forecasts through 2100.

Figure 4: Gas and Electricity Dynamic ATTs

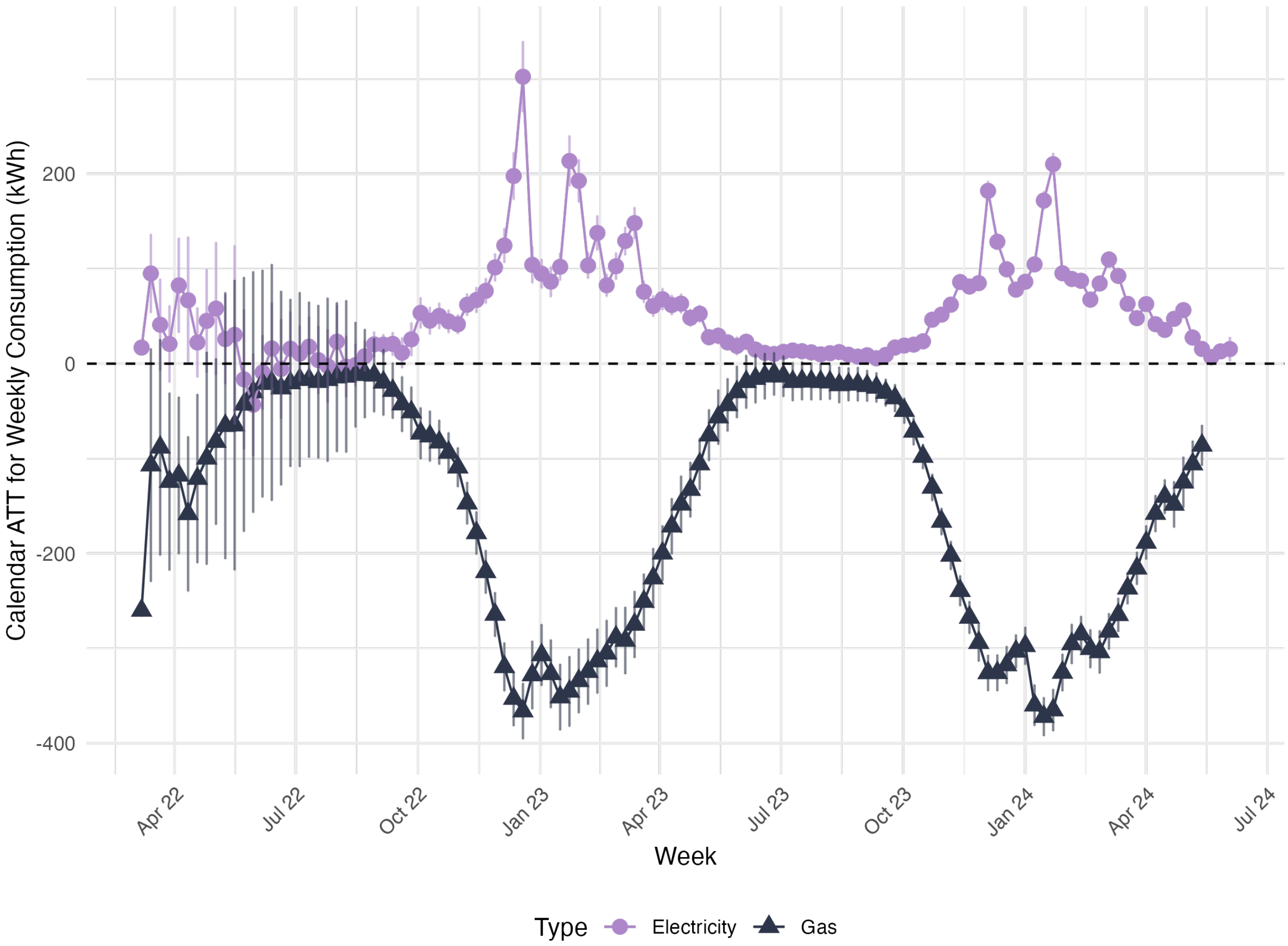


Note: We show dynamic ATTs from our CS models of heat pumps' impact on customers' weekly electricity (purple) and gas (dark gray) consumption (kWh). The outcome on the y-axis is weekly consumption in kWh. The x-axis shows weeks since adoption, where week 0 is the adoption week.

3.1.4 Mechanisms and Threats

Threats to identification are changes to the home including the presence of other low-carbon technologies (LCTs – chiefly solar PV panels, batteries, and electric vehicles) and home fabric improvement that correlate with the timing of when a customer installs their heat pump. To investigate these threats, we conduct several checks on the presence of LCTs. We then discuss how our evidence should be considered in light of fabric changes and other changes to the home. Incorporating these technologies into the analysis is important as all of these technologies are integral to decarbonizing residential energy demand.

Figure 5: Gas and Electricity Calendar ATTs



Note: We show calendar ATT from our CS models of heat pumps' impact on customers' weekly electricity (purple) and gas (dark gray) consumption (kWh). The outcome on the y-axis is weekly consumption in kWh, while the x-axis shows the week of the year.

EV Ownership: First, we look at whether EV ownership interacts with heat pump installation impact. To do this, we create a binary variable for EV ownership.[41] We find that EV ownership does not significantly affect the coefficients on heat pump installation (see Table A.3). EV owners have higher electricity consumption than non-EV-owners, but the impact of the heat pump that we identify is not significantly different for them to non-EV-owners.

We then conduct another analysis, focusing specifically on EV charging events before and after heat pump adoption (see Table A.4). We find that getting a heat pump does not affect

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[41] EV owners are defined as having at least 1 charging event per week for 2 consecutive weeks. EV charging is specifically defined as consumption above 3.5 kWh per half-hour for 4 to 12 consecutive half-hours. The 3.5kWh per half-hour threshold is driven by the assumption that most charging is done by EV chargers that draw 7 kW or more of power. Once an EV is detected, the customer is defined as an EV owner for the remainder of the analysis period.

charging behavior. For each event, we define the main period as the time during which most of the charging occurred; we then examine the probability of the charging event occurring in each period of the time-of-use tariff for heat pump owners we explore in Section 3.2. Our motivation here is to check that EV ownership does not substantially interact with heat pump consumption impacts by time of day; we use *Cosy*'s time-of-use periods as a useful proxy for testing this question. We use a simple linear probability model with customer and day fixed effects. Our findings indicate that, prior to heat pump installation, 95% of the charging events took place during the "Other" period. Following heat pump installation, there was no significant change in habits and charging time.

Solar PV: Before getting a heat pump installed, customers answered a survey to confirm their home's suitability in which they self-reported the presence of other LCTs in the home. Thus, we know that 609 out of 1,213 of the sample that installed a heat pump already had solar PV at home.[42] We interact the presence of solar PV and having a heat pump installed on electricity consumption in a TWFE difference-in-differences estimation in Table A.5. We find that customers with solar PV have lower consumption during the day (afternoon and peak rate) before heat pump installation. This smaller consumption is carried on after the heat pump installation, with a smaller increase in consumption during afternoon and peak rate periods. However, there is no noticeable impact on overall consumption, possibly due to slightly higher heat pump impact in other periods, but also potentially due to low power to detect relatively small interaction effect sizes in our model.

Fabric Improvements and Other Changes to the Home Another potential challenge to identifying the impact of heat pump installation is fabric improvements (better insulation). We do not have a strategy to empirically investigate the extent to which our heat pump installation impacts are confounded with correlated upgrades to a home's insulation. Indeed, improvements to insulation may be inherently linked to a heat pump installation if the heat pump installer recommends fabric improvements along with changing the heating system. However, we note the **immediacy** of the impact of heat pump installation on both gas and electricity consumption in Figure 4. This immediacy strongly suggests that the observed changes are due to the heat pump installation itself, rather than insulation that happened close in time, but not necessarily the *week* of, the heat pump installation. Furthermore, it is likely that any improvements to insulation occurred prior to heat pump installation, given that access to the Boiler Upgrade Scheme (which the vast majority of our sample used) was contingent, until 08 May 2024, on an EPC with no outstanding recommendations for loft and cavity wall insulation. The lack of pre-trends in Figure 4 also implies that fabric improvements in the weeks or months before heat pump installation are minimal, have minimal impact on energy consumption, and/or are so

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[42] The survey is missing for the earliest installations, hence the sample here being 1,213 rather than 1,321.

highly dispersed in time as to be indistinguishable between the treatment and control groups; though it is also possible that this pattern could be driven by insulation being upgraded on the *same* day as heat pump installation.

A final consideration is that significant life changes, such as having a baby, are unlikely to coincide with heat pump installation.[43] However, the control group may experience more such changes, suggesting that we might have some downward bias on our treatment effects.[44] However, the immediate impact of the heat pump installation on energy consumption is again evidence that the impact we have identified is the heat pump installation, not correlated life changes.

3.1.5 Outside Temperature

We use the same heat pump adopters sample to calculate the impact of installing a heat pump by outside temperature. In order to model the interaction between heat pump installation and outside temperature on electricity consumption, we run the following difference-in-differences model using a two-way fixed effects (TWFE) model. We show in Table A.1 how our main CS model compares with the TWFE model. We think that the TWFE model estimates are slightly inflated due to the improper comparisons between earlier and later joiners and thus do not use it as a benchmark here. However, we do not think that the bias impacts the *relative* impacts of temperature and other heterogeneity analyses, and thus we use the TWFE model to plot interactions of interest.

$$\text{Consumption}_{it} = \sum_{d=0,\ldots,25} \omega_d T_{it}^d + \sum_{d=0,\ldots,25} \alpha_d T_{it}^d \times \text{HPinstalled}_{it} + \delta_t + \gamma_i + \epsilon_{it} \tag{7}$$

where: Consumption_{it} is average half hourly electricity consumption in kWh for household i on day t; T_{it}^d is a set of dummy variables for temperature in °C d (ranging from 0 to 25 degrees with temperature below 0 and above 25 degrees boxed). The dummies are equal to 1 if the average temperature on day t and GSP of household i is equal to T^d. HPinstalled_{it} is a dummy variable equal to 1 if the customer had a heat pump installed, 0 otherwise, and δ_t, γ_i are day t and household i fixed effects. The standard errors are clustered at the household (i) level.

We analyze the interaction between having a heat pump installed and the outside temperature on electricity consumption. By including temperature as a separate control variable, we ensure that the interaction terms specifically reflect the impact of having a heat pump at various outside temperatures. We do not include the standalone variable for having a heat pump

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[43] Households would have to have incredible foresight to schedule their hump pump adoption date on exactly the same date when their baby will be born.

[44] Such a criticism will also extend to all studies examining switching to a LCT or a new tariff because you cannot force households to comply – people might comply based on future lifestyle or household characteristics that are unobservable to the researcher.

installed; its effect is captured within the interaction terms. By controlling for temperature independently, we isolate the interaction effect from the direct influence of temperature on electricity consumption.

We plot the results of this analysis in Figure 6. We see an almost linear interaction between temperature and heat pump installation on electricity consumption below 15°C. Past 15°C, the interaction disappears. We show in Section A.1.5 that this relationship holds true across different times of day, including the peak time (which is between 16:00 and 19:00 in the UK).[45] Lower outside temperatures drive higher electricity usage due to increased heating demand.

These variations in outside temperature are crucial to understand how our staggered difference-in-differences results differ from more classic set-ups. Although our effects are persistent in time, they are also seasonal; we capture averages of these seasonal impacts when computing overall difference-in-differences estimates. This dynamic has two implications for our main results (Section 3.1.1) and event study estimates (Section 3.1.2). First, coefficients only capture yearly averages - hiding an almost null effect during summer months and relatively much larger increase during the winter. Second, the event study style analysis will partially capture the composition of cohorts, as discussed in Section 3.1.2. As we have more people adopting during Winter 2024, our event study style dynamic ATT coefficients will partially capture this variation.

3.1.6 Heterogeneity Analysis

Energy Efficiency of the Property: Our analysis reveals that there is no significant interaction between having a heat pump and the Energy Performance Certificate (EPC) rating of the property on electricity consumption (see Figure A.6). This indicates that the impact of heat pump installation on energy usage is consistent regardless of the energy efficiency rating of the house. Whether a property has a high or low EPC rating, the additional electricity consumption due to heat pump installation follows a similar pattern. Note that this should not be confused with the direct impact of EPC on electricity consumption - where lower EPC rating homes do consume more electricity. With all this said, note again that due to the conditions of the Boiler Upgrade Scheme around insulation up until 08 May 2024, it is likely that very few of the homes in our sample have poor insulation.

Floor Area: On the other hand, our analysis reveals that there is a greater increase in electricity consumption after heat pump installation for properties with greater floor area as shown in Figure A.7. In this context, floor area could be a proxy for heat loss, the rate at which a building

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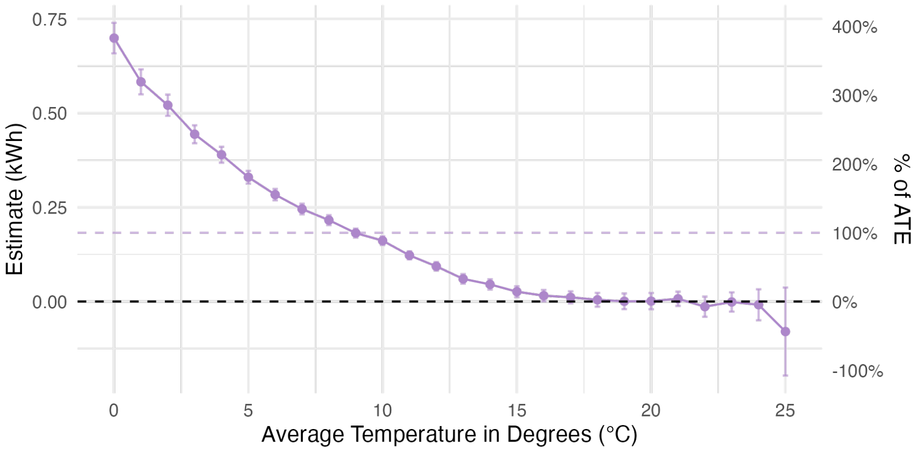
[45] For convenience, we show these impacts by the rate periods of the *Cosy* tariff investigated in Section 3.2.1, but it should be noted that the majority of our heat pump adopting customers are on tariffs other than *Cosy*.

Figure 6: Impact of Heat Pump Installation by Outside Temperature



Note: We show the interaction between temperature (the average temperature on a day) and heat pumps' impact on daily electricity consumption in kWh (left vertical axis) in a TWFE model. We also show the TWFE average treatment effect in dashed grey, and thus on the right vertical axis we show the ratio of the TWFE interaction over the average treatment effect; we interpret this ratio as showing when the temperature-conditional heat pump impact is higher or lower than the heat pump "main effect".

loses heat to the outside environment.[46] Properties with higher floor area likely require more energy to maintain a comfortable indoor temperature, leading to increased electricity consumption after heat pump installation.

Previous Heat Source: We hold data on customers' previous heat source from administrative data related to the heat pump purchase process. These data come from a pre-installation survey with the homeowner carried out by Octopus Energy. As shown in Figure A.10, the increase in electricity consumption after installing a heat pump is the lowest (indeed, is negative) for customers that previously had electric heating or heating usually used in combination with electric heaters (like solid fuel heaters). That said, note that the great majority of the customers in our sample had a gas boiler previously.

Heat Pump Adopter Area Average Income: We also look at whether the heat pump's impact varies by MSOA income in Figure 7. We split MSOA income into deciles (based on all MSOAs in England and Wales) to explore this relationship. We find little evidence of a relationship between heat pump impact on electricity consumption and MSOA income. We see a similarly noisy pattern of heat pump impact by property value decile in Figure A.11, though there may

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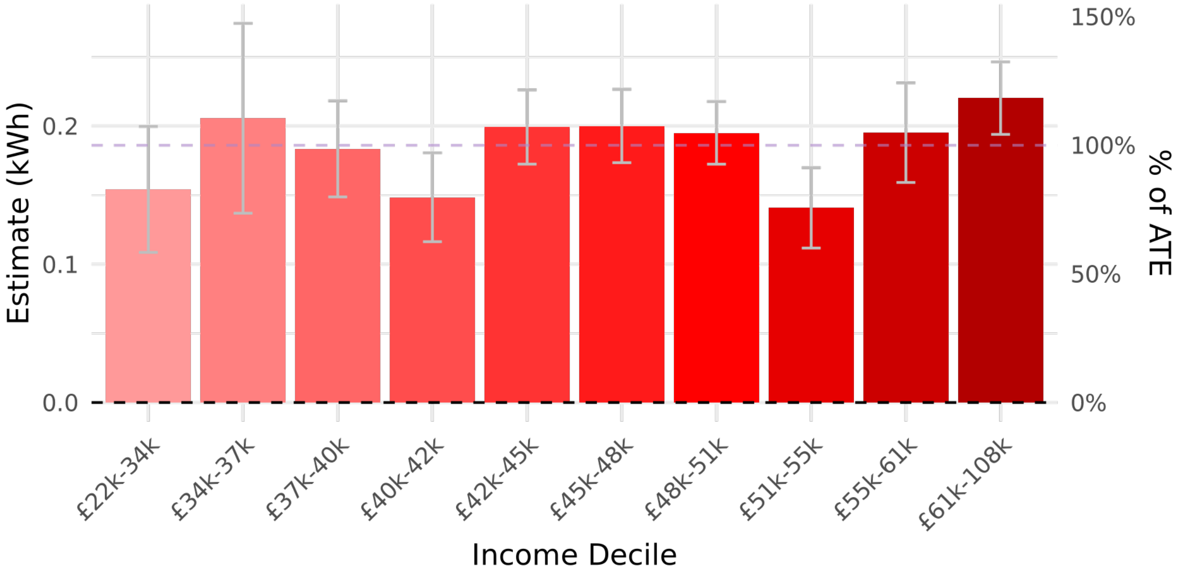
[46] We also show in Figure A.8 a similar pattern of heat pump impact increasing with *predicted* heat loss, using an algorithm developed by Octopus Energy to predict the size of heat pump a home will require based on data from the homes' Energy Performance Certificates. We also believe that some of the regional heterogeneity we see in Figure A.9 may be due to differing average floor area among adopters by region of Great Britain.

be a positive relationship.[47]

Figure 7: Impact of Heat Pump Installation by MSOA Income



Note: We show the interaction between MSOA income and heat pumps' impact on daily electricity consumption in kWh (left vertical axis) in a TWFE model. We also show the TWFE average treatment effect in dashed grey, and thus on the right vertical axis we show the ratio of the TWFE interaction over the average treatment effect; we interpret this ratio as showing when the MSOA-income-decile-conditional heat pump impact is higher or lower than the heat pump "main effect".

3.2 Impact of Heat Pump Specific Tariff on Energy Consumption

We have established that heat pumps substantially increase electricity consumption. We also show in Figure 8 that this increase is fairly similar across all hours of the day, including the traditional evening peak (16:00 to 19:00). In this section, we investigate to what extent a novel time-of-use tariff specially designed for heat pump owners, *Cosy Octopus*, causes customers to shift electricity consumption away from the peak towards less carbon-intensive periods of the day.

3.2.1 Main Results

We implement the same CS difference-in-differences approach as in Section 3.1. In this case, our sample is the 6,631 customers who adopted a the *Cosy* tariff as early as 13 December 2022 or as

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[47] We examine how this and other treatment effect heterogeneity affects our estimates in Table A.21, where we re-weight our sample to have the identical covariate distribution as Octopus Energy smart meter customers on annual electricity consumption, property value, energy performance rating, and floor area.

late as 15 June 2024. Table 2 presents the effects of switching to the "Cosy" tariff on customers' electricity consumption across different times of the day using consumption in kWh per period, along with a separate analysis for overall daily consumption.[48]

Table 2: Cosy Adoption on Half Hourly Electricity Consumption in kWh

Model:	Morning Cosy (1)	Afternoon Cosy (2)	Peak Rate (3)	Other (4)	Overall (5)
Variable					
Has Adopted Cosy $= 1$	0.5071***	0.2926*	-0.2242***	-0.1066***	0.0105
	(0.0126)	(0.0098)	(0.0105)	(0.0072)	(0.0069)
Pre-treatment Average					
Half Hourly Consumption	0.3659	0.3199	0.4404	0.3843	0.3798
Fit statistics					
Number of Households	6,631	6,631	6,631	6,631	6,631
Number of Cohorts	78	78	78	78	78
Number of Time Periods	129	129	129	129	129

Clustered (Household) standard-errors in parentheses
Estimation Method: Doubly Robust
Control Group: Not Yet Treated, Anticipation Periods: 0
Signif. Codes: *** 99% confidence band does not cover 0

Note: We show estimates from five CS estimates of the impact of consumption on customers' electricity during the morning *Cosy* period 4am-7am (column 1), afternoon *Cosy* period 1pm-4pm (column 2), peak period 4pm-7pm (column 3), other hours of the day (column 4), and "overall", i.e,. across all 48 half-hours of the day (column 5).

In summary, switching to the *Cosy* tariff appears to effectively encourage customers to increase their electricity consumption during incentivized periods (*Cosy*'s morning and afternoon off-peak periods) while decreasing usage during peak and standard-rate times. Customers on the *Cosy* off-peak rate from 04:00 to 07:00 increase their electricity consumption by an average of 0.51 kWh per half hour, more than doubling their pre-*Cosy*-adoption consumption during those hours (column 1). There is also a significant increase in consumption during the afternoon *Cosy* period from 13:00 to 16:00, with customers consuming an additional 0.29 kWh per half hour on average, a 91% increase on pre-Cosy consumption during that period (column 2). Consumption during the peak rate period (16:00 - 19:00) decreases by 0.22 kWh per half hour, halving pre-*Cosy*-adoption consumption during those hours (column 3). Consumption during other times of the day, charged at customers' typical marginal price, decreases by 0.11 kWh per half hour, a reduction of approximately 28% on pre-*Cosy*-adoption consumption during those hours (column 4) Finally, despite these shifts in consumption patterns throughout the day, the

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[48] We compare these estimates to TWFE models in Table A.8.

change in overall daily electricity consumption is very close to zero (column 5).

The implied own-price and cross-price elasticities are large. However, interpretation is complex, because multiple prices are changing at the same time. Own-price elasticities may interact with cross-price elasticities. In the simplest analysis – ignoring cross-price elasticities – in the off-peak periods, prices drop by 40% and electricity demand increases by ≈100%, implying an own-price elasticity of -2.5. That said, note that there is variation between the two off-peak periods, with greater own-price elasticity in the morning off-peak period than the afternoon off-peak period. Similarly, in the peak period, prices increase by 60% and electricity demand decreases by 50%, implying an own-price elasticity of -0.8. However, there are interdependencies between periods; this is clear when considering the large reduction in consumption in the standard-rate "other" hours of the day despite no change in price, implying large cross-price elasticities operating alongside own-price elasticities.

3.2.2 Mechanisms and Threats

How *Cosy* Customers Change Their Behavior: To better understand these effects on the level of the half-hour[49], we run a variation of a TWFE model using half-hourly smart meter data for a random sample[50] of 500 Octopus Energy customers (among our heat pump installation analysis sample) and another random 500 customers from our *Cosy* analysis sample, in both cases looking at consumption data from the 13 December 2021 to 06 March 2024. We model:

$$\mathrm{Y}_{it} = \omega_0 \sum_{s=1,\ldots,48} \mathrm{SP}_t^s + \alpha \sum_{s=1,\ldots,48} \mathrm{SP}_t^s \times \mathrm{X}_{it} + \beta \mathrm{HDD}_{it} + \delta_t + \gamma_i + \epsilon_{it} \tag{8}$$

where: Y_{it} is half hourly electricity consumption in kWh for household i on settlement period t; SP_t^s is a set of dummy for all the 48 settlement periods of a day s (so equivalent to half hour; the dummies are equal to 1 if the settlement period s is equal to the settlement period in half hour t; X_{it} is a dummy variable equal to 1 if the customer has a heat pump installed, 0 otherwise (or alternatively a dummy variable equals 1 if the customer has adopted Cosy, 0 otherwise); HDD_{it} is the average heating degrees in day t and GSP of household i; and δ_t, γ_i are day t and household i fixed effects. The standard errors are clustered at the household (i) level.

We visualize these models' results in Figure 8, which illustrates the average electricity consumption by settlement period (half-hour intervals) for customers. This visual representation

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[49] Most Octopus Energy customers' smart meters record half-hourly consumption data; this is thus the most granular level of temporal disaggregation. In Great Britain, retailers procure electricity and settle their customers' consumption against that procurement at the half-hourly level, so half-hours are often known as "settlement periods". We use half-hour and settlement periods synonymously.

[50] We run the analysis on a random subsample due to computational constraints of running a large TWFE interaction model on 220 millions rows

helps to differentiate the impact of each intervention on electricity use over time. We see a tailing off of the effect in each *Cosy* off-peak period. We hypothesize that this is because people set their thermostat setpoints higher in these periods and by the end of the period the home is more likely to have reached the setpoint temperature, so the heat pump is not working as hard. This hypothesis is corroborated by evidence from a survey we sent to customers who had switched to *Cosy Octopus*, discussed immediately below.

We also see strong suggestive evidence that the *Cosy* impacts are driven by customers modulating their heat demand from a particular heterogeneity analysis we conduct. Octopus Energy, for commercial purposes, developed an algorithm to predict homes' heat loss, in kW. Heat loss is an important measure for heat pump installations, as it influences installer recommendations on heat pump size. Octopus Energy created their algorithm using publicly available data, mostly from customers' EPC, for example customers' floor area and the EPC's predicted annual heating and hot water usage (in kWh). We find that higher predicted heat loss is associated with higher *Cosy* impacts in both the off-peak and peak periods (see Figures A.33 and A.34).

Survey Responses: We conducted a survey to understand more about the mechanisms of energy demand shift inside the home, as well as heat pump and other low carbon technology (LCT) interactions. We sent our survey to 1,000 *Cosy* customers on 08 July 2024, in which 39% of recipients responded.[51] According to these customers, three brands – Mitsubishi, Daikin, and Vaillant – constitute the majority of heat pumps. Of the 70% of respondents who know their heat pump's size, the majority have heat pumps between 7-16kW. The implied median size is 9-12 kW.

We also ask about whether and how customers respond to Cosy's different unit rates. 85% of respondents say they change their energy use in response to the time-of-use pricing schedule. Among customers who did not respond affirmatively to this question, some added free-text responses that indicate they charge and discharge a home battery rather than changing other energy consumption behaviors. We see suggestive evidence in Table A.11 that battery charge and discharge is indeed an important part of the *Cosy* impact for customers with home batteries. Among respondents who respond to the time-of-use pricing schedule, 59% do so using a smart thermostat. Respondents could "tick" multiple options to this question; other popular methods included manual adjustments (34%), using alternative heating sources (11%), and activating a special mode on the heat pump (8%). Among this same 85% of respondents, other key changes to the home's electricity consumption included modulating how and when the home battery charges and discharges (38%) and doing likewise with an EV charger (17%). Many free-text responses noted manual and semi-automated strategies involving other appliances, such as avoiding using the dishwasher and other energy intensive appliances during the peak rate

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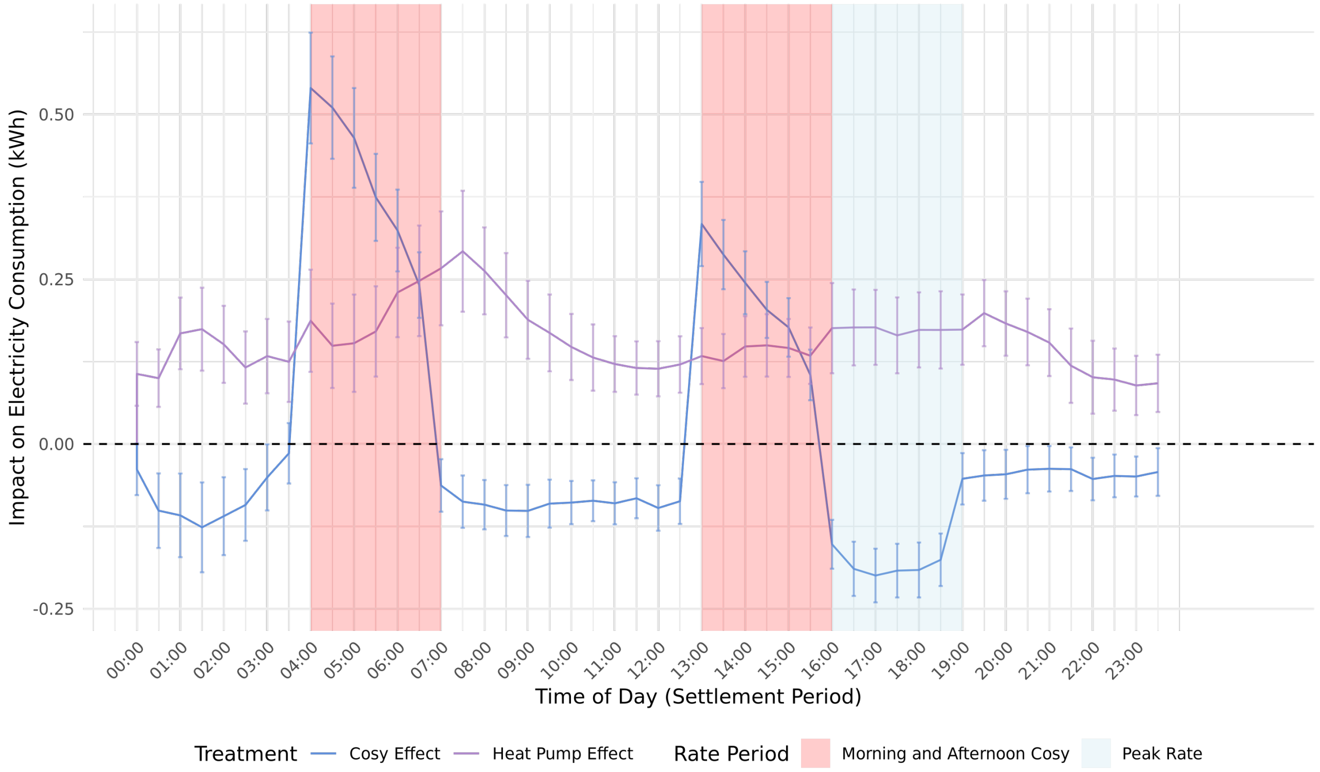
[51] We see in Table A.13 that respondents and non-respondents are similar on key observable characteristics – property energy efficiency rating, floor area, and property value.

Figure 8: Consumption by Half Hour



Note: The purple line is the impact per half-hour of heat pump installation itself in each half-hour of the day. The blue line is the impact of *Cosy* adoption in each half-hour of the day. Coefficients and 95% confidence intervals are from a TWFE model using half-hourly smart meter data for a random sample of 500 Octopus Energy customers (among our heat pump installation analysis sample) and another random 500 customers from our *Cosy* analysis sample, in both cases looking at consumption data from the 13 December 2021 to 06 March 2024. We interact the heat-pump / *Cosy* indicator with half-hour of the day; the omitted category is 1 (midnight). We also control for household, half-hour, and day fixed effects, heating degree days, and suspected EV charging (as indicated by their smart meter consumption signature – 3.5kWh/half-hour, i.e., 7kW, for 4 to 12 consecutive half-hours). To plot the effect of heat pumps, we only use customers without a time-of-use tariff to avoid capturing load shifting from *Cosy* or other time-of-use tariffs that heat pump adopting customers tend to adopt. (We do not exclude them from the daily/weekly analysis of heat pumps in Section 3.1, as we assume that the time-of-use tariffs shift consumption within the day rather than creating or destroying demand, as we find with *Cosy* in Section 3.2.1.) We show in Figure A.20 this same plot, but where we *include* these customers on time-of-use tariffs in the heat pump analysis sample.

period and using special water heaters during specific periods. In summary, customers seem to employ a mix of methods to respond to the time-of-use pricing schedule, but automated methods dominate, in particular using a smart thermostat to set thermostat temperatures in line with the pricing schedule.

Finally, we ask about characteristics about the home and occupants. Among respondents, 60% have solar PV panels, 38% have batteries, and 18% have electric vehicle(s). Only 32% have no LCTs other than their heat pump. We also ask when the customer's heat pump was installed. We find that 18% have heat pumps installed before 2020; there is a relatively uniform spread of installations between 2010 through 2019, with very few before 2010. We see very fast growth in installations in 2020 and beyond: 4% of the 382 customers had installations in 2020, 10% in 2021, 21% in 2022, 27% in 2023, and 17% in (the first half of) 2024.

Heat Pump Ownership: We also consider whether our identification of the impact of *Cosy* might be biased by customers adopting heat pumps *near* in time to adoption of the *Cosy* tariff. We find that our results are similar across a range of model specifications that control for heat pump installation date, among different sets of customers where we know their heat pump installation date (see Figure A.21).

EV Ownership: In Table A.9, we do the same check as in Section 3.1.4 and include a binary variable for whether a customer has the electricity consumption signature of EV ownership. We find that EV ownership does affect the coefficients on *Cosy* adoption; their "Other" period consumption reduction is greater than non-EV-owners, as is their peak period reduction; and their morning *Cosy* period consumption increase is higher than non-EV-owners.

To understand this result in more depth, we then conduct another analysis, focusing specifically on EV charging events before and after *Cosy* adoption. For each event, we define the main period as the time during which most of the charging occurred. For each charging event, we examine the probability of it occurring in each of the four periods of interest in our main analysis (i.e., see Table 2). We use a simple linear probability model with customer and day fixed effects. Our findings indicate that, prior to *Cosy* adoption, 87% of the charging events took place during the "Other" period. Following *Cosy* adoption, charging during the "Other" and "Peak" periods decrease by 62 and 4 percentage points, respectively. This decrease is offset by an increase in charging during the "Morning Cosy" period (+56 percentage points) and the "Afternoon Cosy" period (+10 percentage points).

Table 3: Cosy Adoption on Probability of Charging EV by Period

Dependent Variable:	Charging EV			
	Morning Cosy	Afternoon Cosy	Peak Rate	Other
Model:	(1)	(2)	(3)	(4)
Variables				
Cosy Contract Active = 1	0.5562***	0.1040***	-0.0416***	-0.6185***
	(0.0146)	(0.0074)	(0.0049)	(0.0166)
Pre-Treatment Average Half Hourly Consumption	0.0534	0.0299	0.0472	0.8695
Fixed-effects				
Household	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes
Fit statistics				
Observations	127,789	127,789	127,789	127,789
Number of Households	1,743	1,743	1,743	1,743
R^2	0.53117	0.25667	0.19607	0.64428

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: We show the results of four OLS models where the dependent variable is whether a charging event occurred in the period of interest – morning *Cosy* 4am-7am (column 1), afternoon *Cosy* 1pm-4pm (column 2), peak 4pm-7pm (column 3), and all other hours of the day (column 4). The sample is 127,789 charging events among 1,743 *Cosy* adopters for whom we detect evidence of EV charging. Where a charging events stretches across multiple periods, we attribute it to the period that comprises the *majority* of the event (in minutes). We see that among these EV owning *Cosy* adopters, *Cosy* adoption is associated with more charging the off-peak period and less in the peak and other periods.

Cosy Leavers: Finally, we focus on customers that leave Cosy. We run the main regression but add an interaction for leavers to see if leavers performed differently while they were on Cosy. In Table A.10, we find that leavers actually shift away from the peak as much as other customers. However, they shift load more from other time periods to the morning off-peak period, an indication that they might be more likely to be charging an EV than non-leavers. We explore this hypothesis by examining the share of customers with detected EVs among customers that stay on *Cosy* versus the leavers. We find that leavers are twice as likely to have an EV (38% versus 23%). This pattern may also explain why people that leave *Cosy* are still quite likely to stay on smart tariff. The main reason for leaving is not the hassle or difficulty of being on a smart tariff but the interactions with other LCTs that customers might have.

3.2.3 Dynamic ATTs

We plot dynamic ATTs for half-hourly electricity consumption during the four periods of *Cosy* tariff's pricing in Figure 9.[52] We see immediate impacts on consumption in all four of these periods. As with our analysis of the impact of heat pumps in Section 3.1.1, there appears to be differing impacts over time, but we believe these seeming changes in the dynamic ATT may be caused by the *Cosy* treatment effect sensitivity to temperature/season discussed in Section 3.2.4 and the nonuniform adoption of *Cosy* over time, rather than genuine fatigue, habituation, or learning effects.[53]

3.2.4 Seasonal Variations

In this section, we explore the impact of *Cosy* on electricity consumption throughout the year. We show below the four plots representing the ATT by Calendar Time for each period (Morning Cosy, Afternoon Cosy, Peak Rate, Other and daily Overall) in Figure 10. The two first plots reveal significant load shifting to the two *Cosy* off-peak periods. The shift is largest during colder months (October to March). On the other hand, load shifting is close to zero during warmer months.

The third and fourth plots indicate that the increase in off-peak time consumption is associated with a decrease in peak and other time periods. Interestingly, this effect persists during the summer, indicating that *Cosy* adopters shift not only heating but also other appliance usage. This finding suggests the potential for further comparison with load shifting patterns observed under other tariffs.

In terms of general consumption, we find a moderate increase during the winter but decrease during the summer. Together, these effects average out to a main effect that centers around zero on average. We hypothesize that the peak reduction in summer drives the overall consumption reduction in summer - i.e., at least some demand destruction, rather than purely shifting. However, this may be paired with some demand creation in the winter, causing a higher overall consumption during that season.

The magnitude and persistence of the *Cosy* effects align with the hypothesis discussed in Section 3.2.2 that most customers are responding to *Cosy* by using smart thermostats. Once a customer sets up their smart thermostat schedule to respond to the *Cosy* tariff, such as by having lower thermostat set-points during the peak period and higher thermostat set-points during the off-peak periods, this one-off behavior could plausibly be expected to lead to durable changes to

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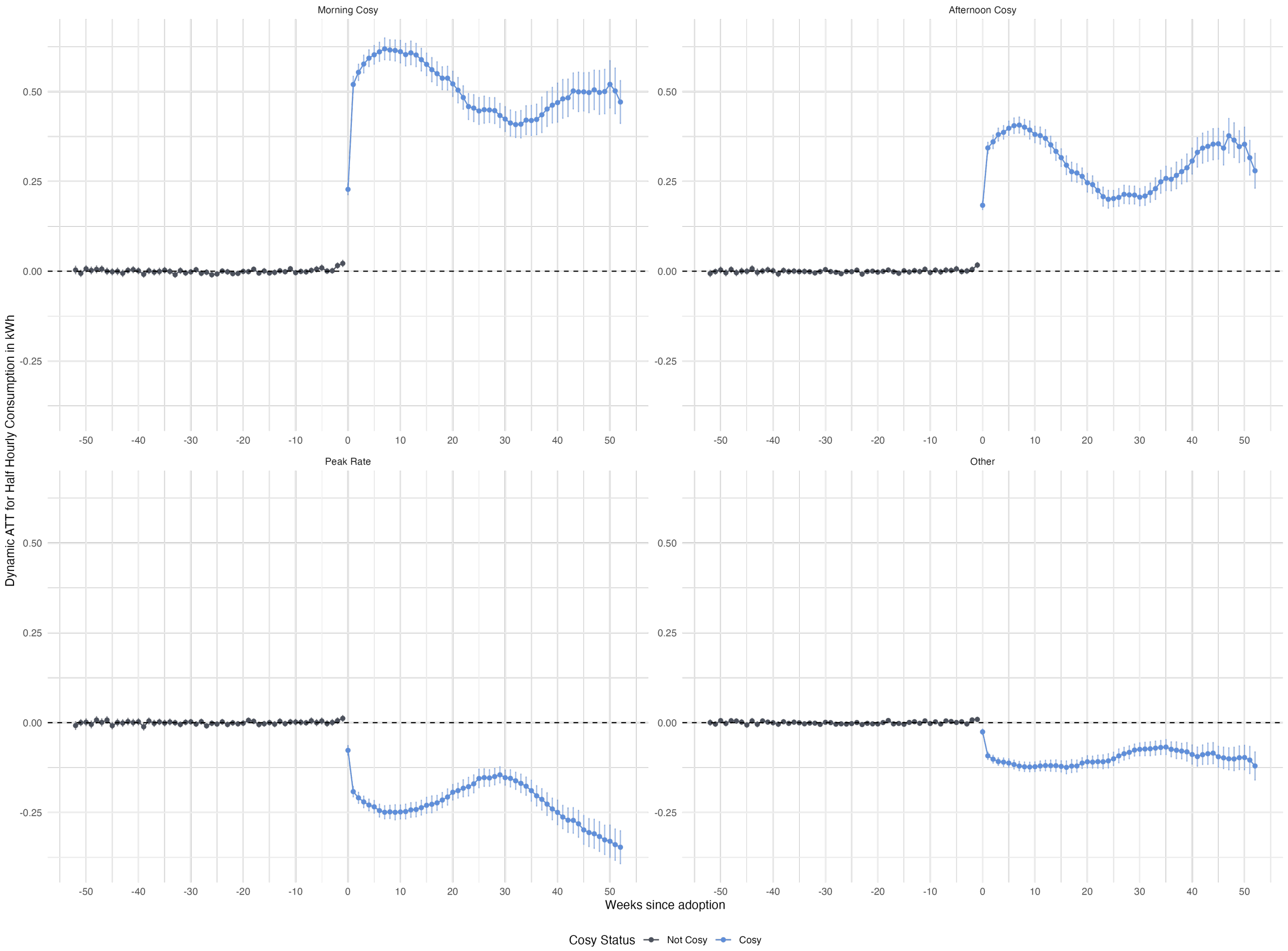
[52] We use a varying baseline here. For the same plots with universal baselines, see Figure A.22; and for an alternative estimator from Borusyak et al. (2024), see Figure A.38. Finally, see Section A.2.12 for TWFE event study visualizations.

[53] For more investigation of how these cohort and seasonal dynamics may interact, see Section A.2.8.

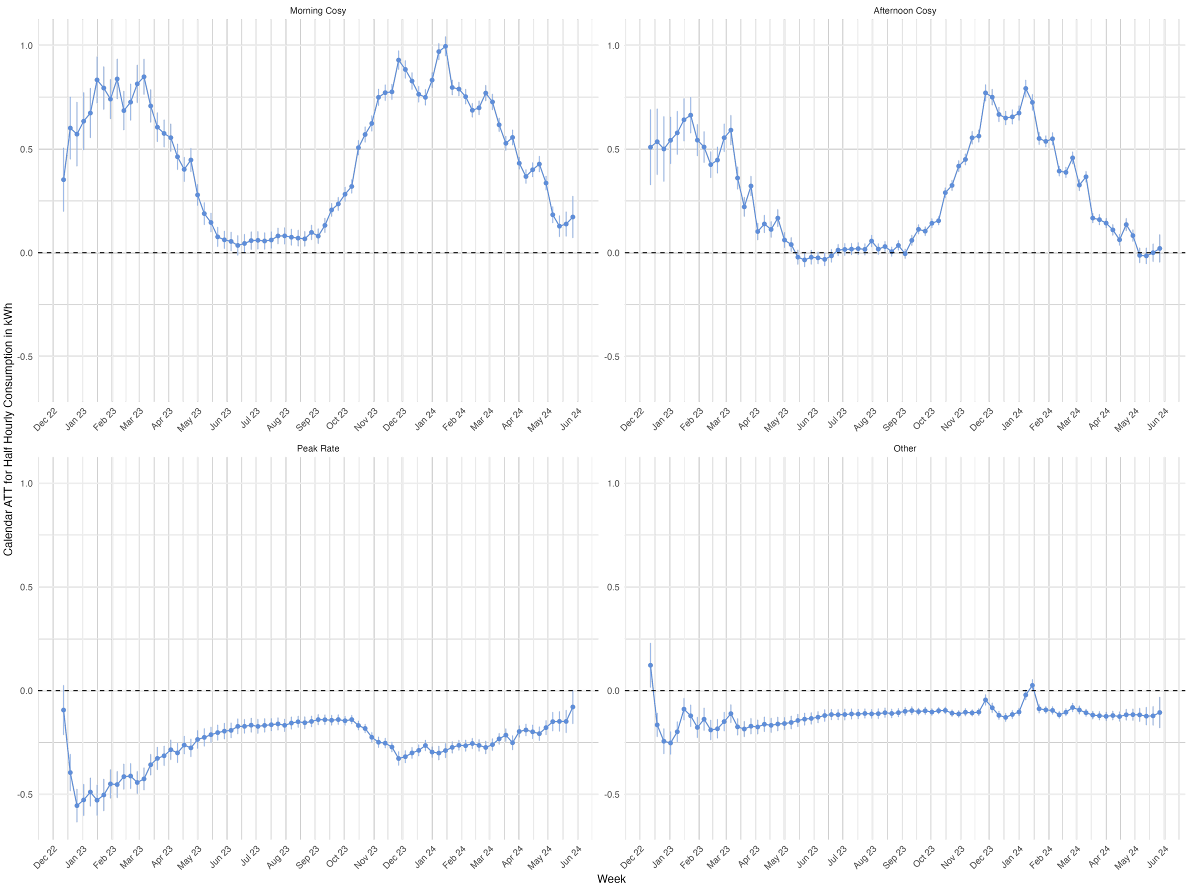
Figure 9: Cosy Dynamic ATTs



Note: We show dynamic ATTs from our CS models of the *Cosy* impact on customers' electricity consumption by *Cosy* period. Colors: black indicates before adoption, while blue indicates after adoption. Top left: morning off-peak. Top right: afternoon off-peak. Bottom left: evening peak. Bottom right: all other periods of the day.

customers' consumption profile. This hypothesis is also consistent with the seasonal pattern of Cosy's impact, given that thermostat set-points only affect the heat pump's consumption when they are above the home's internal temperature. As heating needs abate in warmer months, we would expect to see a diminishing in the impact of *Cosy* if that impact were driven by customers setting up a smart thermostat schedule (or other similar automation). We further explore this relationship between *Cosy* and temperature in Section 3.2.5.

Figure 10: Cosy Electricity Calendar ATTs



Note: We show calendar ATT from our CS models of the *Cosy* impact on customers' electricity consumption by *Cosy* period. Top left: morning off-peak. Top right: afternoon off-peak. Bottom left: evening peak. Bottom right: all other periods of the day.

3.2.5 Outside Temperature

In order to investigate the relationship between load shifting induced by *Cosy*'s prices and the seasonal variations that we observe in Section 3.2.4, we plot the interaction between the average outside temperature in degrees normalized by the TWFE coefficient for that period [54] and *Cosy* adoption in Figure 11. We control for customer and day fixed effects as well as daily average outside temperature in ºC, meaning that we only capture the additional impact of a change in temperature after adopting *Cosy*. The direct impact of temperature on electricity consumption is not plotted in this graph.

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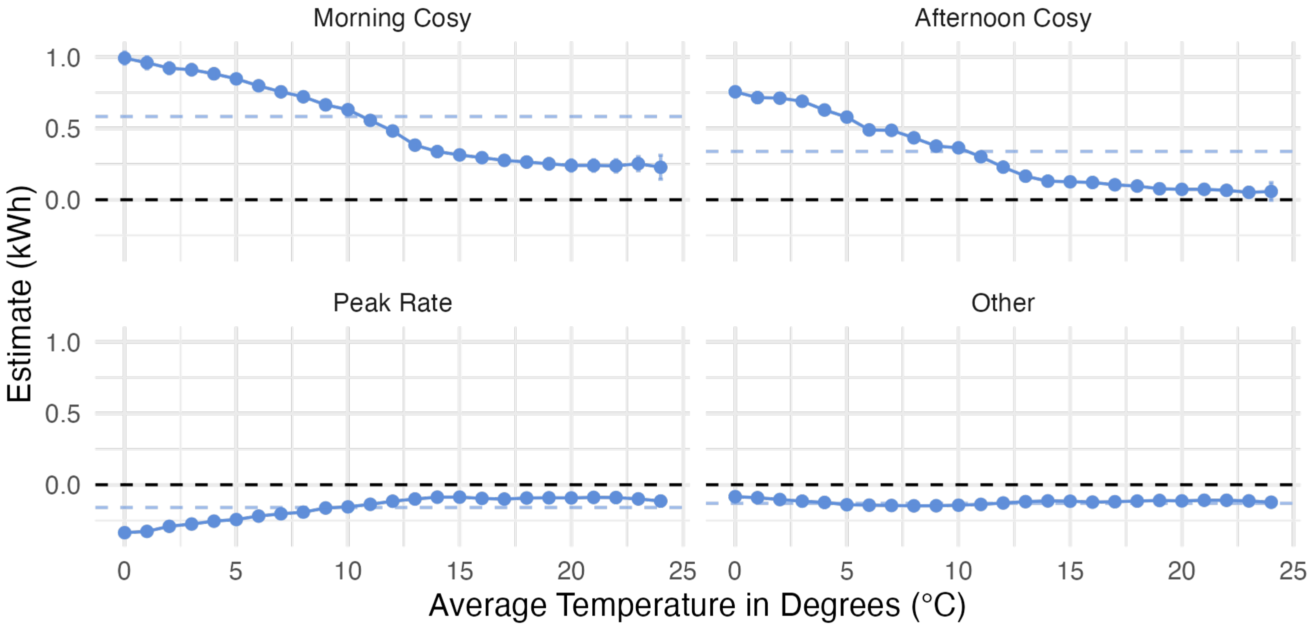
[54] We use average daily temperature measured at the GSP Group level, based on the highest-quality weather station in the GSP Group. GSP Groups are zones commonly used in the energy sector in Great Britain to divide customers geographically. There are 14 GSP Groups. These are the same regions that determine slight variations in the exact prices of *Cosy*, as shown in Section A.2.1.

Figure 11: Impact of *Cosy* by Outside Temperature



Note: We show the interaction between temperature (the average temperature on a day) and heat pumps' impact on daily electricity consumption in kWh (left vertical axis) in a TWFE model. We also show the TWFE ATE main effect in dashed blue, and thus on the right vertical axis we show the ratio of the TWFE interaction over the main effect; we interpret this ratio as showing when the temperature-conditional heat pump impact is higher or lower than the *Cosy* "main effect".

For all periods, the impact of *Cosy* is double the average treatment effect from Table 2 for the coldest outside temperatures (shown in blue-dashed line in Figure 11). For both off-peak periods, we find that the colder the period, the more shift in consumption takes place. The relationship between increased shifting and temperature stops around 14ºC, giving credence to the idea that this extra shifting is heating from peak time being displaced at cheap periods. During the peak period, we observe the reverse relationship, where more and more consumption is shifted away after adoption as temperatures get colder. There does not seem to be a point where customers are unable to shift more, but it is important to note that we do not observe many very cold days, with very few peak periods where the average temperature was below 0ºC.

This result of *greater* shifting when it is colder outside may be considered surprising. One might expect an attenuation in shifting – especially of shifting away from the peak period – when the temperature was colder outside, based on the idea that customers might be less willing to sacrifice comfort at these periods. However, the relationship with temperature makes sense when one considers the counterfactual consumption in these homes is also higher than usual when it is colder outside, as shown in Section 3.1.5.[55] Finally, we do not observe a strong relationship between outside temperature and *Cosy* adoption for other periods.

3.2.6 Heterogeneity analysis

We conduct heterogeneity analyses to understand the moderators for our treatment effects. We examine treatment effects for customers with differing annual electricity consumption, EPC ratings, floor area, and whether or not the most recent tariff before adopting *Cosy* was a time-of-use tariff. Higher annual electricity consumption and floor area are both associated with larger reductions in peak time consumption, suggesting that larger consumers load shift more than smaller consumers, in absolute terms. Customers who previously had a time-of-use tariff also achieve greater peak-period reductions, indicating they might be more responsive to the incentives provided by Cosy. However, the impact of *Cosy* adoption does not significantly differ by EPC rating (A to G), suggesting that home energy efficiency does not play a major role in the effectiveness of *Cosy* in reducing peak time consumption, or that these overall ratings are noisy proxies for properties' efficiency.

Annual electricity consumption: As shown in Figure A.29, higher annual energy consumption is associated with a larger *Cosy* reduction of peak time consumption.[56] For context, the median annual consumption is 5,258 kWh (5.258 MWh) and the mean is 6,106 kWh (6.106 MWh), with the distribution being quite skewed to the left. Therefore, while the average treatment effect is a reduction of 1.2 kWh, large consumers are driving this result. When we normalize consumption by share of total energy per period, we find no significant difference in the impact of adopting *Cosy* depending on customers' annual consumption (see Figure A.30).[57]

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[55] Even so, one might expect a treatment effect that neither diminishes nor increases with lower temperature. There is theoretically a linear relationship between energy input and heat output because the rate of heat diffusion is proportional to the difference in temperatures (the "gradient"), and this would imply no change in the absolute kWh difference between *Cosy*- and non-*Cosy-adopting* homes depending on external temperature. Instead, we see a pattern of greater shifting at lower temperatures. We believe the reason for this pattern may be due to heat pumps' load compensation, where heat pumps raise their flow temperatures, sacrificing some efficiency, when the difference between indoor desired temperature and indoor actual temperature widens. This load compensation would be more dramatic in homes with higher thermostat setpoints, creating greater shifting away from the peak period in homes who adopt *Cosy* and in doing so set lower setpoints during the peak period.

[56] In the British energy sector, EAC, an acronym for Estimated Annual Consumption, is an important measure that retailers hold for all customers for billing and settlement purposes.

[57] We examine how this and other treatment effect heterogeneity affects our estimates in Table A.24, where we re-weight our sample to have the identical covariate distribution as Octopus Energy smart meter customers on annual electricity consumption, property value, energy performance rating, and floor area.

Energy Performance Certificate ratings: We see in Figure A.28 that there is no significant interaction between *Cosy*'s impact on peak time consumption reduction and a home's EPC rating (A to G). This finding suggests that the energy efficiency of the home, as indicated by EPC ratings, does not significantly affect the impact of *Cosy* adoption on peak time consumption; or that the EPC ratings are noisy proxies for energy efficiency, at least among our sample. We also note that, due to the previous requirement that recipients of the Boiler Upgrade Scheme have no recommendations for loft and cavity wall insulation, the differences in EPC ratings within our sample is less likely to be due to significant differences in insulation.

Floor area: We see in Figure A.31 that there is a clear interaction between *Cosy* impact on peak rate period consumption and floor area. We believe this interaction is driven by floor area being a proxy for a home's heat loss rate, and thus is related to our annual consumption heterogeneity analysis results. Greater floor area homes shift more electricity consumption away from the peak, in absolute terms, than smaller floor area homes. Similar to the annual consumption analysis, this pattern is much less clear for *Cosy*'s impact on *share* of electricity consumption spent during the peak period, as seen in Figure A.32.[58]

Income and property value: We see a similar interaction between the average income level in a customer's area and shifting in Figure A.35, perhaps driven by different property sizes in these areas. We also look at heterogeneity in impacts by property value, finding again a similar pattern of higher shifting in higher-value homes. Finally, in Figure A.37, we plot savings from adopting *Cosy* (due to both structural winnings and gains from demand shifts), finding higher absolute savings in higher-value homes but similar savings as a proportion of customers' pre-*Cosy* bills.

Previous contract being a time-of-use tariff: In Table A.12, we interact $PrevIsToU$ (a binary indicator equal to 1 if the customer's most recent tariff before *Cosy* was a time-of-use tariff) with their current tariff being *Cosy*. We see greater load shifting when this is the case. For example, in Column 3, we see that the interaction term is significant (-0.0679 kWh per period), indicating that customers previously on a time-of-use tariff reduce their peak time consumption significantly more after adopting *Cosy*. This pattern could be due to the presence of additional LCTs that prompted the original change to a time-of-use tariff before moving to *Cosy*, or to some other latent advantage these customers have in shifting their electricity consumption that drives their tariff choices even before *Cosy* adoption. However, these customers constitute a small minority (8.7% of our sample); our main results are mostly driven by the more than 90% of customers who were on flat-rate tariffs before adopting *Cosy*, given that the coefficients on $OnCosy_{it} = 1$ are similar in Table 2 as they are in Table A.12.

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[58] Heterogeneity by region (**??** may be related to differing average floor area among *Cosy* adopters by region.

4 Welfare analysis

In this section, we use the causal impacts we identify in Section 3.1.1, regarding the adoption of heat pumps, and Section 3.2.1, regarding the adoption of a time-of-use tariff specially designed for heat pumps, to investigate the two interventions' effects on customers' private expenditure, government spending on the subsidy for heat pump adoption, and societal welfare.[59] We use the marginal value of public funds (MVPF) as a measure of welfare and use resource, government, and social cost per tonne of CO_2eq as our measures of cost-effectiveness.

Environmental and economic benefits: For all of the above measures, we need to value the environmental and economic private benefits from heat pumps. In order to calculate and monetize greenhouse gas emissions abatement, we use a series of UK Government outputs for most calculations, supplemented with data from WattTime, a nonprofit that models marginal emissions intensities for each half-hour of the year. We use conversion factors from Department for Energy Security and Net Zero (2023*b*) to calculate the CO_2eq per kWh of natural gas consumption. This output also provides CO_2eq per kWh of electricity consumption in 2023, but we instead use a different UK Government (2024*a*) output to estimate long-run marginal emissions per kWh of domestic consumption for the years 2024 through 2043; this is necessary to account for electricity carbon intensity declining towards near-zero by 2050.[60] We use carbon values (£ per tonne of CO_2eq), akin to the Social Cost of Carbon, from the Department for Energy Security and Net Zero (2023*a*) valuation of greenhouse gas emissions for policy appraisal and evaluation.[61] We use UK Government (2024*a*) conversion factors for kWh of gas and electricity to monetize avoided air quality harms. In order to understand the CO_2eq abatement impacts of the causal effects of adopting *Cosy*, we use modeled marginal emissions intensities from WattTime; this is necessary because the UK Government emissions intensity factors we use for our other calculations do not estimate different emissions intensities by hour of day, whereas *Cosy*'s key behavioral impacts are related to *what time of day* customers consume electricity.

In our welfare and cost-effectiveness analyses, it should be noted that the estimates we use

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[59] The key results we use are: (i) Heat pump causal impact on **electricity** consumption (kWh, annual): 3,080; (ii) heat pump causal impact on **gas** consumption (kWh, annual): –9,351; (iii) *Cosy* adoption impact on consumption in the **peak** period (16:00 to 19:00) of the day (kWh, per half-hour): -0.2242; (iv) *Cosy* adoption impact on consumption in the **morning off-peak** period (04:00 to 07:00) of the day (kWh, per half-hour): 0.5071; (v) *Cosy* adoption impact on consumption in the **afternoon off-peak** period (13:00 to 16:00) of the day (kWh, per half-hour): 0.2926; and (vi) *Cosy* adoption impact on consumption in the **other** hours of the day (kWh, per half-hour): -0.1066.

[60] We use the latest estimates from UK Government (2024*a*), but there is inherent uncertainty in forecasting long-run emissions, which are sensitive to economic, societal, and technological developments.

[61] We use a 3.5% discount rate, as recommended by HM Treasury (2020) "Green Book" guidance, for all calculations of net present value. We do this even for avoided air quality harms, despite UK Government guidance to use a lower 1.5% discount rate for these specific harms. We use UK Government (2024*b*) data to convert $£_{non-2023}$ values into $£_{2023}$.

for the impact of heat pumps on electricity versus gas consumption is based on two slightly different samples, as discussed in Section 3.1.1. Our gas consumption impacts come from a sample of customers who overwhelmingly had gas boilers as their previous heating source. In contrast, our electricity consumption impacts include customers who had heating systems other than gas boilers before their heat pump installation. As we show in Figure A.10, heat pump impacts do vary by previous heating source. We believe this average impact is the correct estimate for welfare calculations given that the population of British households itself comprises a range of heating sources, not just gas boilers.[62]

We make a series of assumptions about the Boiler Upgrade Scheme subsidy and how it affects demand for heat pumps. The subsidy value per heat pump became £7,500 in October 2023. We assume that 50% of those who used the subsidy to purchase their heat pump were marginal adopters, and 50% were inframarginal, based on research into other subsidies for large energy related investments for homeowners (Hahn et al., 2024), similar to Davis (2023*a*)'s assumptions regarding uptake of a US tax credit for heat pumps.[63]

In estimating running cost differences between heat pumps and gas boilers, we use the UK Government (2024*a*) retail energy price forecast. In estimating the savings from adopting *Cosy*, however, we use Octopus Energy (2024) prices as of 15 June 2024. The reason for this difference is that, for analysis of *Cosy*'s impacts on customer bills, we need to compare within-retailer unit rates depending on customers' tariff choice, rather than using average electricity tariff rates across all British retailers.

Finally, we make assumptions about the average costs of air source heat pumps and gas boilers. As we discuss in Section 2.1, we estimate average total expenditure (private expenditure + subsidy) of Boiler Upgrade Scheme installations between November 2023 and June 2024 to be £12,713, implying a private expenditure of £5,213. We also assume that the alternative capital expenditure facing householders would be a gas boiler costing £2,250 (Myers et al., 2018).

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[62] Our sample composition is similar to the general public, with 85% of our sample previously having gas boilers, matching the Committee on Climate Change (2016) estimate for the proportion of British homes connected to the gas grid using a boiler and wet-based central heating system.

[63] We assume that inframarginal heat pump adopters value the subsidy "pound for pound" (i.e., a 100% transfer from Government to consumers), while marginal heat pump adopters value the subsidy at 50% of its value on average. For these marginal customers who are induced to get the heat pump from the subsidy, we do not know whether it was the first or last £1 of the policy that induced their response. If it was the first £1, then they would value roughly the entirety of the transfer at its cost. If it were the last £1, then they would have a near-zero valuation of the subsidy. Following the classic triangle approximation to deadweight loss in Harberger (1964) (and the approach taken in Hendren and Sprung-Keyser (2020) and Hahn et al. (2024)). The underlying assumption is that the latent value of the subsidy varies uniformly in the population, implying a linear demand curve. We also conduct a set of analyses assuming 25% of customers are marginal and 75% are inframarginal. In brief, these assumptions mean that in our MVPF estimations, we assume that customers enjoy 75% of the subsidy value in the analyses where we assume 50% of customers are marginal (or 87.5%, in the analyses where we assume only 25% of customers are marginal).

Private energy expenditure, carbon impacts, and avoided air pollution: Based on these assumptions, we find large impacts of heat pumps on CO_2eq and a range of impacts on private expenditure depending on whether customers adopt time-of-use tariffs like *Cosy*.

We find that heat pumps have somewhat higher operating expenditure (i.e., "running costs") than gas boilers, based on the consumption impacts we identify and current and forecast future retail prices. Heat pumps cost £190 more per year to run, based on Octopus Energy's standard tariff's electricity and gas prices as of 15 June 2024 (or £323 more per year based on the Government's estimated retail energy costs in 2024).[64] This latter estimate decreases over time, according to the UK Government (2024*a*) estimated retail energy costs in future years (where electricity retail prices decline relative to gas retail prices).[65] Currently, customers pay approximately £100 per year for their mains gas connection; insofar as a heat pump enables full disconnection from mains gas, this disconnection further reduces annual costs by £100. To derive a net present value of the higher or lower running costs of heat pumps compared to gas boilers, we assume that customers do disconnect from mains gas. Under this assumption, customer operating costs are slightly higher for heat pumps than gas boilers over the 20-year time horizon between heat pump versus gas boiler; the net present cost of the heat pump's higher operating expenditure is £1,159 over the 20 years (using UK Government (2024*a*) estimated retail energy costs). We choose 20 years as an important time bound given that heating systems tend to last for approximately 20 years (for example, Davis (2023*a*) also assumes 20-year lifespan in evaluating the welfare impacts of a heat pump subsidy in the US).

In total, the net private cost of the heat pump is then £4,121. This figure is the £5,213 private capital expenditure on the heat pump, minus the £2,250 avoided expenditure on a gas boiler, plus the £1,159 higher net present cost in terms of operating expenditures (all sums are rounded to the nearest £1).

Heat pumps have large impacts on customers' CO_2eq decrease in emissions, starting at 1.16 tonnes CO_2eq and increasing to 1.86 tonnes as the marginal emissions intensity of electricity approaches zero by 2043, totaling 32.9 tonnes of CO_2eq abated in the 20 years from 2023 through 2043. Overall, this indicates that heat pumps can reduce a household's CO_2 equivalent emis-

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[64] For context, we estimate that customers would pay approximately £2,200 per year for their energy pre-heat-pump-adoption on Octopus Energy's current standard tariff.

[65] We do not test whether consumers' expectations of the price match the Government data, but based on previous research on people using existing prices for forecasting (Anderson et al., 2013), our welfare estimates would not change.

sions by 68% throughout their operational lifespan.[66] For context, we calculate that 1.16 tonnes is 36% of the customers' pre-heat-pump adoption annual energy consumption CO_2eq footprint. The net present value of these CO_2eq benefits is £6,954.

Heat pumps also cause some reduction in air pollution in the UK associated with gas consumption. Their increase in electricity consumption is associated with some additional air quality harms, but the net impact of these two impacts is a benefit to air quality starting at £11/year in 2024. As with CO_2eq abatement, the impacts rise over time, to £16/year by 2043, as the UK electricity grid is forecast to decarbonize and therefore become cleaner from the perspective of air pollution as well. The net present value of these air pollution benefits is £206.

The impacts of *Cosy* result in near-zero impacts on CO_2eq abatement and large reductions in customers' annual expenditure on energy. Switching to *Cosy* saves customers £318 per year compared to if they were on the standard tariff at Octopus Energy. This is 17.9% of their pre-*Cosy* adoption electricity bill, assuming they were on Octopus Energy's standard non-time-of-use tariff. Of this £318 in savings, £78 is "structural" winnings (customers would save £78 per year even if their consumption patterns did not change), while £240 comes from their annualized consumption changes by period, multiplied by the difference in marginal price between the *Cosy* tariff and Octopus Energy's standard tariff, for each period of the day. Assuming these figures persist across 20 years, the net present value of these savings is £4,675.[67]

Fiscal externalities: The adoption of heat pumps causes four changes in Government revenue above and beyond the direct subsidy cost. First, we examine changes in VAT from avoided gas boiler purchases, which incur 20% VAT in the UK, whereas heat pumps receiving the Boiler Upgrade Scheme subsidy incur no VAT. Given our assumption that gas boilers cost £2,250 (Myers et al., 2018), £375 is VAT that the Government does not receive when customers instead purchase a heat pump.

Second, heat pumps also cause higher electricity and lower gas consumption, as shown in

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[66] This figure is based on the assumption that the impact of heat pumps and pre-heat pump energy consumption remain constant over time, with the only variable being the decreasing carbon intensity of electricity as it becomes cleaner. By way of comparison, Davis (2023*a*) estimates that a heat pump tax credit in the US abates only four tonnes of CO_2 over 20 years; suggesting that heat pumps themselves abate eight tonnes of CO_2eq given his assumption, similar to ours, that 50% of those receiving the credit are marginal. We believe the large difference in our estimates of CO_2eq abatement impact per heat pump is mostly due to assumptions about the carbon intensity of electricity versus natural gas. The US carbon intensity figure that Davis (2023*a*) uses implies that electricity is about twice as CO_2eq-intensive as natural gas. In contrast, our assumption, based on UK Government (2024*a*), is that the two sources of energy are nearly equal in CO_2eq intensity today, with electricity CO_2eq intensity falling to near-zero by 2043.

[67] In our welfare calculations, we do not measure any thermal discomfort, because due to the envelope theorem, people who adopt heat pumps and/or *Cosy* should be indifferent between more comfort and paying more in comparison to less comfort and paying less.

Section 3.1.1, but overall the running costs are higher, as discussed just above; across 20 years, the net present value of this extra VAT is £137. Third, heat pumps also cause extra Government revenue from the UK's Emissions Trading Scheme, which covers gas consumption from generators to produce electricity but *not* domestic gas consumption for heat. For each year from 2024 through 2043, we multiply the annual increase in electricity consumption from heat pump adoption (3,080 kWh) by the forecast long-run marginal carbon intensity from UK Government (2024*a*) and the forecast ETS allowance price (£ per tonne CO_2eq) from UK Government (2023). We find a net present value of this increased revenue of £355.

Finally, we model the benefit to future UK Government tax revenue from abated CO_2eq from the Boiler Upgrade Scheme. As Hahn et al. (2024) discuss, the costs of CO_2eq are partly driven by reductions in gross domestic product from climate change, which reduce tax revenue. We assume that the UK proportion of global GDP is 3.2% (PwC, 2024) and the proportion of UK GDP that the Government receives as tax revenue is 33.5% (Office for Budget Responsibility, 2024). We multiply the product of these proportions (1.07%) by the monetized benefits of the CO_2eq abatement caused by the heat pumps each year from 2024 through 2043. The net present value of this climate change abatement fiscal externality is £75.

The total value of these fiscal externalities is £191 in *extra* Government revenue per heat pump adoption. In our estimations (immediately below) of costs per tonne CO_2eq abatement and welfare analyses associated with the Boiler Upgrade Scheme specifically, we multiply this figure by the proportion of customers assumed to be *marginal* in adopting the heat pump due to the Boiler Upgrade Scheme, so as to avoid crediting or penalizing the subsidy for the impact of heat pumps that would have been adopted notwithstanding the subsidy.[68]

Costs per tonne CO_2eq abatement and welfare analysis: Next, we examine how these estimates relate to welfare and cost-effectiveness. Following Hahn et al. (2024), we examine in Table 4 how impacts vary depending on whether we look at resource cost per tonne of CO_2eq abatement, social cost per tonne, government cost per tonne, or the MVPF. As Hahn et al. (2024) discuss, resource cost per tonne of CO_2eq abstracts from the causal effects of a policy, ignoring

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[68] There are a range of *potential* fiscal externalities we believe do not apply in this context. We do not model changes to electricity and gas prices caused by the changes in electricity and gas consumption that heat pumps cause (known as spillovers or rebound effects) because the UK demand is small in the context of global trade of natural gas, and prices for natural gas for domestic heating as well as electricity are both ultimately set to a great extent by the cost of globally traded natural gas commodity benchmarks. We do not model changes in corporate profits and therefore corporate tax revenue to the UK Government on the assumption that the markets we analyze are competitive. We do not anticipate changes in Government revenue or expenditure on programs to support renewable generation such as the Renewable Obligation, Feed-in-Tariff, or Contracts for Differences because they are all subsidies for non-marginal generators. We also model no changes to revenue from the Climate Change Levy, as it only covers non-domestic electricity and gas consumption, whereas the Boiler Upgrade Scheme incentivizes heat pump adoption by domestic households.

the cost of subsidizing purchases by inframarginal customers. Social cost per tonne captures a comprehensive set of non-resource benefits, including the benefits of avoided air pollution, but the canonical formulation still ignores the cost of transfers to inframarginal customers. Government cost per tonne of CO_2eq does account for the cost of transfers to inframarginal customers, but it counts only the cost of these transfers without crediting that transfer as a partial benefit to recipients.

The MVPF calculates the net benefits of policies relative to net government cost, accounting for both costs and benefits of transfers to inframarginal customers. Following Hahn et al. (2024), we assume perfect competition in the market for heat pumps x (i.e., no producer profits), assume V captures all the environmental benefits due to a change in the quantity of heat pumps x, we can calculate the MVPF as:

$$MVPF = \frac{xd\tau + Vdx}{xd\tau + \tau dx} \tag{9}$$

$$= \frac{1 + \frac{V}{p}(-\epsilon)}{1 + \frac{\tau}{p}(-\epsilon)} \tag{10}$$

where $-\epsilon = \frac{dx}{-d\tau}\frac{p}{x} = \frac{dx}{dp}\frac{p}{x}$ is the percentage change in consumption of heat pumps in response to a 1% increase in consumer price (i.e., ϵ is the price elasticity of heat pump demand). Here, the environmental impact of the policy change is given by the elasticity, ϵ, times the environmental externality of the heat pump relative to the price of the good, $\frac{V}{p}$. The fiscal externality is given by the elasticity, ϵ, times the tax rate relative to the price of the good $\frac{\tau}{p}$.

We find that the social/resource cost per tonne diverges sharply from the government cost per tonne, demonstrating the sensitivity of cost per tonne analyses to their definition.[69] Indeed, we see negative social and resource cost per tonne (-£20/tonne and -£17/tonne, respectively) when assuming that 100% of heat pump owners adopt *Cosy*. This result stems from the net private cost of the heat pump (£4,121) being lower than the net present value of the savings we calculate from switching to *Cosy* (£4,675). The MVPF figures are similar to each other whether or not we assume adoption of *Cosy*, as these private benefits of *Cosy* do not influence the MVPF of the Boiler Upgrade Scheme subsidy specifically. As shown in Table 4, we find MVPFs above 1, both where we assume that 50% of BUS recipients are marginal and where this figure is only 25%, indicating that the Boiler Upgrade Scheme has positive welfare benefits. Our preferred specification is the second row Table 4 – 1.24. We show the benefits and costs that drive this estimate in Figure 12.

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[69] Interestingly, we find similar cost per tonne as Davis (2023*a*), who estimates that a $2,000 heat pump credit in the US would be associated with a $500 cost per tonne of CO_2eq. This similarity to our result hides some underlying differences. We estimate approximately four times higher CO_2eq abatement from heat pumps, due to Great Britain's lower carbon intensity of electricity compared to the US, but the UK heat pump subsidy is also approximately four times higher than the US subsidy that Davis (2023*a*) investigates. Note that it is not clear to us whether Davis (2023*a*) looks at cost per imperial or metric ton. All of our calculations are in terms of tonnes (i.e., metric tons).

Table 4: MVPF and Other Measures of Cost Effectiveness

	Discount Rate	% Marginal	MVPF	Resource Cost per tonne	Government Cost per tonne	Social Cost per tonne
Just BUS	3.5%	25%	1.12	£125	£906	£122
Just BUS	3.5%	50%	1.24	£125	£450	£122
BUS + Cosy	3.5%	50%	1.24	-£17	£450	-£20
Just BUS	2%	25%	1.16	£128	£904	£125
Just BUS	2%	50%	1.32	£128	£448	£125
BUS + Cosy	2%	50%	1.32	-£33	£448	-£36

Note: There are many ways of evaluating the benefits and costs of the UK's heat pump subsidy, the Boiler Upgrade Scheme (BUS). We show the marginal value of public funds (MVPF) as a measure of welfare and use resource, government, and social cost per tonne as measures of cost-effectiveness. We show how these measures vary depending on the discount rate (HM Treasury (2020) recommends 3.5%, but we also show results for the more traditional 2% discount rate, percentage of customers who are marginal (i.e., motivated by BUS to adopt a heat pump) versus inframarginal (i.e., would have adopted a heat pump regardless of the subsidy), and whether we assume heat pump adopters also adopt Cosy. Our preferred specification is the second row, with no *Cosy* adoption, a discount rate of 3.5%, and an assumption that 50% of customers are marginals and 50% are inframarginals.

The above welfare calculations do not include any learning by doing benefits. Hahn et al. (2024) show that these learning by doing benefits can increase MVPFs significantly, and indeed are the largest component of the numerator of the MVPF for certain policies. However, we lack evidence on the extent to which heat pump costs are declining as cumulative production increases. There is evidence of a 14% learning rate for gas boilers (Weiss et al., 2009), but it is unclear whether this rate would transport well to heat pumps.[70] If we assume that the learning rate for gas boilers is similar to heat pumps, then we can construct an MVPF with learning by doing. We use the worldwide heat pump cumulative production up until 2023 and then the 2023 production.[71] We also assume the price elasticity of demand of heat pumps is -1.2, the learning rate is 14%, and 100% pass through to consumers. We then can estimate the two benefits of the learning rate: the benefits to all of the inframarginals around the world of reducing prices and the benefits to the environment from getting marginal households to adopt heat pumps faster. We estimate the MVPF to be 1.90 when we include such benefits of learning by doing

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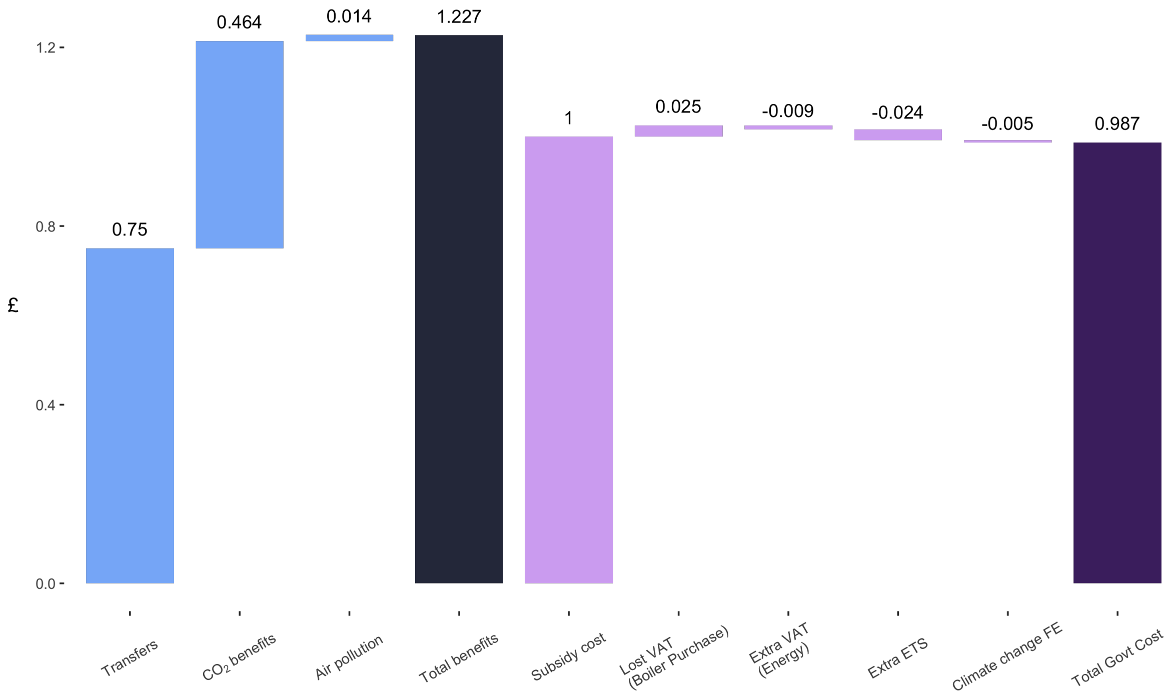
[70] Some evidence shows very small or zero decrease in heat pump prices, so far, in the UK (Heptonstall and Winskel, 2023, Sissons et al., 2022), but there may be learning by doing masked by inflation in the cost of key inputs, temporarily constrained supply enabling high mark-ups, more complex homes being attempted over time (making simple year-to-year comparisons invalid), or incomplete pass-through of the subsidy to consumers. There is no publicly available data on the marginal cost of a heat pump.

[71] By the end of 2023, there was 1220 GW of heat pump capacity operating worldwide (up from 500 GW in 2010 (IEA, 2023)), with sales in 2023 being 110 GW. For this analysis, we assume 8kW heat pumps, based on 8kW being the average size in our sample.

Figure 12: Marginal Value of Public Funds (MVPF) of Boiler Upgrade Scheme



Note: We show the welfare benefits and costs of the Boiler Upgrade Scheme's subsidy for air-source heat pumps – specifically, for the second row of Table 4 ("Just BUS", 3.5% discount rate, 50% of customers as marginal). We show these benefits and costs per £7,500, which from October 2023 is the level of the subsidy offered to British households for adopting an air-source heat pump. In blue, we show benefits: transfers to customers receiving the subsidy, CO_2eq abatement benefits from marginal customers, and air quality benefits from marginal customers. These total £9,205 per £7,500 subsidy (1.227, in navy). In light purple, we show the costs. First, the subsidy itself. Next, lost VAT from avoided boiler purchases from marginal customers. Then, three increases in Government revenue that reduce the Government cost: extra VAT from increased energy expenditure, extra Emissions Trading Scheme (ETS) revenue from marginal customers, and the "climate change fiscal externality" of tax revenue from avoided climate change. These total £7,404 per £7,500 (0.987, in dark purple). The MVPF is then 1.227/0.987 = 1.24.

(£1,698 of benefits to future inframarginals, or £0.23 per £1 subsidy cost; and £3,193 from future environmental benefits, or £0.43 per £1 subsidy cost).

Optimal subsidy: In this section, we estimate the optimal subsidy of the BUS, which is where the MVPF=1. This is the point at which £1 additional subsidy generates no further societal benefit, maximizing welfare benefits. In our calculations above, the average MVPF of BUS across every pound of the £7,500 subsidy with a price elasticity of -1.2. When we use this elasticity for the last £1 of the £7,500, the MVPF is 0.99.[72] We want to estimate the subsidy level at the optimal

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[72] The first £1 of the BUS subsidy has an MVPF of 1.71, which is higher than the MVPF of the first $1 of EV subsidies in the US.

value.[73]

For the heat pump subsidy (BUS), that would be:

$$1 = \frac{1 + \frac{6{,}954+206}{12{,}713-\tau}(-1.2)}{1 + \frac{\tau-191}{12{,}713-\tau}(-1.2)} \tag{11}$$

where £191 is extra revenue the government receives per heat pump installed. We solve for τ and estimate the optimal subsidy at £7,351, which is remarkably close to the current subsidy of £7,500. If we include the learning-by-doing benefits in the calculation, the optimal subsidy rises to £12,240. We can argue that this optimal subsidy is a lower end estimate because we do not include: (i) future grid benefits of heat pumps and time-of-use tariffs; and (ii) if the price expectation of gas prices is too low and the price expectation of electricity prices is too high.

Limitations and omissions: There may be benefits to the Boiler Upgrade Scheme and to heat pumps in general that we ignore in these MVPF calculations, which should be kept in mind in interpreting our results. These omissions mean that the MVPFs we present are likely lower bounds.

First, as discussed above, the 1.24 MVPF assumes no learning by doing benefits, which has a significant impact. We have estimated accounting for learning by doing could increase the average MVPF to 1.90, noting the limitations in evidence on heat pump learning rates.

Second, heat pumps may cause customers to adopt other low-carbon technologies such as home batteries and solar panels. Heat pumps increase customers' electricity consumption (as shown in Section 3.1.1), and this increased electricity consumption may increase the private benefits to homeowners from adopting home batteries and solar panels. Insofar as these additional technology adoptions cause further CO_2eq reductions, we undervalue the impact of heat pumps on CO_2eq abatement. However, there is not yet good evidence on the strength of the causal association between heat pump adoption and the adoption of other low-carbon technologies, so we ignore this potential benefit.

Third, the CO_2eq benefits we model from adoption of heat pumps increase meaningfully in the future due to the grid decarbonization assumed by UK Government (2024*a*). If the grid were to decarbonize faster (or more slowly) than expected, the CO_2eq benefits from *Cosy* adoption would be higher (or lower). A related issue is that adoption of time-of-use tariffs is an important *enabler* of a decarbonized grid, by making demand more responsive to grid needs, thereby allowing system operators to avoid using dispatchable fossil fuel generation to match unresponsive demand. We do not directly model this benefit.

Finally, there is an important uncertainty about retail energy prices in Great Britain in the

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[73] The non-marginal MVPF at the optimal subsidy could still be above 1.

near future: whether certain levies on electricity and implicit subsidies on gas will be reversed.[74] Lower retail electricity prices and higher retail gas prices would increase the private benefits from heat pump adoption by making electricity cheaper and gas more expensive per kWh; in turn, the resource and social costs per tonne of heat pumps would decrease. These regulatory changes would not directly affect the Government cost per tonne nor our MVPFs, except insofar as they affect customers' elasticity of demand for heat pumps.

5 Conclusion

Our study finds large impacts of heat pumps on customers' energy consumption – an overall reduction in energy consumption of 40% and a 36% reduction in CO_2eq (with the CO_2eq reduction per heat pump rising over time as the electricity grid decarbonizes). These effects are large and go a long way to decarbonizing heat in the energy market. We find that heat pumps reduce gas consumption (kWh) by three times as much as the electricity consumption (kWh) increase that they cause. Given that one unit of electricity currently costs more than one unit of gas, despite this large decrease in overall energy, we estimate that heat pumps cause slightly higher running costs between gas-heated homes and comparable homes heated with heat pumps. Policymakers in Great Britain can ensure that this lower consumption translates to savings for adopters of heat pumps by lowering the cost ratio of electricity to gas. This could include rebalancing the higher levies imposed on electricity compared to gas in Great Britain, and removing the exemption of domestic gas consumption from the UK Emissions Trading Scheme (where gas for electricity generation is not exempt).

We also find that heat pump owners' electricity hourly consumption profile is sensitive to the marginal prices they face during each hour of the day. Based on Octopus Energy's *Cosy Octopus* tariff designed for heat pump owners, we see an approximate doubling of consumption during off-peak periods and a halving of consumption during the evening peak. At current Octopus Energy tariff prices, switching to this tariff reduces customers' electricity expenditure by £318 per year (18% of annual energy costs), on average. Such private economic benefits should help the UK move away from the path dependence of using natural gas for heating (Gross and Hanna, 2019). We find little CO_2eq impacts of the tariff, at least at 2024 marginal carbon intensities modeled by WattTime. The greater impact may be on peak demand for future electricity grids: our findings show that, despite temporal and comfort constraints inherent in heat flexibility, heat pump owners respond to price signals to shift demand away from peaks. This shift could reduce network reinforcement needs and lower system costs associated with electrification, as suggested in energy system modeling (Franken et al., 2025), as well as reduce

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[74] The UK Government has committed to removing certain levies on retail electricity. The implicit subsidy for domestic gas consumption is that it is exempt from UK Emissions Trading Scheme costs, an exemption that may be removed in the future. See Department for Energy Security and Net Zero (2023*c*,*d*).

running costs to support heat pump affordability.

We see this load shifting away from peak periods even on the coldest days of the year and from all building types in our sample, contrary to concerns that load shifting from heat pump owners will not be possible under the temperature and grid conditions when it is needed most. Indeed, we find evidence that load shifting *increases* on the coldest days of the year. We see more load shifting from properties with greater floor size which, as a proxy for heat loss, suggests that flexibility remains possible from these buildings. We also find no correlation between load shifting and ratings from Energy Performance Certificates.

We find that the welfare impacts of the United Kingdom's main subsidy for heat pumps is welfare-enhancing under a range of assumptions about its effect on heat pump adoption, given our findings on the impacts of heat pump adoption. The average MVPF from the subsidy is £1.24 for every £1 spent. This MVPF is favorable in comparison to other energy efficiency subsidies and provides evidence to justify the continuation of the subsidy. The societal value of heat pump adoption would increase further if technology costs fall, including from learning by doing seen in the deployment of other technologies, and if the carbon intensity of electricity generation falls faster than expected.

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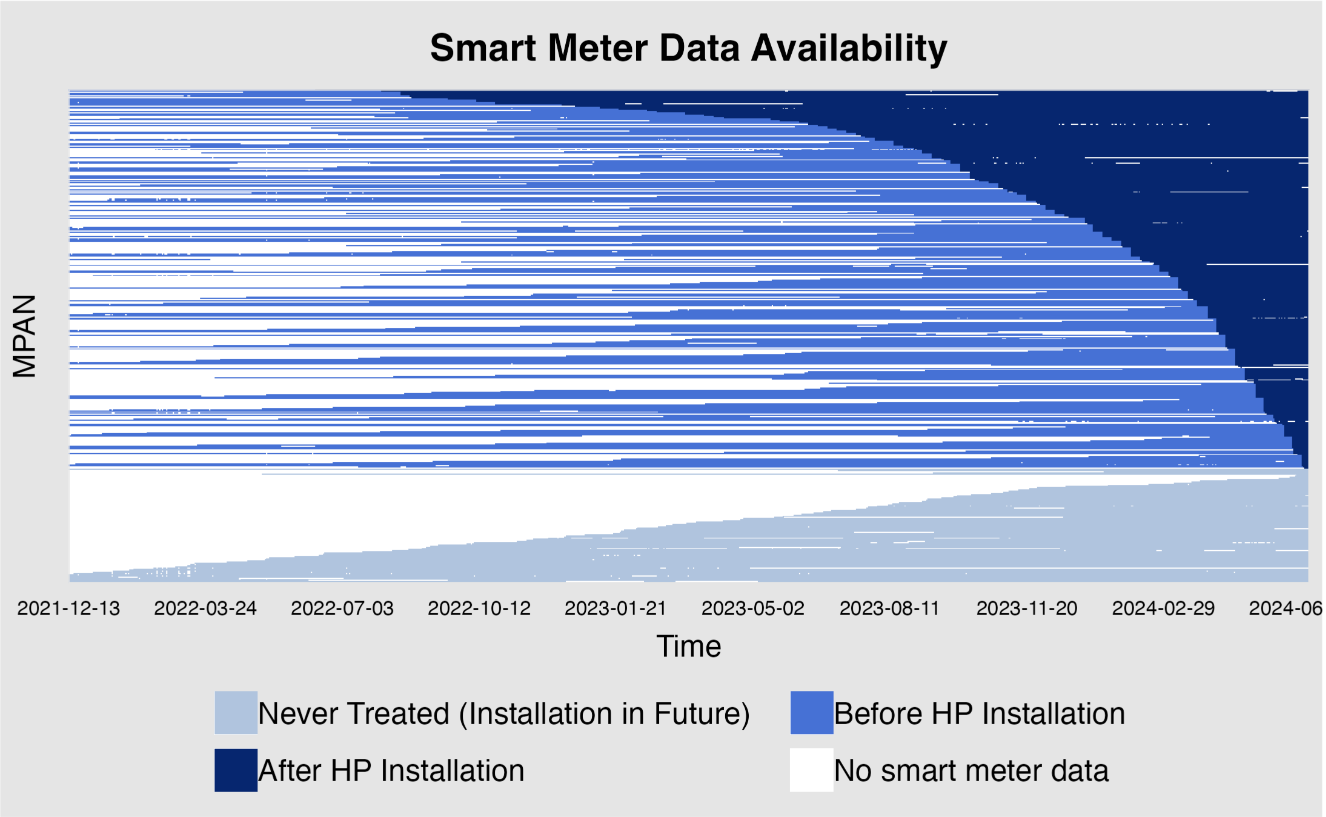
A Appendices

Contents

A.1 Heat Pump Appendix

A.1.1 Smart Meter Data Availability

Figure A.1: Smart Meter Data Availability for Heat Pump Customers



A.1.2 Main Results comparing TWFE and CS

Table A.1: HP Installation on Yearly Energy Consumption in kWh

	TWFE			CS		
	Electricity	Gas	Total	Electricity	Gas	Total
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Is HP Installed = 1	3,325.9***	-11,198.0***	-7,619.0***	3,080.0***	-9,350.7***	-6,119.8***
	(115.4)	(421.0)	(333.1)	(140.8)	(347.9)	(401.9)
Pre-Treatment Average						
Yearly Consumption	4,924.05	10,307.32	15,267.14	5,062.07	10,335.72	15,287.19
Fixed-effects						
Household	Yes	Yes	Yes			
HDD	Yes	Yes	Yes			
Week	Yes	Yes	Yes			
Fit statistics						
Observations	99,655	74,390	74,390			
Number of Households	1,113	1,079	1,079	1,321	1,079	1,079
Number of cohorts (CS)				100	98	98
Number of Time Periods	129	129	129	127	127	127
R^2	0.66962	0.76414	0.78657			

Clustered (Household) standard-errors in parentheses for TWFE

Clustered cohort (Week of adoption) standard-errors in parentheses for CS

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.1.3 Main Results using both not-yet-treated and never-treated as control

We model the impact of heat pumps on electricity, gas, and overall energy consumption (all in kWh) including customers who had a deal but had not yet had an installation by 15 June 2024. In this analysis, we do not include any anticipation impacts (whereas our main analyses have one week anticipation.)

Table A.2: HP Installation on Yearly Energy Consumption in kWh

		TWFE			CS	
	Electricity	Gas	Total	Electricity	Gas	Total
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Is HP Installed = 1	3,031.0***	-11,091.5***	-7,699.9***	2,884.0***	-8,795.8***	-5,676.9***
	(100.8)	(413.6)	(323.5)	(124.1)	(329.8)	(349.6)
Pre-Treatment Average						
Yearly Consumption	4,522.83	10,193.30	15,228.02	5,062.07	10,335.72	15,287.19
Fixed-effects						
Household	Yes	Yes	Yes			
HDD	Yes	Yes	Yes			
Week	Yes	Yes	Yes			
Fit statistics						
Observations	161,931	109,372	109,372			
Number of Households	1,942	1,544	1,544	1,942	1,544	1,544
Number of cohorts (CS)				101	99	99
Number of Time Periods	129	129	129	129	129	129
R^2	0.69622	0.76791	0.78394			

Clustered (Household) standard-errors in parentheses for TWFE
Clustered cohort (Week of adoption) standard-errors in parentheses for CS
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.1.4 EV charging and Solar PV

Table A.3: HP Installation on Electricity Consumption Controlling for EV Ownership

Dependent Variable:	Yearly Consumption in kWh	
Model:	(1)	(2)
Variables		
Is HP Installed = 1	3,264.2***	3,014.0***
	(112.5)	(98.00)
Has EV		2,251.2***
		(174.9)
Has EV × Is HP Installed = 1		520.8***
		(194.1)
Pre-Treatment Average		
Yearly Consumption	4,519.75	4,519.75
Fixed-effects		
HDD	Yes	Yes
Household	Yes	Yes
Day	Yes	Yes
Fit statistics		
Observations	776,464	776,464
Number of Households	1,325	1,325
Number of Time Periods	897	897
R^2	0.54292	0.55078

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.4: HP Installation on Probability of Charging EV by Period

Dependent Variable:	Charging EV			
	Morning Cosy	Afternoon Cosy	Peak Rate	Other
Model:	(1)	(2)	(3)	(4)
Variables				
Is HP Installed = 1	-0.0012	0.0044**	0.0014	-0.0046
	(0.0061)	(0.0021)	(0.0026)	(0.0073)
Pre-Treatment Average				
Charging EV	0.02	0.01	0.02	0.95
Fixed-effects				
Household	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes
Fit statistics				
Observations	77,424	77,424	77,424	77,424
Number of Households	516	516	516	516
R^2	0.25291	0.16432	0.11802	0.26085

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.5: HP Installation and Solar PV on Electricity Consumption

Dependent Variable:	Yearly Consumption in kWh				
rate_period	Morning Cosy	Afternoon Cosy	Peak Rate	Other	Overall
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Is HP Installed = 1	675.5***	469.0***	448.8***	2,174.2***	3,766.6***
	(46.45)	(28.40)	(33.35)	(123.0)	(172.8)
Has Solar PV × Is HP Installed = 1	-19.56	-93.28***	-90.88**	64.58	-140.3
	(53.97)	(31.45)	(37.02)	(150.5)	(194.0)
Pre-Treatment Average					
Yearly Consumption No Solar PV	445.10	459.00	665.06	3,192.23	4,758.98
Yearly Consumption Has Solar PV	410.10	266.93	426.78	3,217.89	4,320.39
Fixed-effects					
HDD	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	610,464	610,640	610,606	611,307	611,308
Number of Households	1,096	1,096	1,096	1,096	1,096
Number of Time Periods	897	897	897	897	897
R^2	0.34410	0.31895	0.36380	0.52250	0.54230

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.1.5 Heat Pump Impact by Outside Temperature

Figure A.2: Impact of Temperature After Heat Pump Installation on 4am-7am Consumption

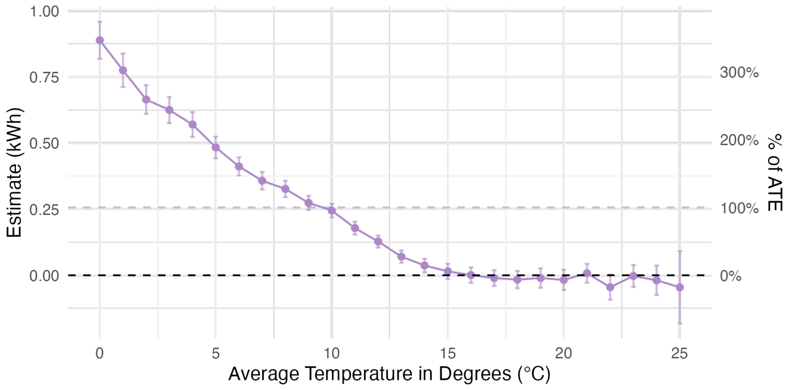


Figure A.3: Impact of Temperature After Heat Pump Installation on 1pm-4pm Consumption

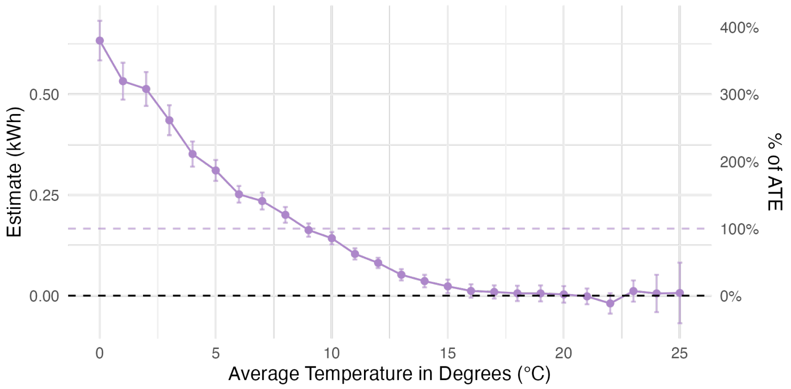


Figure A.4: Impact of Temperature After Heat Pump Installation on 4pm-7pm Consumption

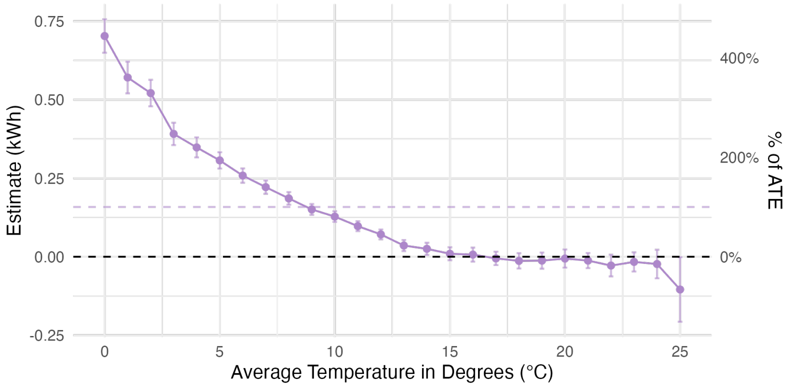
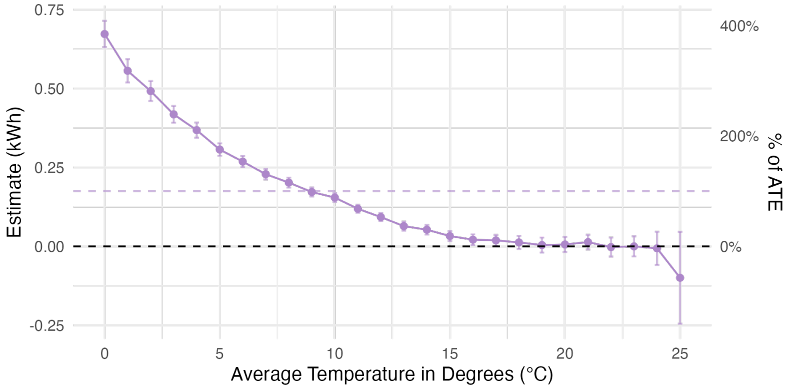


Figure A.5: Impact of Temperature After Heat Pump Installation on Consumption During All Other Hours



A.1.6 Heterogeneity Analysis

Figure A.6: Impact of Heat Pump Installation by EPC Rating

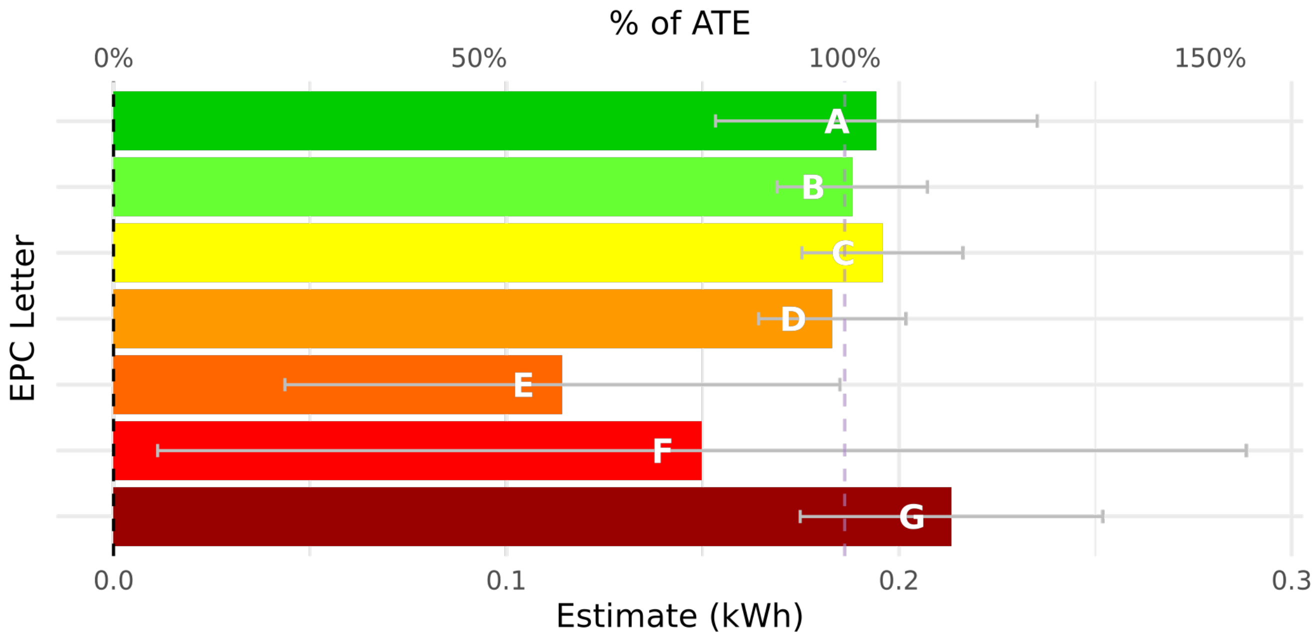


Figure A.7: Impact of Heat Pump Installation by Floor Area

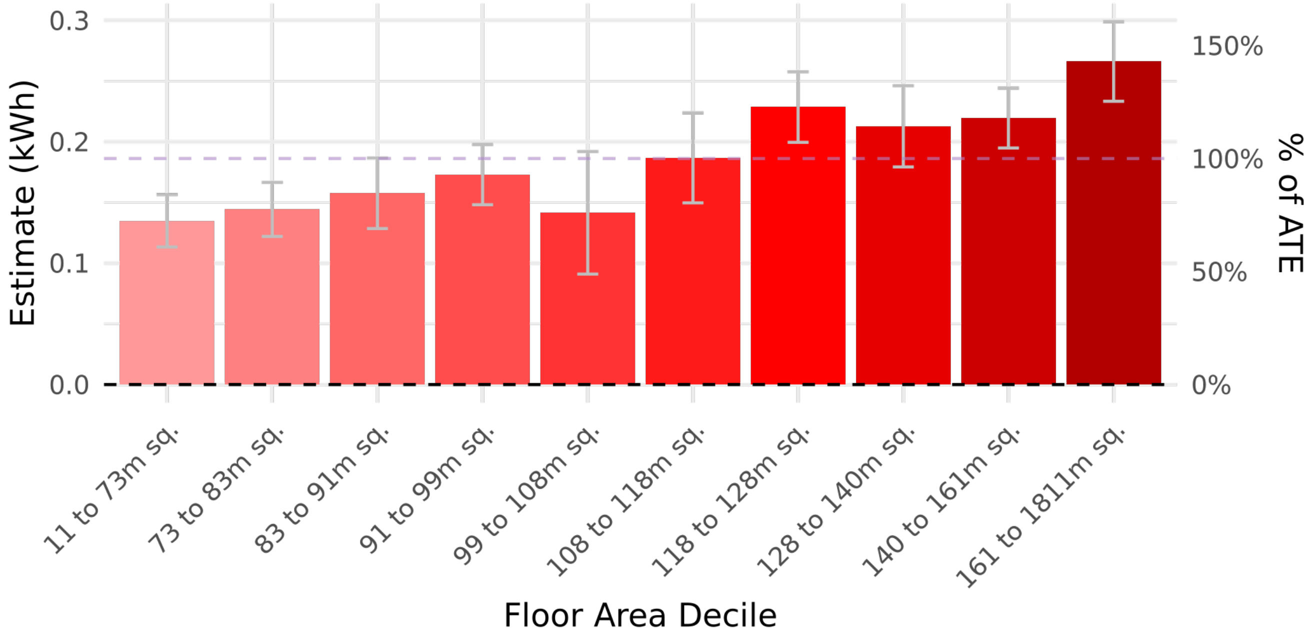


Figure A.8: Impact of Heat Pump Installation by Heat Loss Decile

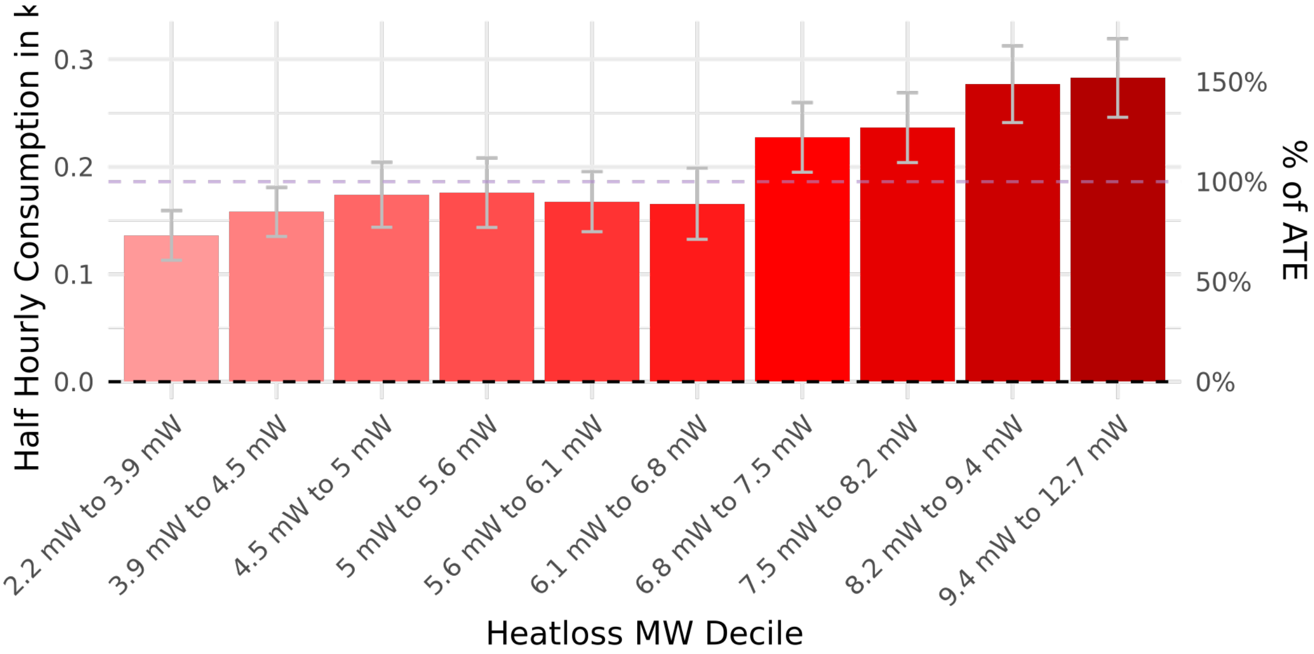


Figure A.9: Impact of Heat Pump Installation on Half-Hourly Electricity Consumption by Region

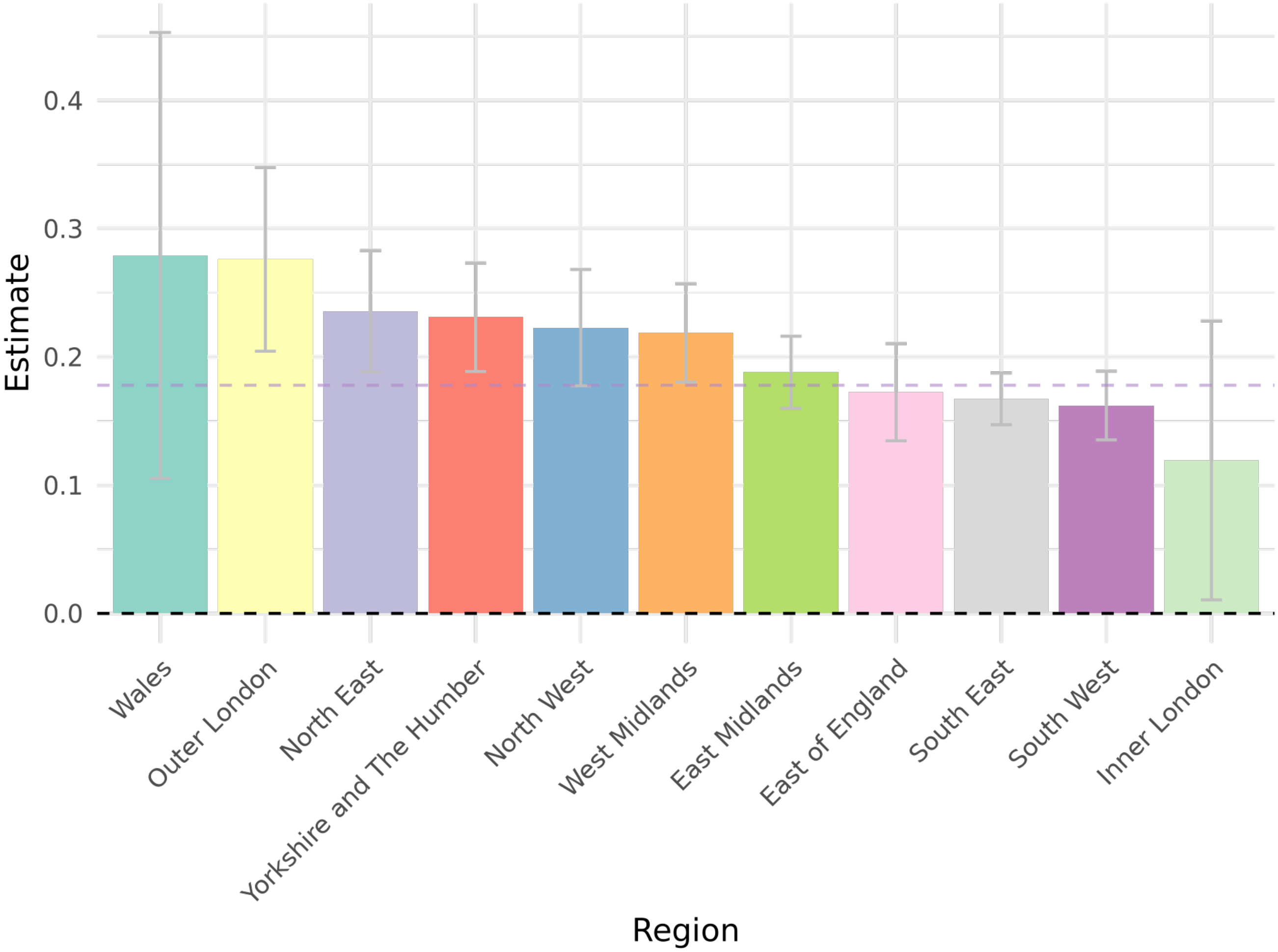


Figure A.10: Impact of Heat Pump Installation by Previous Heat Source

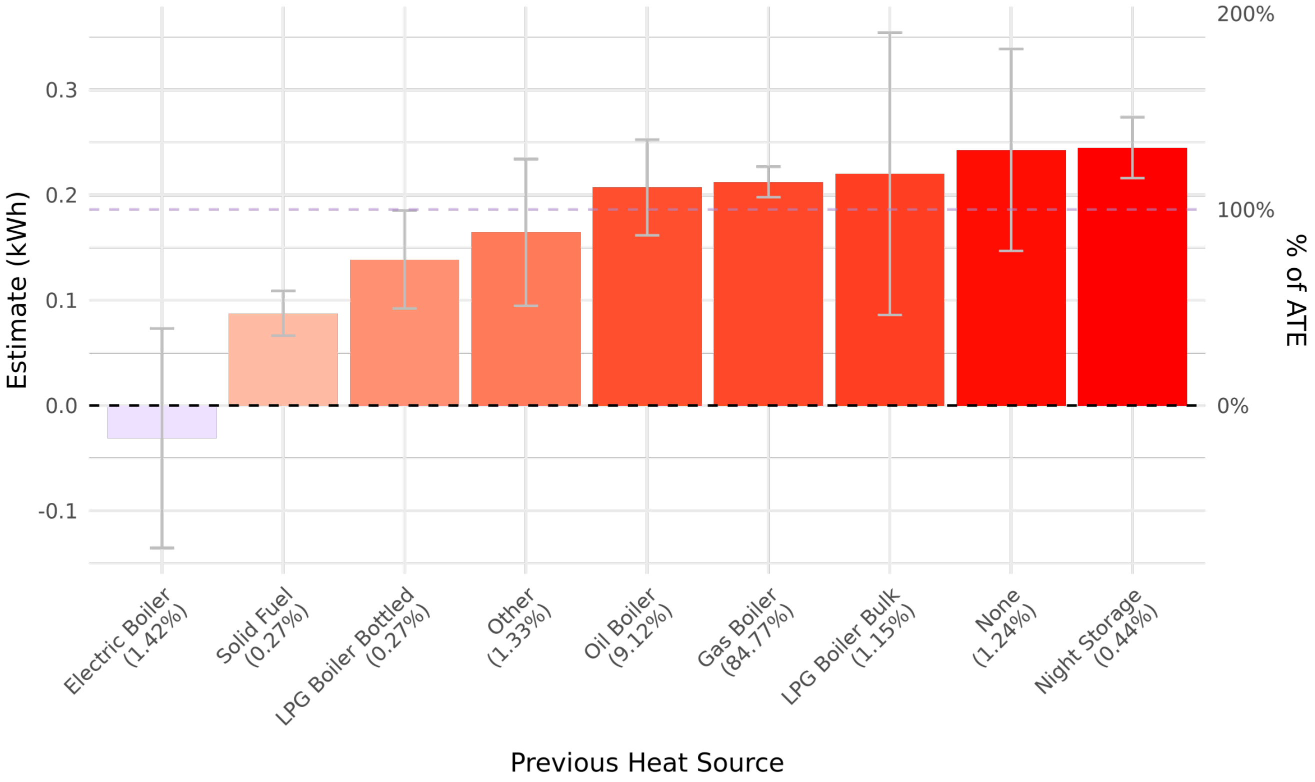
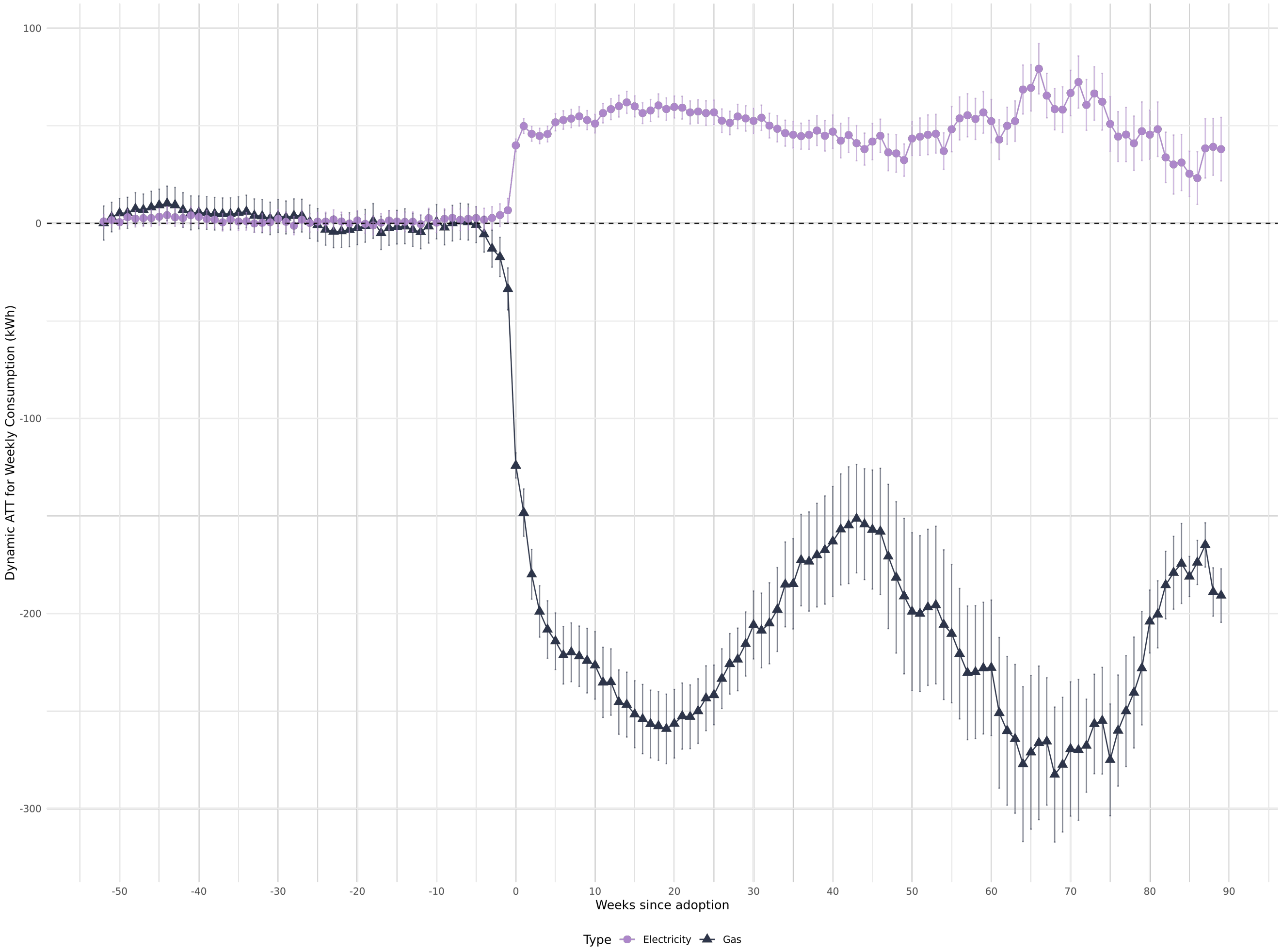


Figure A.11: Impact of Heat Pump Installation by Property Value Decile

A.1.7 DID Impute Estimate

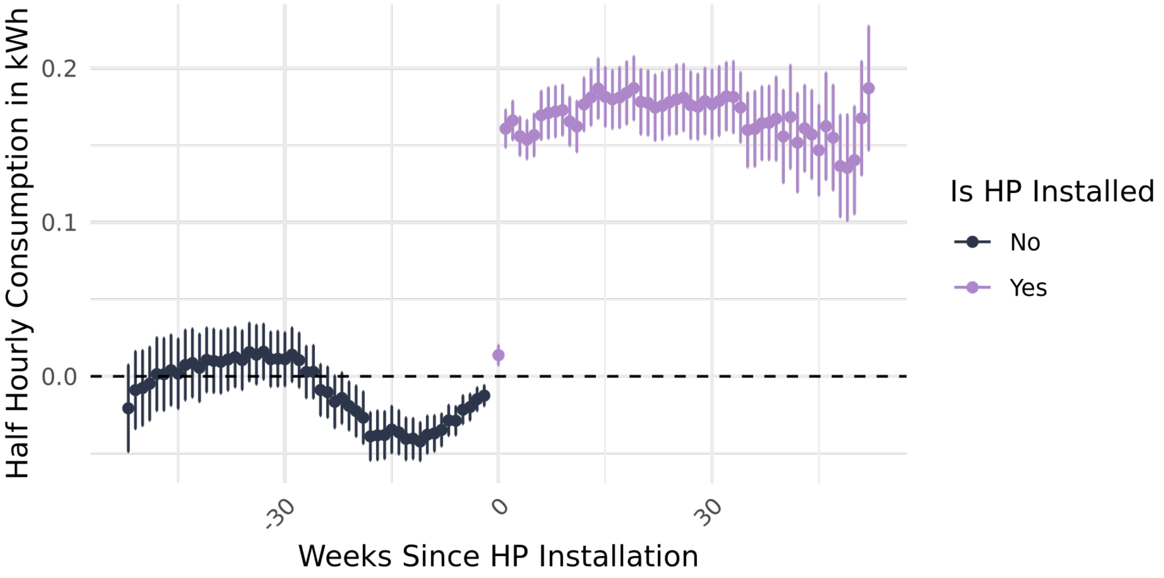
In this analysis, we apply the Borusyak et al. (2024) estimator (imputation DID) to evaluate the robustness of our findings against alternative methods. The resulting plots, as shown in Figure A.12, closely resemble those produced using the Callaway and Sant'Anna (2021) estimator with a robust universal base period (Figure A.14). The primary distinction between the two approaches is that the Callaway and Sant'Anna (2021) estimates incorporate a one-week anticipation period to account for the timing of heat pump installations.

Figure A.12: DID Impute Estimate for Heat Pump Installation



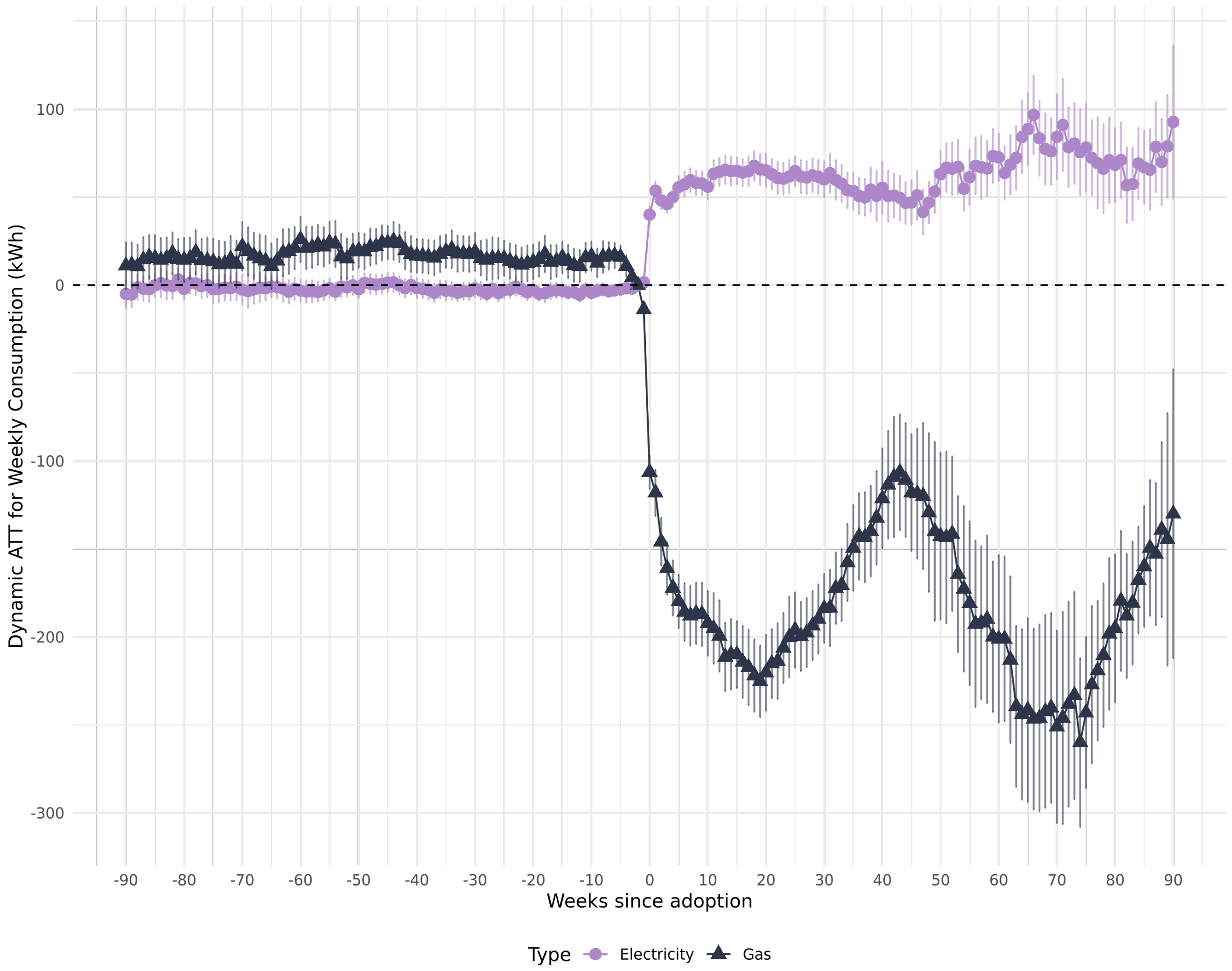
A.1.8 TWFE Event Study

Figure A.13: Event Study - Heat Pump Installation on Daily Average of Customers' Half-Hourly Electricity Consumption



A.1.9 Dynamic ATT Using Universal Base Period

Figure A.14: Dynamic ATT using universal base period



A.1.10 CS estimates with gas as a previous heat sources only

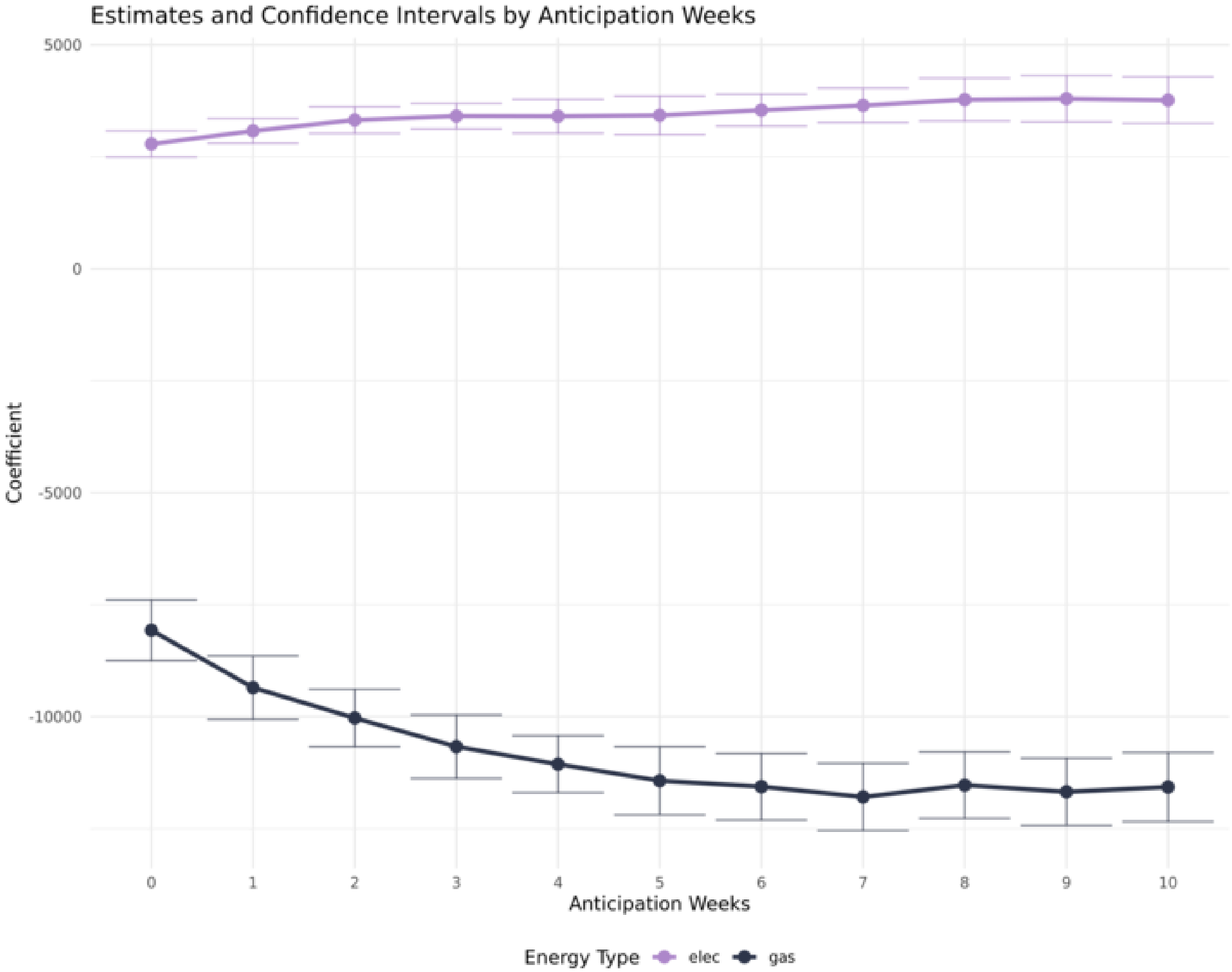
Table A.6: HP Installation on Yearly Energy Consumption in kWh

Model:	Electricity (1)	Gas (2)	Overall (3)
Variable			
Is HP Installed = 1	3,230.9*	-9,350.7*	-6,119.8*
	(230.6)	(344.7)	(382.6)
Pre-treatment Average			
Yearly Consumption	4,951.5	10,335.7	15,287.2
Fit statistics			
Number of Households	1,079	1,079	1,079
Number of Cohorts	98	98	98
Number of Time Periods	127	127	127

Clustered (Household) standard-errors in parentheses
Estimation Method: Doubly Robust
Control Group: Not Yet Treated, Anticipation Periods: 1
Signif. Codes: *** 99% confidence band does not cover 0

A.1.11 Heat Pump Impacts Depending on Assumed Anticipation Period

Figure A.15: Heat Pump Impacts Depending on Assumed Anticipation Period (in Weeks)



A.2 *Cosy* Appendix

A.2.1 Rates by GSP Group and Across Time

Figure A.16: Rates by Rate Period and GSP Group as of 01 June 2024

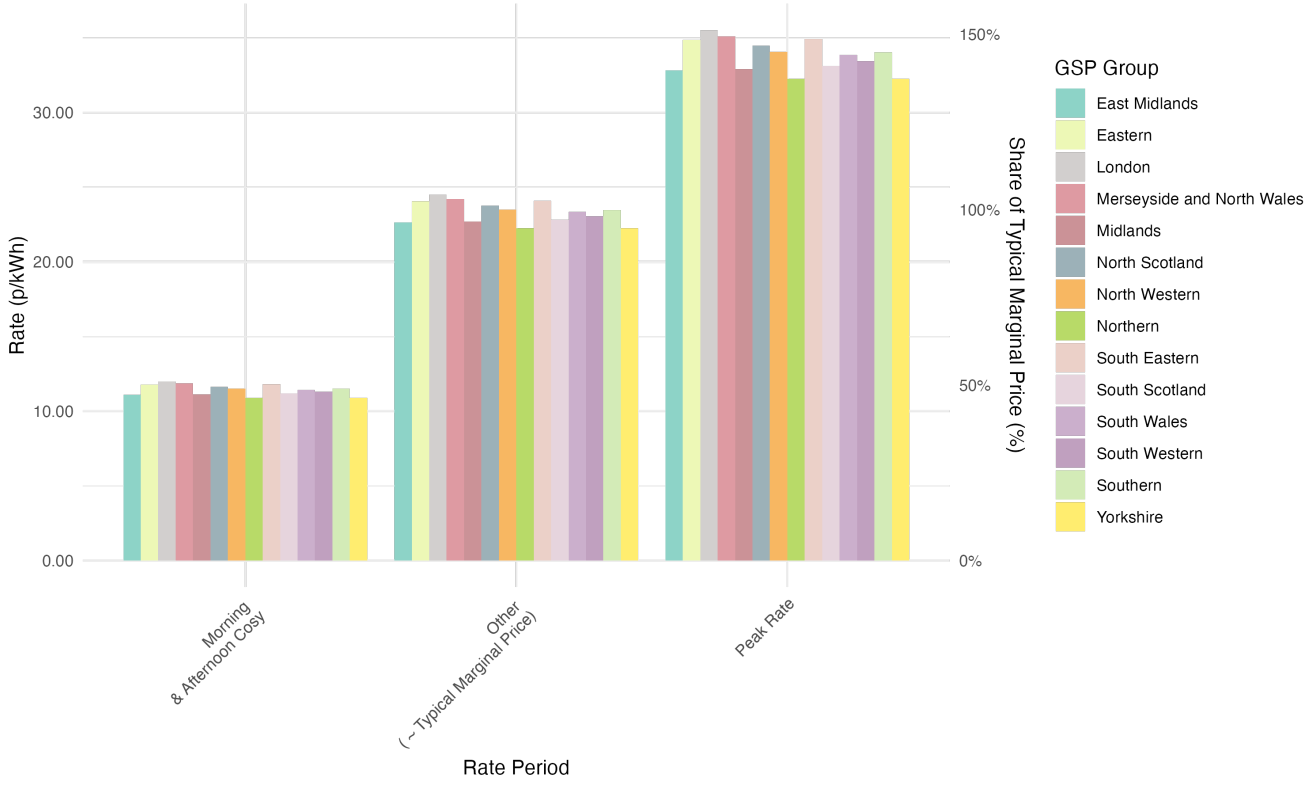


Figure A.17: Rates Over Time

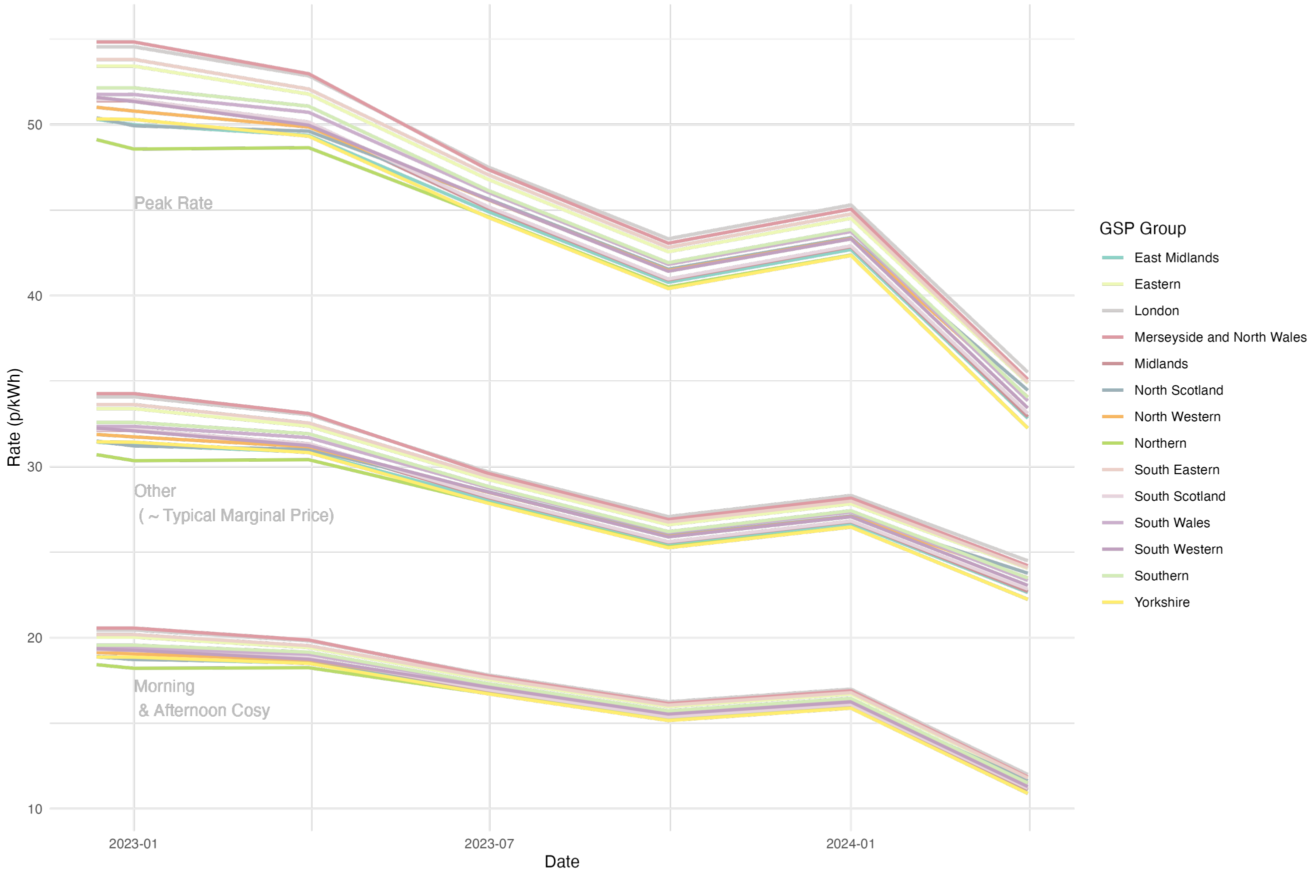
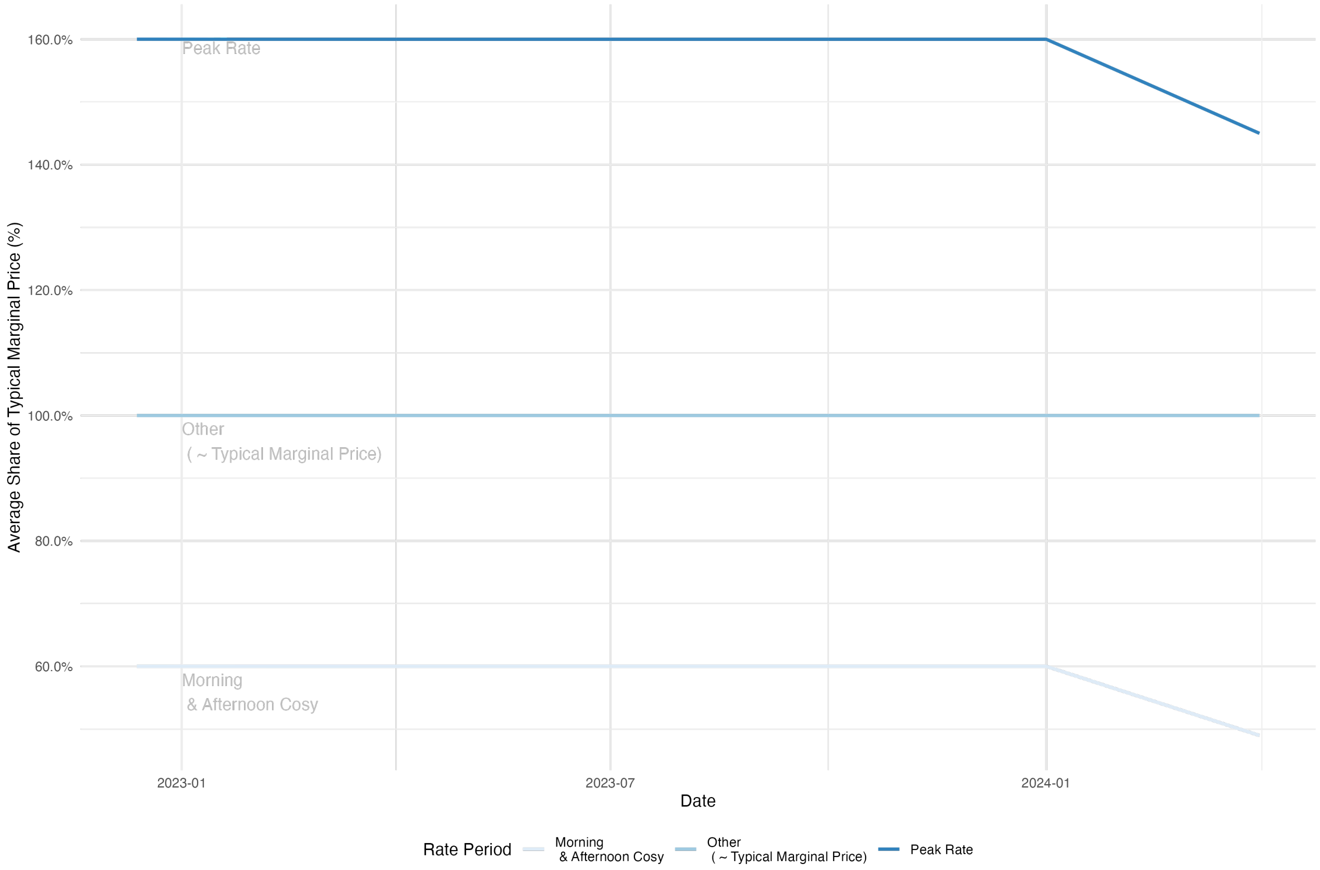


Figure A.18: Rates as Share of Typical Marginal Price Over Time



A.2.2 Wholesale prices by *Cosy* tariff time-of-use period

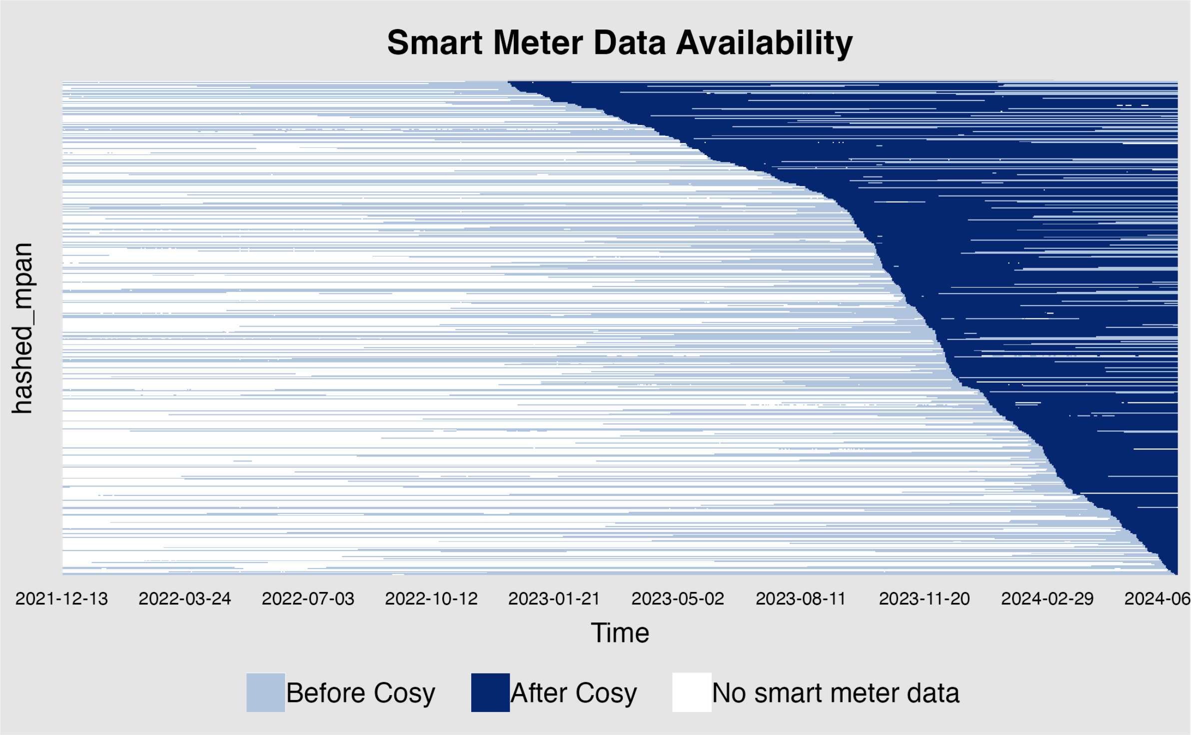
Table A.7: Wholesale Price Averages for *Cosy* Periods in 2022, 2023, and 2024

Period	**2022 (£/MWh)**	**2023 (£/MWh)**	**Jan-Jun 2024 (£/MWh)**
Cosy morning period (04:00 - 07:00)	175	86	55
Cosy afternoon period (13:00 - 16:00)	193	91	57
Cosy peak period (16:00 - 19:00)	242	179	77
Other 15 hours of the day	198	97	64

Note: We show average wholesale prices during the four key periods where *Cosy*-adopting customers faced different marginal prices across 2022, 2023, and 01 January through 15 June 2024, based on data from (LCP Delta, 2024).

A.2.3 Data Availability Graphs

Figure A.19: Smart Meter Data Availability for *Cosy* Adopters



A.2.4 Main Results Comparing TWFE and CS

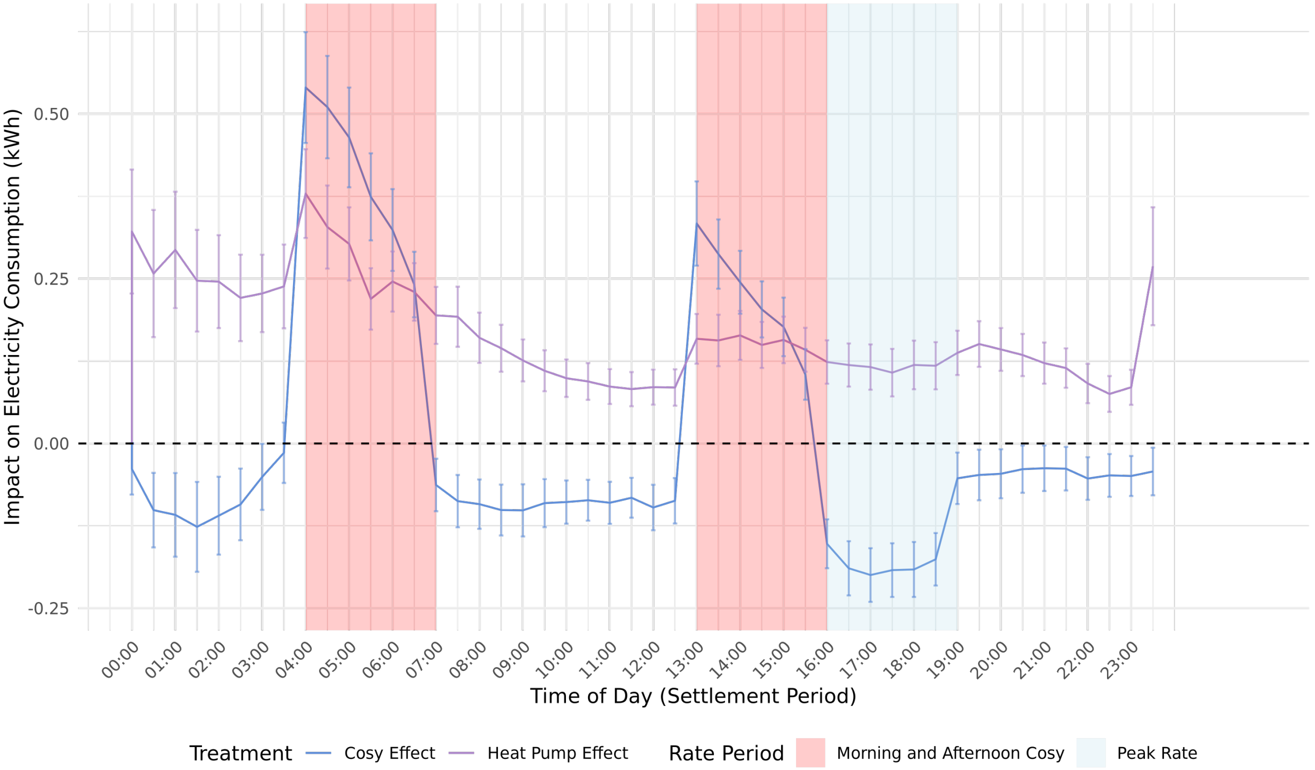
Table A.8: Cosy Adoption

Dependent Variable:	Half Hourly Consumption in kWh									
	TWFE					CS				
	Morning Cosy	Afternoon Cosy	Peak Rate	Other	Overall	Morning Cosy	Afternoon Cosy	Peak Rate	Other	Overall
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
Cosy Contract Active = 1	0.5824***	0.3378***	-0.1593***	-0.1302***	0.0155***	0.5071***	0.2926***	-0.2242***	-0.1066***	0.0105
	(0.0121)	(0.0075)	(0.0045)	(0.0041)	(0.0029)	(0.0135)	(0.0094)	(0.0097)	(0.0073)	(0.0071)
Pre-Treatment Average										
Half Hourly Consumption	0.3952	0.3300	0.4262	0.3980	0.3922	0.4378	0.3822	0.3174	0.3625	0.3776
Fixed-effects										
HDD	Yes	Yes	Yes	Yes	Yes					
Household	Yes	Yes	Yes	Yes	Yes					
Day	Yes	Yes	Yes	Yes	Yes					
Fit statistics										
Observations	3,148,935	3,149,498	3,149,471	3,154,107	3,154,109					
Number of Households	6,657	6,657	6,657	6,657	6,657	6,631	6,631	6,631	6,631	6,631
Number of cohorts (CS)						78	78	78	78	78
Number of Time Periods	916	916	916	916	916	129	129	129	129	129
R^2	0.57653	0.49802	0.49420	0.62126	0.67389					

Clustered (Household) standard-errors in parentheses for TWFE
Clustered cohort (Week of adoption) standard-errors in parentheses for CS
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2.5 Half Hourly Results - Expanded Sample

Figure A.20: Half Hourly Impacts *including* customers on time-of-use tariffs



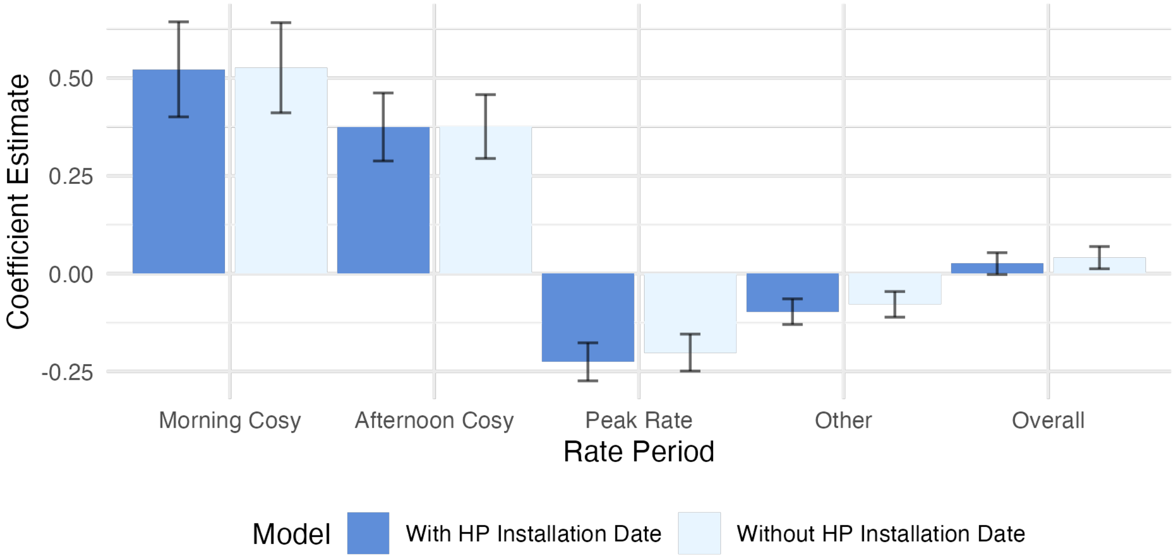
A.2.6 *Cosy* Adoption Impact: Interactions With Customer Adoption of Low Carbon Technologies

Heat Pump Installation: We have 316 customers who responded to our survey and provided the installation date of their heat pump. We use this data to assess the potential omitted variable bias that might result from not including the installation date in our analysis as shown in Figure A.21. It is likely that the closer the heat pump installation is to the tariff change, the more our estimates for *Cosy* might inadvertently capture the impact of the heat pump installation. This could result in an upward bias for all coefficients (representing an upward bias in the absolute value of the Morning and Afternoon coefficients and a downward bias in the absolute value of the Peak and Other coefficients).

Our findings show that the average installation date among these customers is June 2021, which is approximately one and a half years before the launch of the *Cosy* tariff. Additionally, this date is before the introduction of most smart tariffs, such as *Intelligent Octopus Go*, which was launched in early 2022.

This timing suggests that not including the heat pump installation date in our analysis does not significantly bias our results. In addition, comparing main results coefficients with and without controlling for heat pump installation shows minimal differences between the two models' results.

Figure A.21: Main Results Coefficients With and Without Controlling for Heat Pump Installation



EV Charging:

Table A.9: Cosy Adoption on Electricity Consumption Controlling for EV Charging

Dependent Variable:	Half Hourly Consumption in kWh				
Rate period	Morning Cosy	Afternoon Cosy	Peak Rate	Other	Overall
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Cosy Contract Active = 1	0.3968***	0.2406***	-0.1252***	-0.0695***	0.0226***
	(0.0090)	(0.0060)	(0.0043)	(0.0034)	(0.0027)
EV User	0.1903***	0.0736***	0.0076	0.1917***	0.1555***
	(0.0251)	(0.0165)	(0.0134)	(0.0111)	(0.0091)
EV User × Cosy Contract Active = 1	0.7637***	0.4014***	-0.1426***	-0.2636***	-0.0379***
	(0.0369)	(0.0216)	(0.0136)	(0.0113)	(0.0079)
Pre-Treatment Average					
Half Hourly Consumption	0.3952	0.3298	0.4261	0.3979	0.3922
Fixed-effects					
HDD	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,148,057	3,148,620	3,148,593	3,153,228	3,153,230
Number of Households	6,657	6,657	6,657	6,657	6,657
Number of Time Periods	916	916	916	916	916
R^2	0.60993	0.51253	0.49699	0.63251	0.67832

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2.7 Customers that switch away from Cosy

Table A.10: Impact of *Cosy* for Leavers

Dependent Variable:	Half Hourly Consumption in kWh				
Rate period	Morning Cosy	Afternoon Cosy	Peak Rate	Other	Overall
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Cosy Contract Active = 1	0.5160***	0.3126***	-0.1574***	-0.1044***	0.0209***
	(0.0162)	(0.0097)	(0.0065)	(0.0052)	(0.0040)
Leavers × Cosy Contract Active = 1	0.1530***	0.0579***	-0.0045	-0.0596***	-0.0125**
	(0.0292)	(0.0173)	(0.0098)	(0.0085)	(0.0060)
Pre-Treatment Average					
Half Hourly Consumption	0.3952	0.3298	0.4261	0.3979	0.3922
Fixed-effects					
HDD	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,148,057	3,148,620	3,148,593	3,153,228	3,153,230
Number of Households	6,657	6,657	6,657	6,657	6,657
Number of Time Periods	916	916	916	916	916
R^2	0.57744	0.49833	0.49426	0.62202	0.67398

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2.8 Heterogeneity by Low Carbon Technology Ownership Among Survey Respondents

When an Octopus Energy customer adopts a smart tariff, Octopus Energy sends them an on-boarding survey that includes questions about which low-carbon technologies (LCTs) they own. A total of 2,439 *Cosy* adopters in the sample responded to this survey, indicating which other LCTs they have in their homes. (Note that this is different from the survey we sent to 1,000 *Cosy* adopting customers asking about their experience and behavior in responding to the tariff (Section 3.2.2). A limitation of this analysis is that we do not know how respondents compare to non-respondents, and some respondents may have acquired more LCTs since completing the survey. In addition, the interpretation of the coefficients is nuanced – it is the impact of *owning* the LCT, not directly using it. In this way, the coefficients contain both the impact of the LCT itself, and the fact that people with more LCTs might be more affluent, having larger properties and thus higher electricity consumption.

We use the survey responses to examine how *Cosy* adoption interacts with ownership of other LCTs. For respondents without any other LCTs, the impact of *Cosy* on energy use in the morning and afternoon is significantly smaller.

A key finding is that battery owners tend to increase consumption during cheaper periods and reduce it during normal and peak periods, suggesting they charge their batteries when prices are lower. Solar PV owners show less variation, likely using their solar electricity in the afternoon.

Finally, as discussed in Section 3.2.2, EV owners seem to shift their charging from normal and peak periods to *Cosy*'s morning and afternoon periods.

Table A.11: Impact of Cosy by LCTs Ownership

Dependent Variable:	Half Hourly Consumption in kWh				
Rate period	Morning Cosy	Afternoon Cosy	Peak Rate	Other	Overall
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Cosy Contract Active = 1	0.2212***	0.1968***	-0.0900***	-0.0530***	0.0094
	(0.0210)	(0.0165)	(0.0113)	(0.0083)	(0.0065)
Homebattery × Cosy Contract Active = 1	0.7317***	0.3693***	-0.0973***	-0.1660***	0.0210*
	(0.0415)	(0.0277)	(0.0178)	(0.0141)	(0.0110)
HasSolarPV × Cosy Contract Active = 1	-0.0072	-0.0622**	-0.0182	0.0078	-0.0061
	(0.0350)	(0.0250)	(0.0189)	(0.0131)	(0.0105)
HasEV × Cosy Contract Active = 1	0.4127***	0.2025***	-0.0850***	-0.1155***	-0.0055
	(0.0549)	(0.0360)	(0.0202)	(0.0193)	(0.0132)
Pre-Treatment Average					
Half Hourly Consumption	0.3853	0.3165	0.3963	0.3874	0.3790
Fixed-effects					
Household	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes
HDD	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	1,222,705	1,222,888	1,222,889	1,224,531	1,224,531
Number of Households	2,439	2,439	2,439	2,439	2,439
Number of Time Periods	11,551	11,551	11,551	11,551	11,551
R^2	0.59743	0.50536	0.48882	0.61786	0.66379

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Other CS ATT Plots

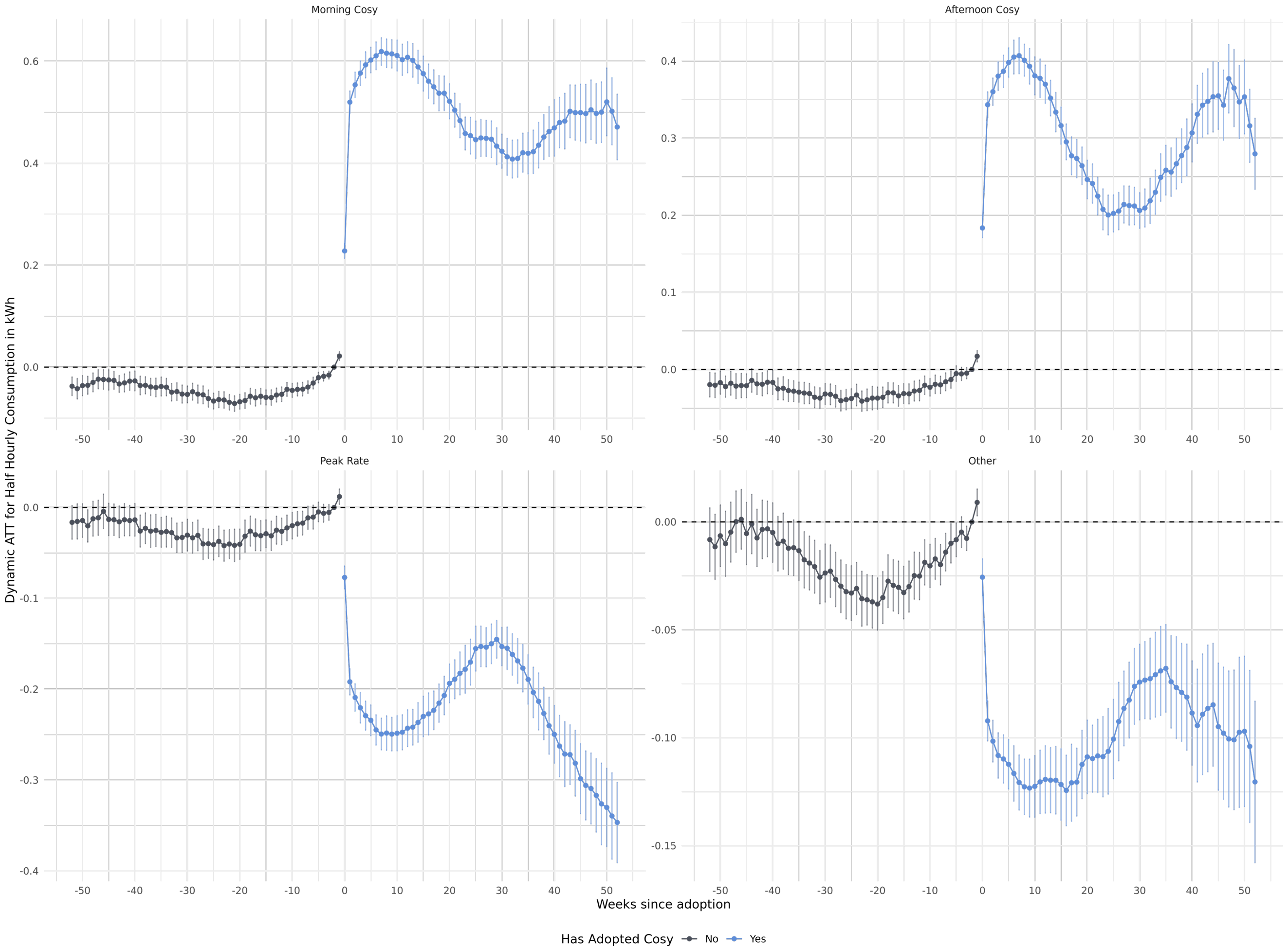
Dynamic ATT Using Universal Base Period: The CS dynamic ATT analyzes how the treatment effect changes over time, offering insights into whether the impact of *Cosy* grows stronger, weaker, or remains consistent in the weeks following adoption. This can help identify any adaptation period or delayed effects.

The x-axis represents weeks since adoption. The y-axis is daily consumption per period in kWh.

In the main analysis, we present the analysis using a varying base period. With a varying base period, the reported effects are pseudo-ATTs – the estimated effect treatment if the treatment had occurred in that period (instead of when it actually occurred). On the other hand, the universal base period is comparing all outcomes to the base period outcome, set before the treatment starts. The estimates show how the treatment outcomes evolve over time. In both cases, the post-adoption ATTs are always the same.

We plot below the dynamic and calendar ATTs using universal base periods. Similar to the event study estimates, the pre-treatment estimates do not show any major upward or downward trends in consumption, but are more sensitive to seasonal effects.

Figure A.22: Dynamic ATTs using Universal Base Period



Group and Calendar ATT: In the graphs below, we show the calendar ATT for each cohort (starting from early adopters in light blue to late adopters in dark blue), for each week post *Cosy* adoption.

Early adopters have slightly larger load shifting than later adopters which is consistent with them having higher EAC.

There are clear seasonable effects for all cohorts.

Figure A.23: Group and Calendar ATT - Morning Cosy

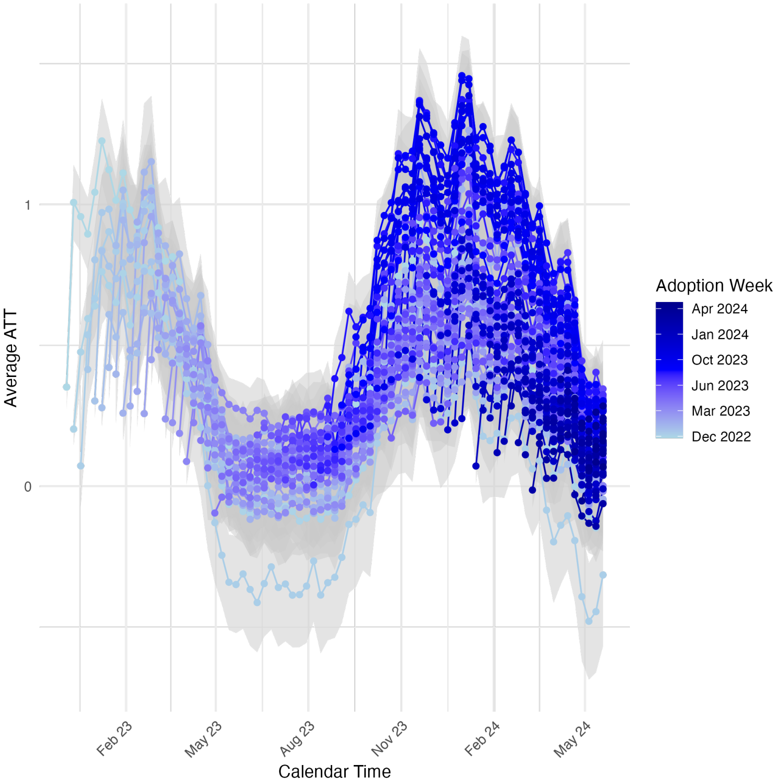


Figure A.24: Group and Calendar ATT - Afternoon Cosy

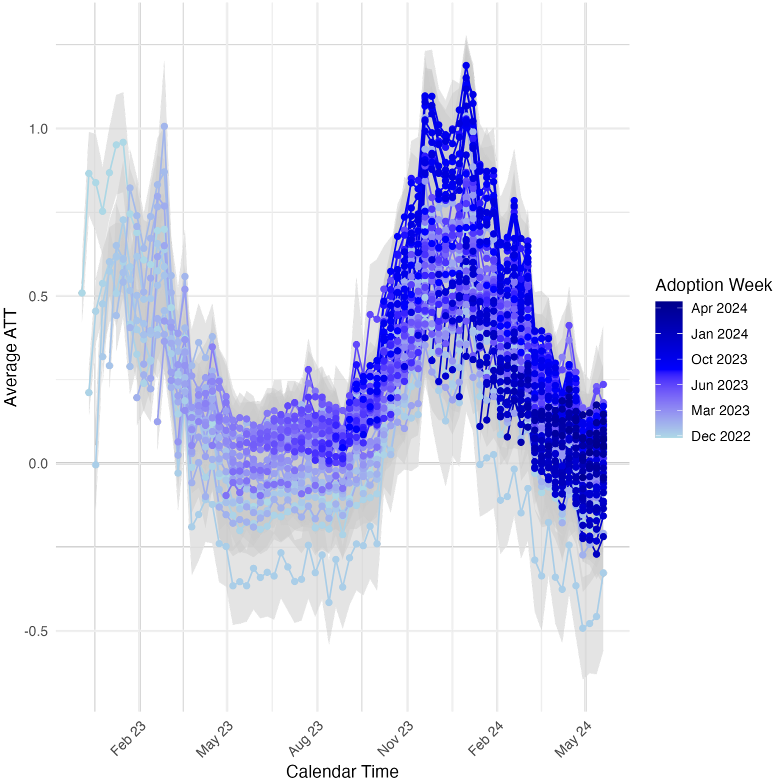


Figure A.25: Calendar and Group ATT - Peak Rate

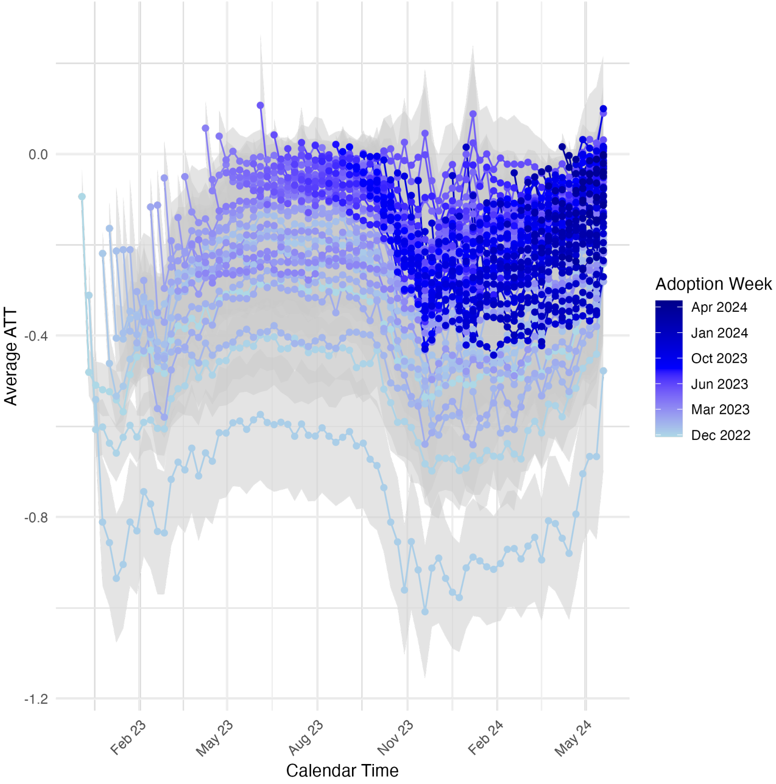


Figure A.26: Calendar and Group ATT - Other Rate

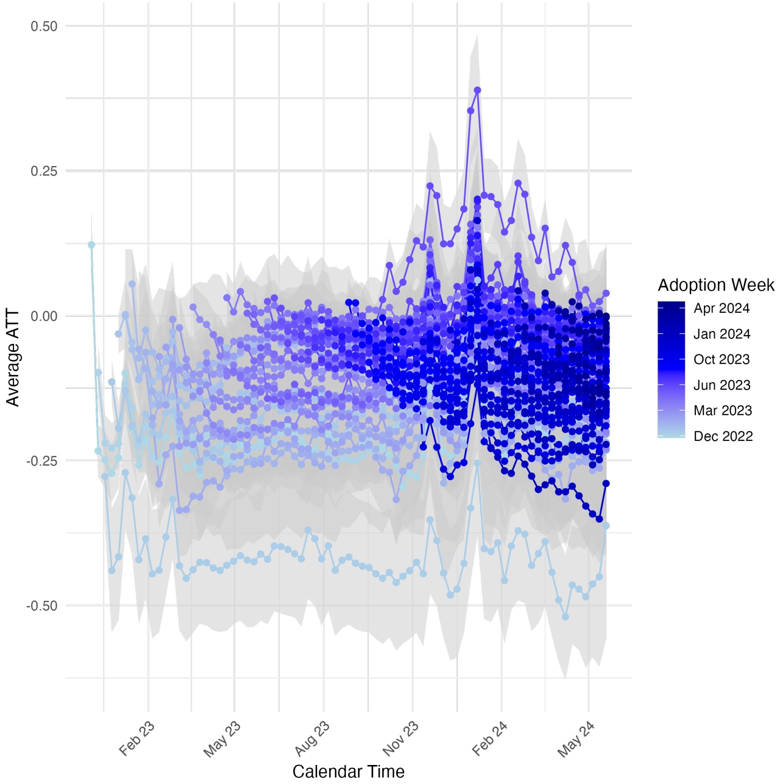
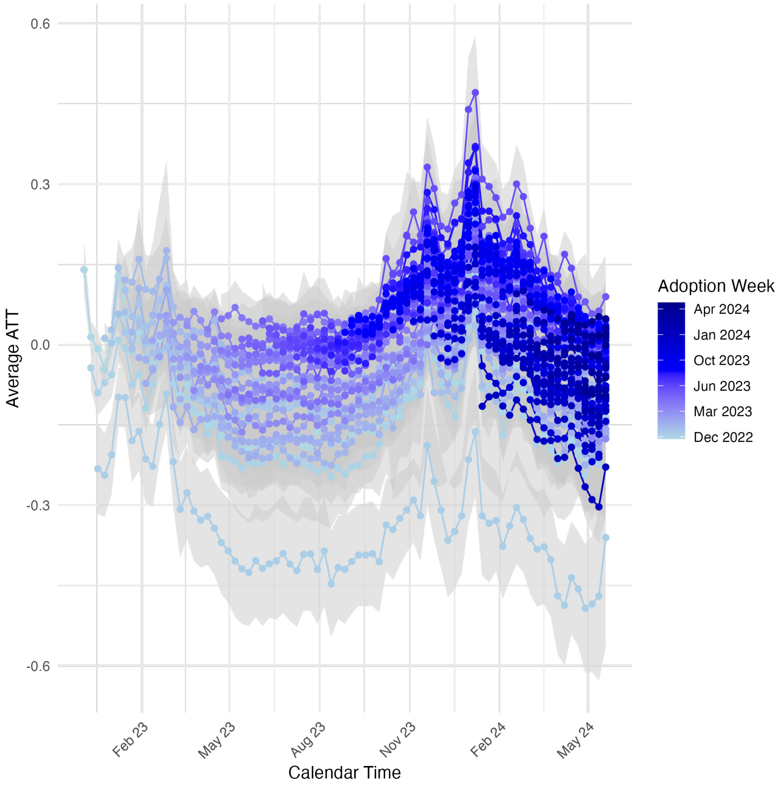


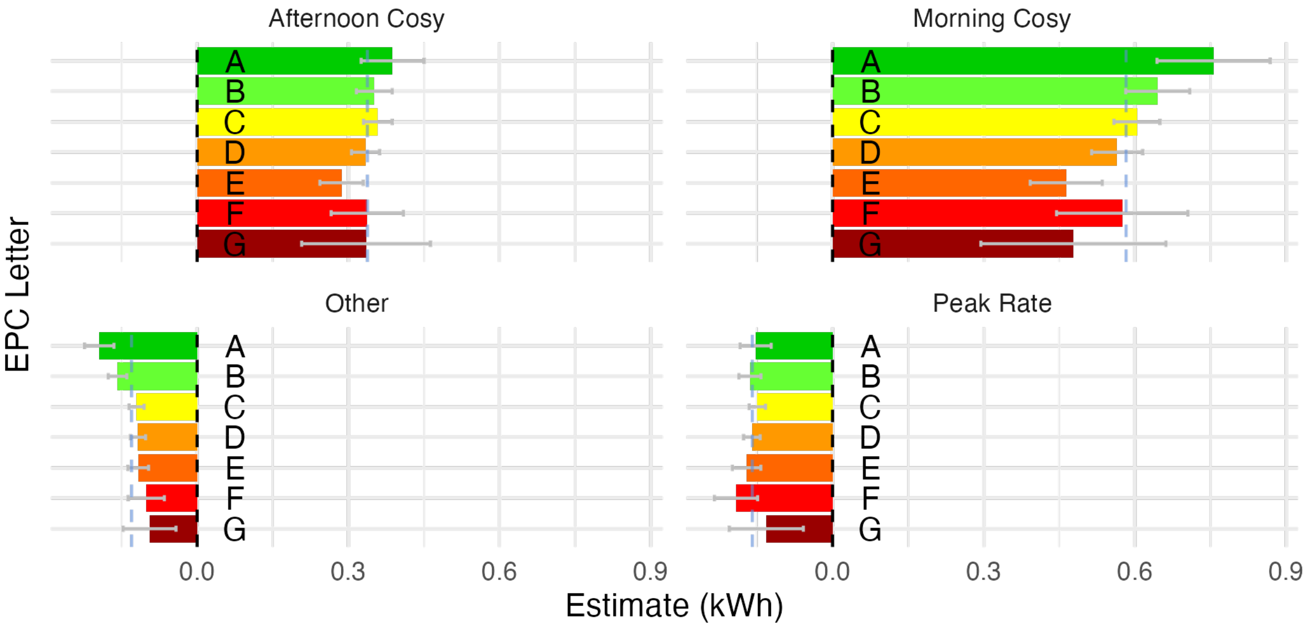
Figure A.27: Calendar and Group ATT - Daily Overall



A.2.9 Heterogeneity Analysis

Energy Efficiency Plots

Figure A.28: Impact of *Cosy* Adoption by EPC Score on Consumption



Estimated Annual Consumption Plots

Figure A.29: Impact of *Cosy* Adoption by EAC on Consumption

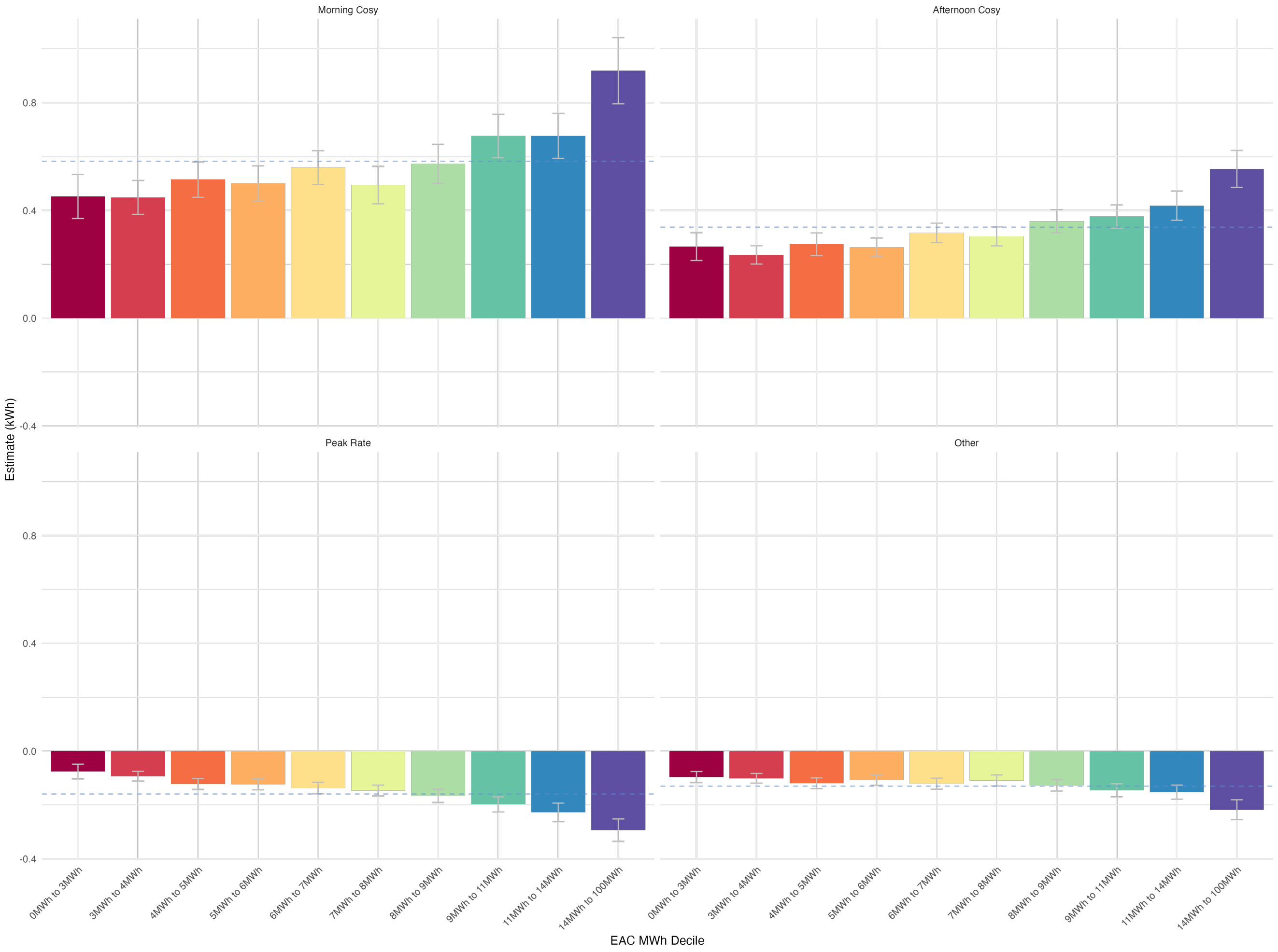
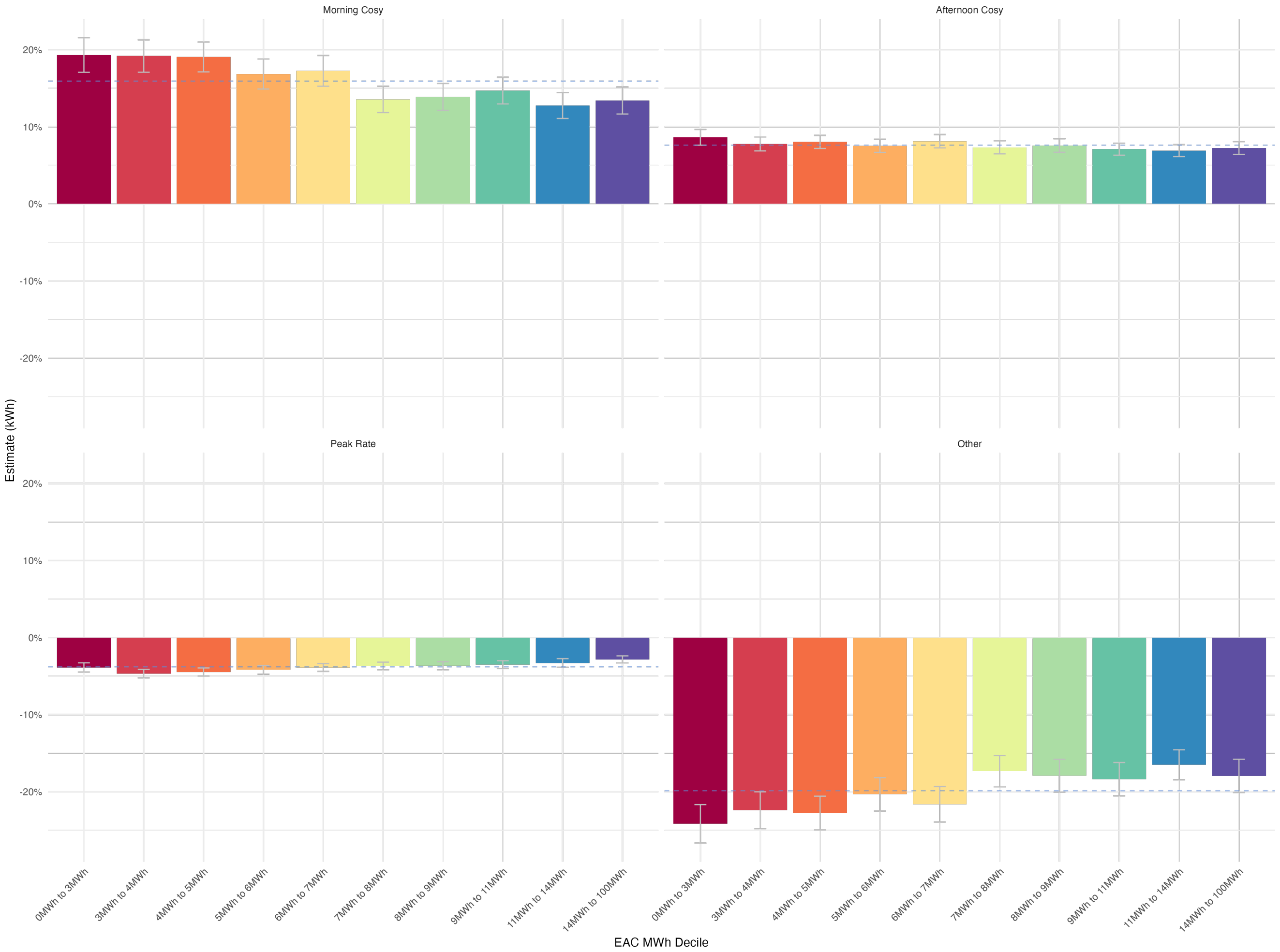


Figure A.30: Impact of *Cosy* Adoption by EAC on Share of Consumption



Floor Areas Plots

Figure A.31: Impact of *Cosy* Adoption by Floor Area on Consumption

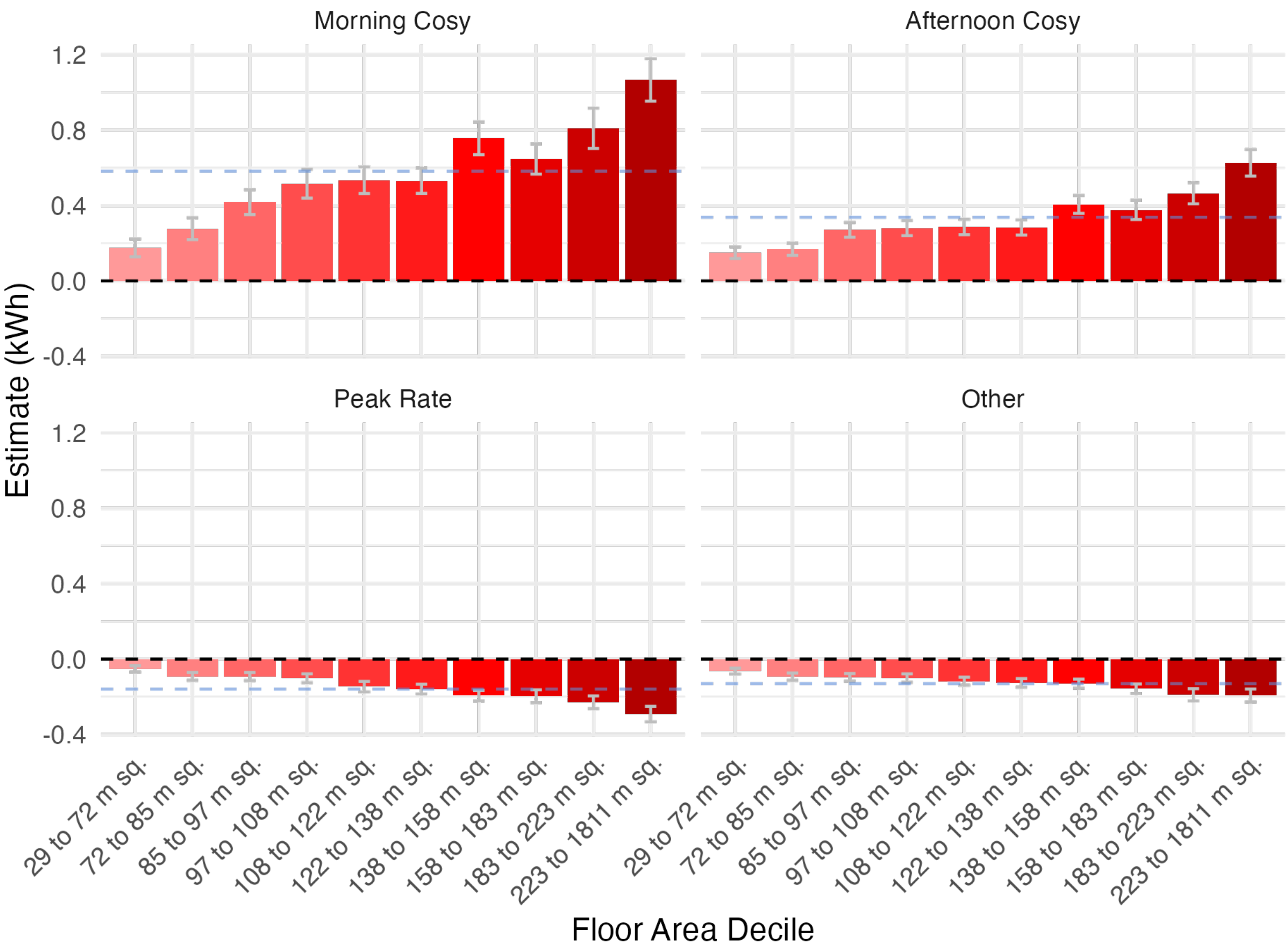
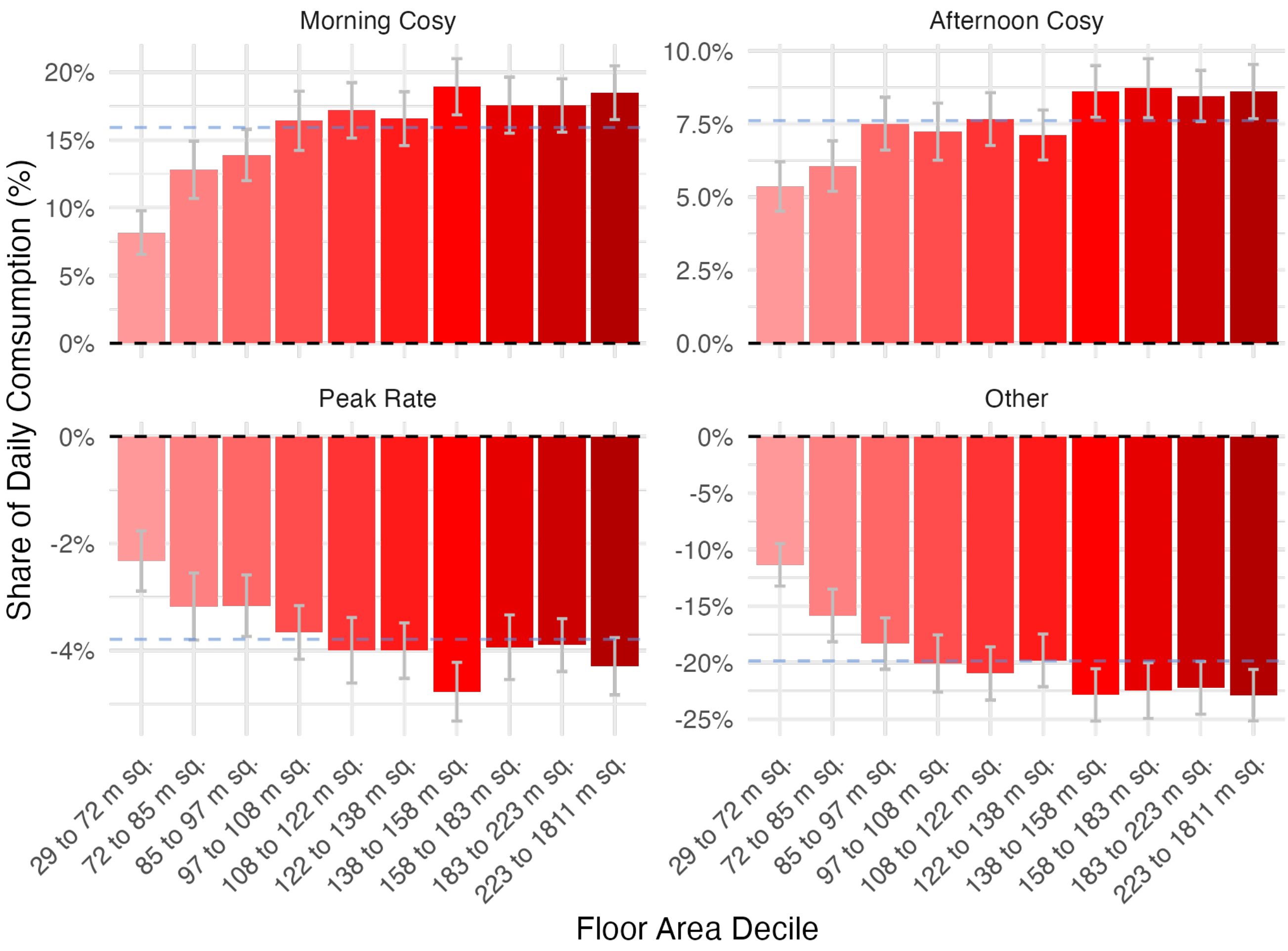


Figure A.32: Impact of *Cosy* Adoption by Floor Area on Share of Consumption



Heat Loss Plots

Figure A.33: Impact of *Cosy* Adoption by Heat Loss on Consumption

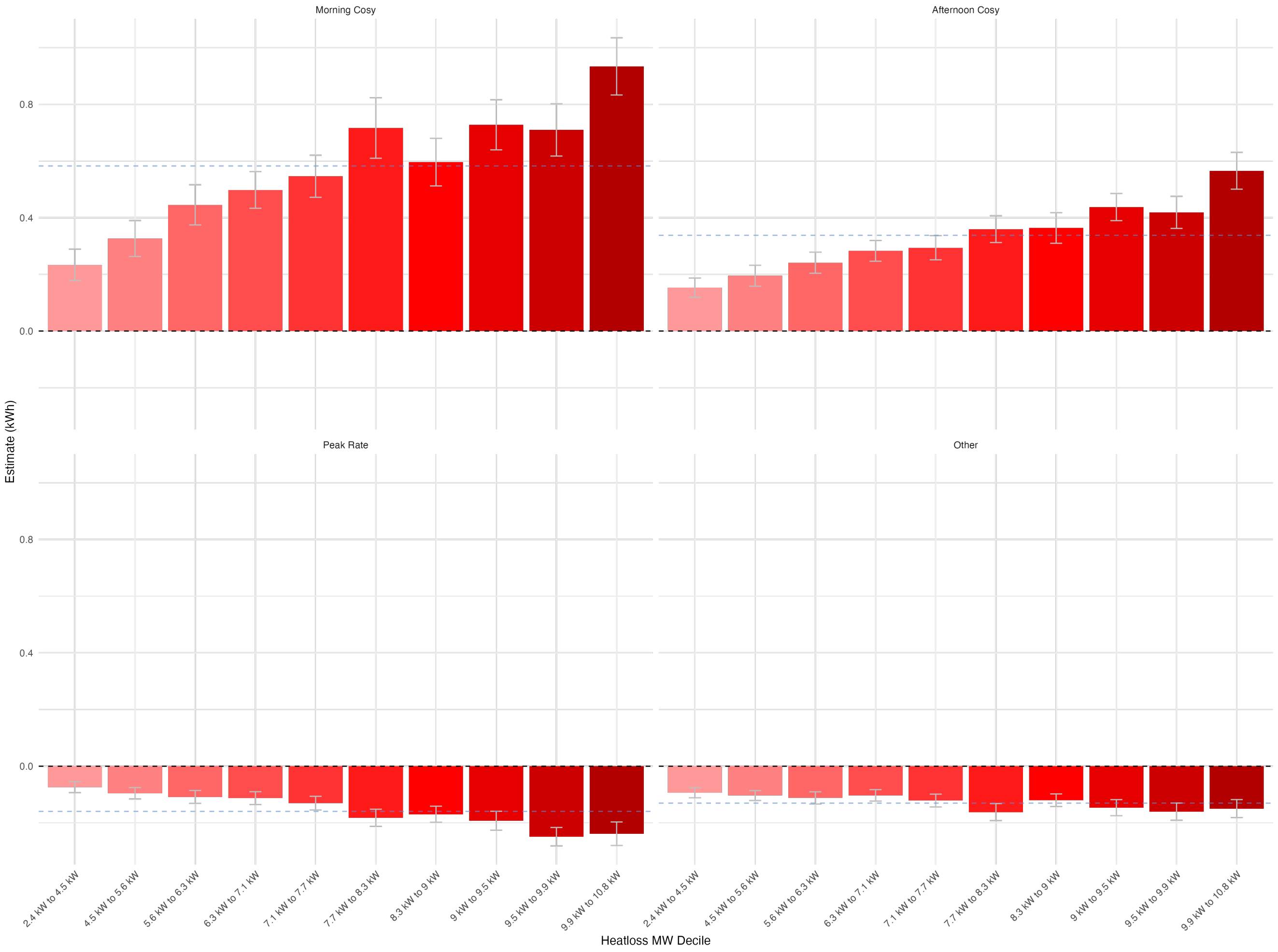
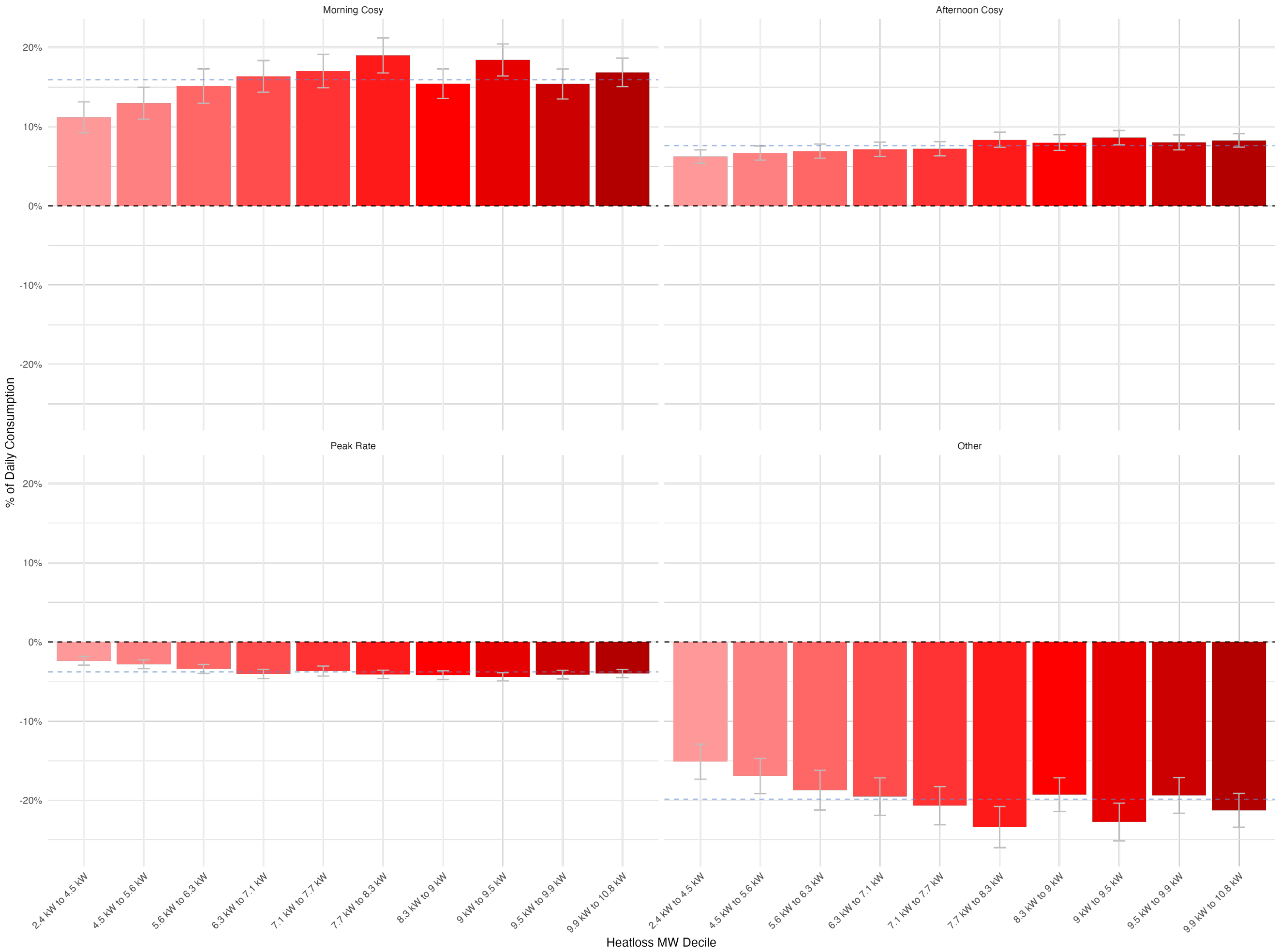
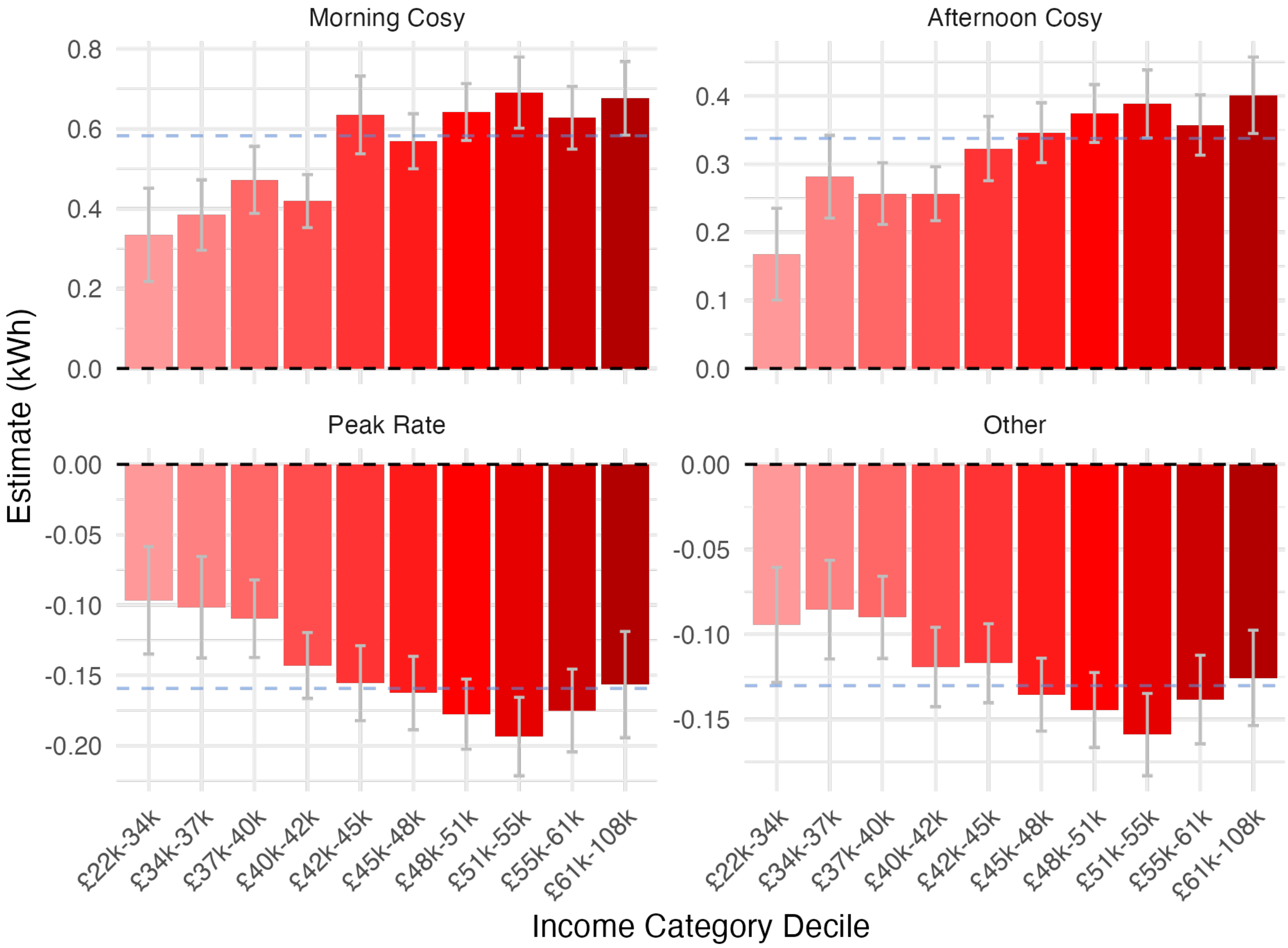


Figure A.34: Impact of *Cosy* Adoption by Heat Loss on Share of Consumption



MSOA Income

Figure A.35: Impact of *Cosy* Adoption by MSOA Income on Consumption



Customers Previously on Time-of-Use Tariffs

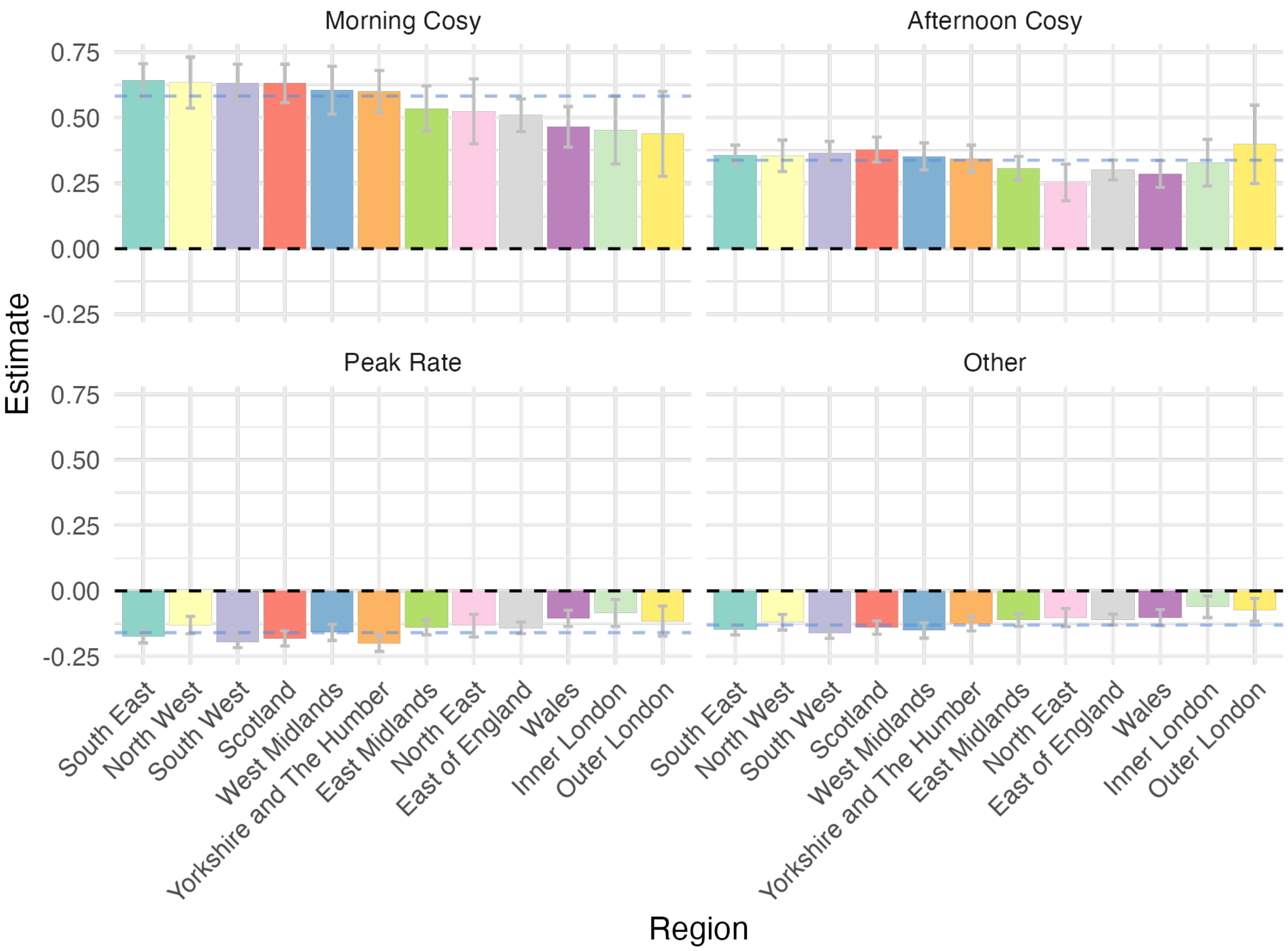
Table A.12: Cosy Adoption by Previous Tariff Type

Dependent Variable:	Half Hourly Consumption in kWh				
Rate period	Morning Cosy	Afternoon Cosy	Peak Rate	Other	Overall
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Cosy Contract Active = 1	0.4613***	0.2899***	-0.1468***	-0.0994***	0.0154***
	(0.0118)	(0.0077)	(0.0050)	(0.0042)	(0.0032)
Prev is ToU × Cosy Contract Active = 1	0.6613***	0.2621***	-0.0679***	-0.1680***	0.0010
	(0.0402)	(0.0227)	(0.0109)	(0.0105)	(0.0072)
Pre-Treatment Average					
Half Hourly Consumption Non-ToU	0.3625	0.3355	0.4665	0.3783	0.3814
Half Hourly Consumption ToU	0.3861	0.2597	0.3365	0.4141	0.3815
Fixed-effects					
HDD	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,144,333	3,144,896	3,144,869	3,149,497	3,149,499
Size of the 'effective' sample	6,645	6,645	6,645	6,645	6,645
Number of Time Periods	916	916	916	916	916
R^2	0.58846	0.50112	0.49444	0.62512	0.67373

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Regions Finally, we plot the interaction between customers' regions and adopting *Cosy*. In these regressions, we control for days and customers fixed effects, and isolate the impact of adopting Cosy. We compare the impact of adopting *Cosy* for all the regions. We do not find clear regional differences, as shown in Figure A.36. We find that while the sample average estimate falls in almost every regional estimates' confidence interval, London seems to have generally smaller load shifting than other regions. We hypothesize that this particular effect is linked to London homes having smaller floor areas, which have lower load shifting as seen in Figure A.31.

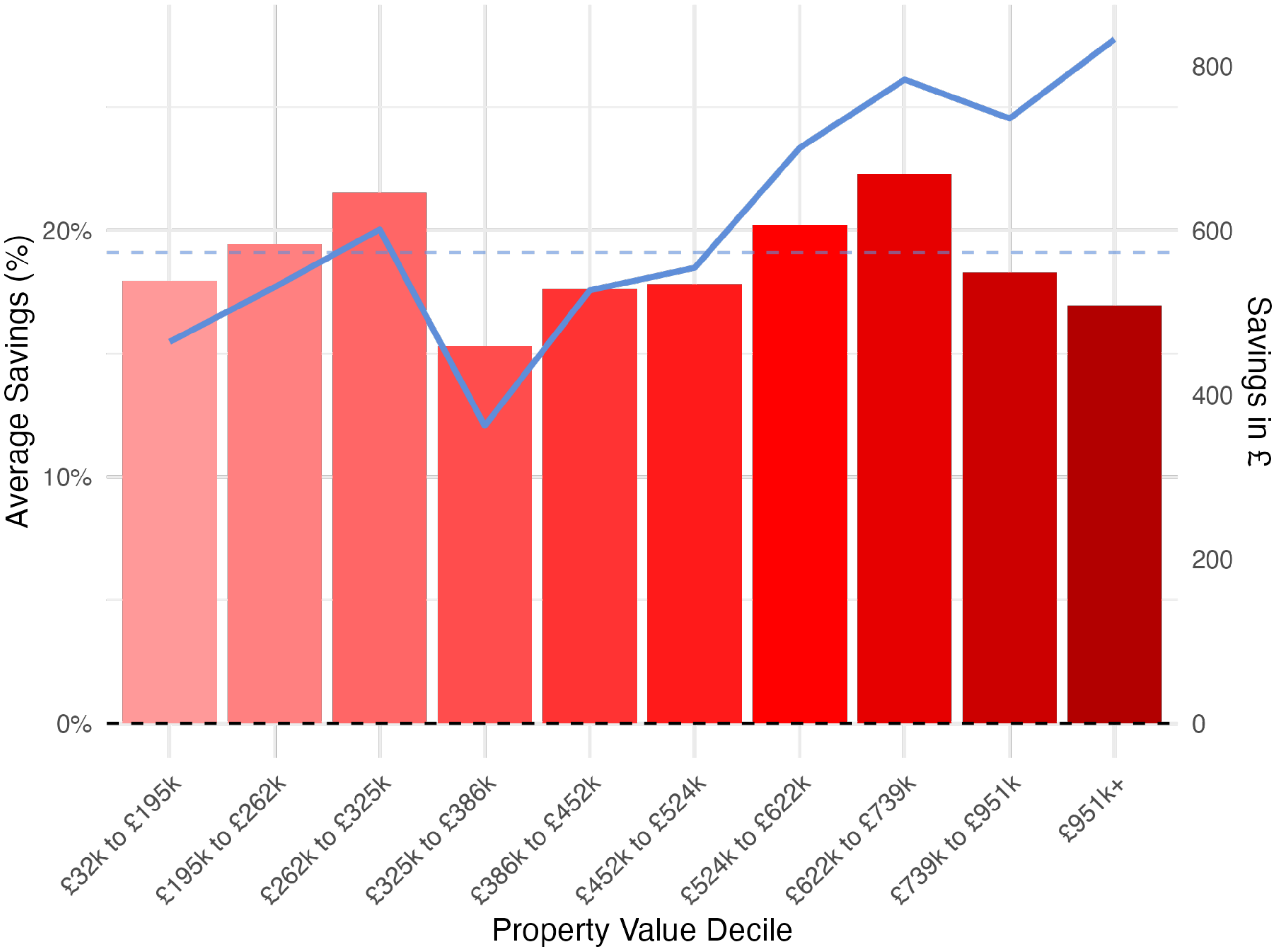
Figure A.36: Impact of *Cosy* by Region



A.2.10 Average Savings by Property Value

In this section, we calculate the average savings by comparing the cost difference between the average marginal price and the Cosy tariff for each rate period ("structural savings", assuming their consumption per rate period does not change), as well as the savings from load shifting, using the coefficients from the difference-in-differences analysis by property value decile. The results show that average savings hover around 18% across all property value deciles (based on estimated property prices), as depicted by the red bars and the blue dashed average line in Figure A.37. The bold blue line represents the average savings in pounds per year, shown on the secondary axis. We observe that higher property value deciles tend to have larger savings, but these households also have higher overall pre-*Cosy*-adoption energy bills.

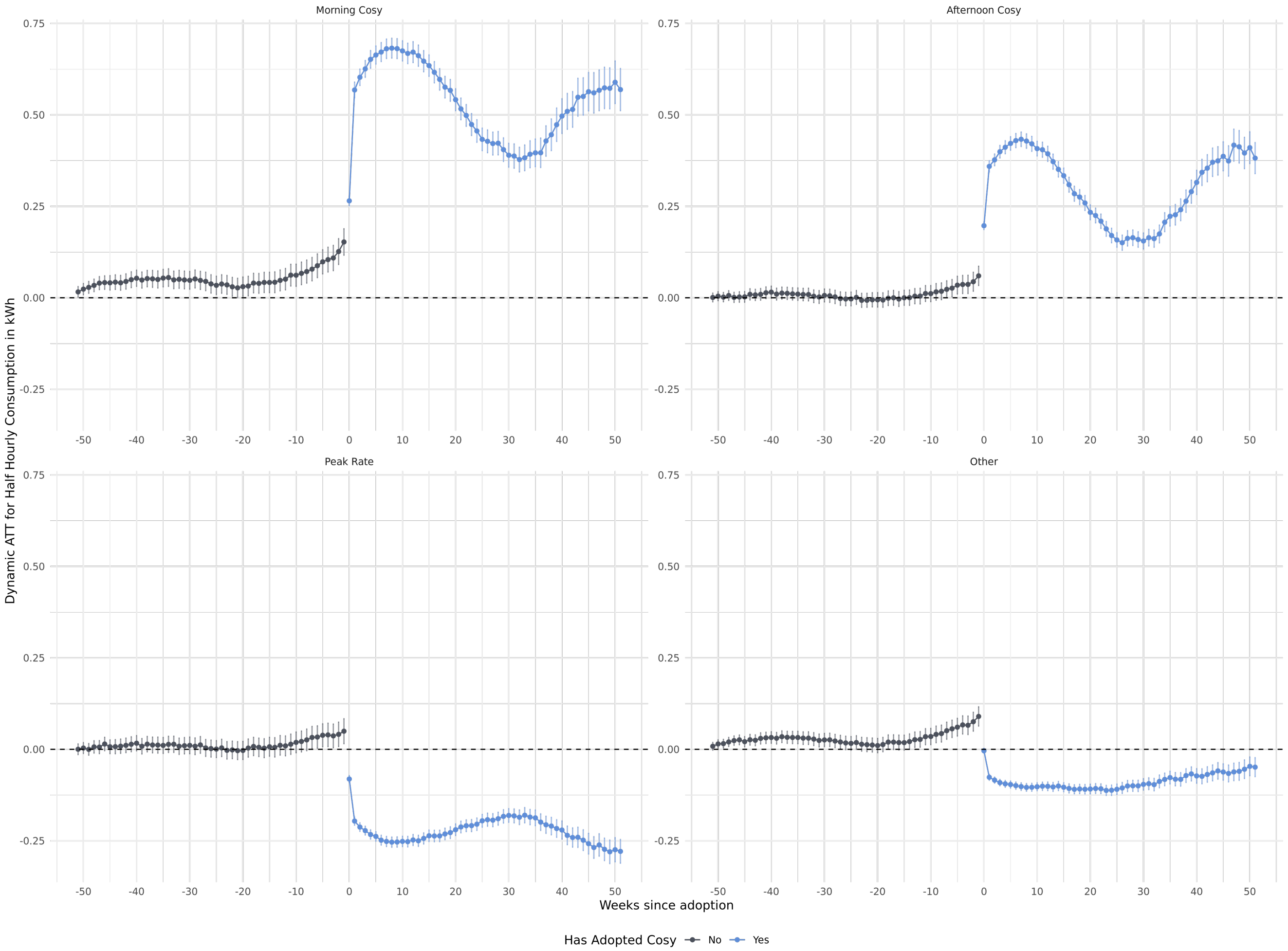
Figure A.37: Average *Cosy* Savings by Property Value



A.2.11 DID Impute Estimate

In this section, we use the same strategy as in the Section A.1.7, but for the impact of *Cosy*, using the Borusyak et al. (2024) estimator (imputation DID) to assess the robustness of our results compared to the CS estimators. We find that the plots are very similar when comparing Figure A.38 to the Callaway and Sant'Anna (2021) estimates with a robust universal base period (Figure A.22). The main difference between the two approaches is that in the Callaway and Sant'Anna (2021) estimates, we account for a one-week anticipation period to account for individuals who start receiving treatment on different days before the first full week of treatment (which we define as the point when they are fully treated).

Figure A.38: DID Impute Estimate for *Cosy* Periods



A.2.12 TWFE Event Study

We run the following model by period for all customers that have adopted *Cosy* in the past year:

$$Consumption_{it} = \sum_{w=-52,-9,...,1,..,52}^{W} \alpha_w WeeksSinceCosy_{it}^{w} + X\beta + \delta_t + \gamma_i + \epsilon_{it}$$

where: - $WeeksSinceCosy_{it}^{w}$ is a categorical variable equal to the number of weeks before and after the adoption of Cosy. We use the week prior adoption as the omitted category.

The charts show the event study coefficients for each specified period. We find that coefficients are consistent with those from the difference-in-differences analysis for the Morning and Afternoon *Cosy* periods.

Figure A.39: Event Study - *Cosy* on Morning *Cosy* Half Hourly Electricity

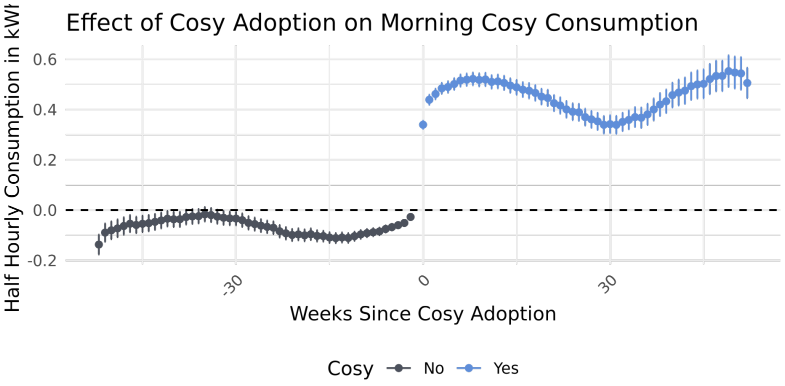


Figure A.40: Event Study - *Cosy* on Afternoon *Cosy* Half Hourly Electricity

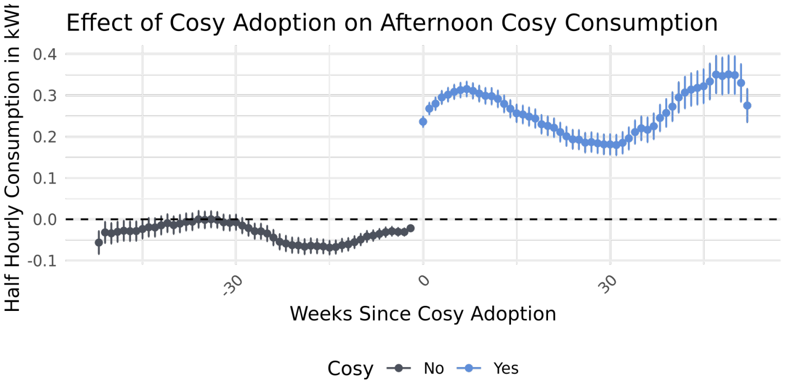


Figure A.41: Event Study - *Cosy* on Peak Rate Half Hourly Electricity

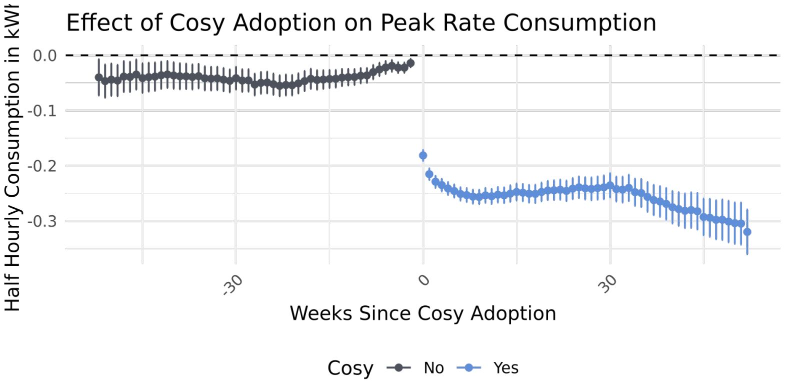


Figure A.42: Event Study - *Cosy* on Other Periods Half Hourly Electricity

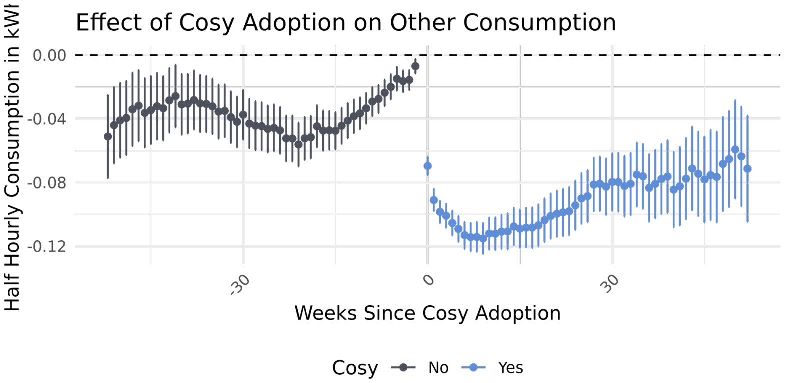
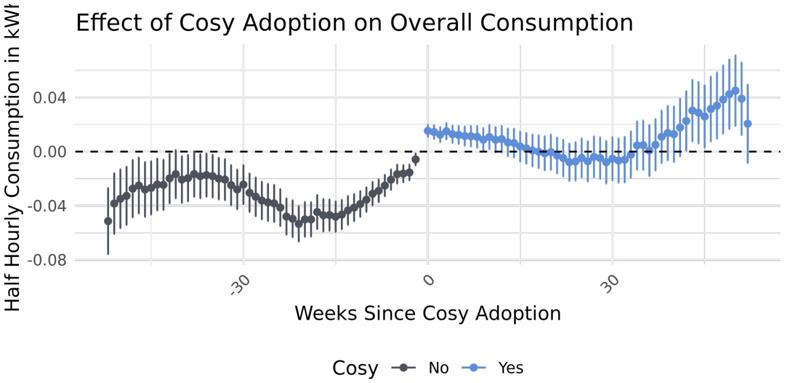


Figure A.43: Event Study - *Cosy* on Overall Half Hourly Electricity



A.2.13 Survey Respondents versus Non-Respondents

Table A.13: Comparing *Cosy* Survey Respondents and Non-Respondents

Variable	Survey Respondents [N=321]	Non-Respondents [N=459]
Energy Efficiency	65.38	64.12
	(18.17)	(18.61)
Floor Area	146.84	143.09
	(76.35)	(81.51)
Property Value	543,038.73	523,676.32
	(391,945.68)	(386,740.94)

Note: Values are means, with standard deviations in parentheses.

A.3 External Validity

A.3.1 External Validity Tables

Table A.14: External Validity by Area for Heat Pump Installations

	Weighted Mean	
Variable	MSOAs with HP Installations (N = 1,104)	Other MSOAs (N = 5,976)
Total annual income (£)	49,323.84 (9,700.39)	46,079.25 (11,290.53)
Property price (£)	384,517.82 (159,046.28)	367,330.35 (264,659.20)
Average HH Size	2.36 (0.17)	2.39 (0.28)
HH Not Deprived in Any Dim. (%)	52.08 (7.43)	47.33 (8.90)
Average Age	42.26 (4.08)	40.46 (4.74)
Share Level 4 Qualifications (%)	28.33 (7.70)	27.27 (9.98)

Note: Population weighted standard deviations in parenthesis

Table A.15: External Validity by Area for *Cosy* Adopters

	Weighted Mean	
Variable	MSOAs with Cosy Adopters (N = 2,860)	Other MSOAs (N = 4,220)
Total annual income (£)	48,596.70 (10,660.63)	45,235.41 (11,208.87)
Property price (£)	403,053 (211,457)	347,408 (272,039)
Average HH Size	2.34 (0.18)	2.41 (0.31)
HH Not Deprived in Any Dim. (%)	51.64 (7.65)	45.67 (8.81)
Average Age	42.57 (4.41)	39.49 (4.45)
Share Level 4 Qualifications (%)	29.49 (8.91)	26.03 (9.89)

Note: Population weighted standard deviations in parenthesis

Table A.16: External Validity by Housing Characteristics for *Cosy* and Heat Pump Adopters

Variable	*Cosy* Adopters [N=6016]	Heat Pump Adopters [N=1208]	Smart Meters Customers [N=3391]
Energy Efficiency	65.50	72.42	64.91
	(18.00)	(13.52)	(12.74)
Floor Area	145.54	115.03	99.14
	(78.02)	(60.85)	(67.91)
Property Value	536,924.36	468,954.05	396,600.69
	(401,408.02)	(224,706.07)	(325,056.25)

We define *Early* versus *Late* Adopters using the adoption or installation date that divide our sample in two for the balance tables Table A.17 and Table A.18. In both cases, we find that early adopters have slightly more expensive and larger properties, which is linked to higher EAC (an estimate of annual electricity consumption).

Table A.17: Balance Table for Heat Pump Early and Late Adopters

Variable	Early (N = 635)	Late (N = 668)
Energy Efficiency	72.33	72.33
	(12.94)	(13.84)
EAC	6,066.52	4,529.37
	(3,896.16)	(3,257.05)
Floor Area	117.87	111.78
	(37.22)	(75.39)
Property Value	489,720.79	438,104.64
	(226,353.89)	(208,237.57)

Table A.18: Balance Table for *Cosy* Early and Late Adopters

Variable	Early (N = 3023)	Late (N = 3039)
Energy Efficiency	67.20	63.80
	(17.41)	(18.40)
EAC	8,179.71	7,183.82
	(5,660.98)	(5,007.10)
Floor Area	151.57	139.48
	(72.84)	(82.37)
Property Value	562,231.96	512,052.21
	(396,946.68)	(403,517.94)

A.3.2 External Validity: Reweighting to General Smart Meter Population

In this matching exercise, we aim to compare three groups of customers: the heat pump adopters, the *Cosy* customers, and a randomly selected control group of Octopus Energy customers with smart meters. We have full data on pre-trial (December 2021) Estimated Annual Consumption (EAC) and property-related characteristics for a sub-sample these three groups: 658 heat pump adopters, 2,618 *Cosy* customers, and 1,948 of the 5,000 randomly selected Octopus Energy customers with smart meters. We do not have the full sample of any of the three groups, as we do not have 2021 EAC data for customers who joined Octopus Energy after this date.

As in Section A.3.1, we see in Table A.19 and Table A.22 that heat pump adopters and *Cosy* customers have larger and more expensive properties. Heat pump adopters and *Cosy* also consume more electricity; while this may be due to heat pump consumption for *Cosy* customers, it is noteworthy that even heat pump adopters have higher pre-heat-pump consumption than a typical smart meter customer. *Cosy* customers have a similar EPC rating to Octopus Energy smart meter customers, while heat pump adopters have better energy efficiency. This makes sense given that our heat pump adopter sample adopted heat pumps due to the Boiler Upgrade Scheme, which until recently had minimum energy efficiency requirements.

We performed matching based on key customer attributes (property value, estimated annual consumption, energy efficiency, and floor area). This process helps to balance the distribution of these covariates between the heat pump, *Cosy* and random samples. Specifically, we applied a full matching method with an "ATC" (Average Treatment effect on the Controls) estimand so that our heat pump adopters and *Cosy* customers resemble the random sample of smart meters customers on observables. The matching involved setting calipers (allowable differences) for the covariates to ensure that matched pairs are as similar as possible on these characteristics. Post-matching, we see in Table A.20 and Table A.23 that our groups are now much more similar with property value, EAC, energy efficiency and floor size much closer to the random sample of customers. Due to the matching process with calipers, we excluded 47 heat pump customers, 437 *Cosy* customers, and 47/45 customers from the random sample for the heat pump and *Cosy* matching procedures, respectively.

Once we achieved a good balance between the two groups, we re-estimated the treatment effect using a TWFE model, as shown in Table A.21 and Table A.24. For this, we applied weighted regressions, with the weights coming from the matching procedures.

We obtain similar coefficients for the impact of adopting a heat pump to our non-matching TWFE regressions (Table A.1). Total electricity consumption increases by 3,326 kWh, gas decreases by 10,294 kWh, and the overall decrease is 6,956 kWh. The estimates are slightly smaller than the heat pump adopters group before weighting, but so are their pre-treatment averages.

For *Cosy* adoption, we observed that the load-shifting coefficients were smaller after matching than in our non-matching TWFE regression outputs (Table A.8). Additionally, the relative shares of load shifting compared to pre-adoption averages were reduced. These results are consistent with the fact that the general population (a random sample of smart-meter customers) tends to have smaller homes than heat pump adopters and especially *Cosy* adopters.

Table A.19: Summary of Balance for All Data (Heat Pump)

	Means Heatpump	Means Random	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
Distance	0.32	0.23	0.81	1.51	0.20	0.32
Property Value	473, 410.90	389, 879.90	0.27	0.49	0.16	0.28
EAC	4, 158.31	3, 946.74	0.07	0.80	0.04	0.08
Energy Efficiency	72.50	65.04	0.59	1.01	0.08	0.24
Floor Area	117.50	99.20	0.33	1.89	0.08	0.29

Table A.20: Summary of Balance for Matched Data (Heat Pump)

	Means Heatpump	Means Random	Std. Mean Diff.	Var. Ratio	eCDF Mean
Distance	0.23	0.23	0.01	1.04	0.005
Property Value	357, 478.50	342, 181.00	0.05	0.80	0.04
Estimated Annual Consumption	3, 484.10	3, 463.07	0.01	0.94	0.01
Energy Efficiency	66.17	66.47	-0.02	0.98	0.01
Floor Area	95.37	92.16	0.06	0.77	0.02

Table A.21: TWFE using Matching Weights (Heat Pump)

Dependent Variables:	Monthly Electricity Consumption (kWh)	Monthly Gas Consumption (kWh)	Consumption in kWh per period
		Electricity	
		Gas	
		Total	
Model:	(1)	(2)	(3)
Variables			
Is HP Installed = 1	3,326.8***	-10,294.2***	-6,956.2***
	(125.8)	(303.5)	(265.2)
Pre-Treatment Average			
Yearly Consumption	4,163.43	10,051.97	14,057.57
Fixed-effects			
HDD	Yes	Yes	Yes
Household	Yes	Yes	Yes
Week	Yes	Yes	Yes
Fit statistics			
Observations	64,891	55,398	55,398
Number of Households	609	543	543
Number of Time Periods	129	129	129
R^2	0.70449	0.73921	0.78051

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.22: Summary of Balance for All Data (Cosy)

	Means Cosy	Means Random	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
Distance	0.64	0.48	1.04	1.55	0.25	0.37
Property Value	526, 517.40	389, 879.90	0.44	1.41	0.14	0.23
EAC	6, 312.48	3, 946.74	0.82	3.50	0.19	0.29
Energy Efficiency	66.11	65.04	0.08	1.90	0.04	0.13
Floor Area	143.38	99.20	0.81	2.23	0.12	0.33

Table A.23: Summary of Balance for Matched Data (Cosy)

	Means Cosy	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
Distance	0.48	0.48	0.01	1.02	0.003	0.02
Property Value	372, 723.80	365, 276.60	0.02	0.94	0.01	0.06
Estimated Annual Consumption	3, 791.23	3, 809.88	−0.01	1.09	0.01	0.04
Energy Efficiency	65.50	65.29	0.02	1.11	0.01	0.03
Floor Area	97.15	95.98	0.02	1.00	0.004	0.03

Table A.24: TWFE using Matching Weights

Dependent Variable:	Half Hourly Consumption in kWh				
	Matching				
	Morning Cosy	Afternoon Cosy	Peak Rate	Other	Overall
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Cosy Contract Active = 1	0.4151***	0.2519***	-0.1012***	-0.0624***	0.0324***
	(0.0237)	(0.0132)	(0.0080)	(0.0071)	(0.0049)
Pre-Treatment Average					
Half Hourly Consumption	0.3274	0.2976	0.3991	0.3511	0.3473
Fixed-effects					
HDD	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	1,473,787	1,474,007	1,473,933	1,475,591	1,475,593
Number of Households	2,181	2,181	2,181	2,181	2,181
Number of Time Periods	916	916	916	916	916
R^2	0.50570	0.44212	0.43951	0.55244	0.61421

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*