# It's About Time: Transitioning to Time-of-Use Pricing and Consumer Demand for Electricity

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Greg Kirwin

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**Abstract**

Using high-frequency data from a public utility company, I investigate the impact of switching residential consumers from traditional multi-part electricity tariffs to a time-dependent one. I find evidence of adverse selection out of the program by higher-volume consumers. Consumers that were automatically transitioned to the new plan structure show little evidence of re-optimizing their usage to account for higher prices during peak periods, muting the impact of the program.

## 1 Intro

## 2 Previous Literature

This paper's primary contribution is to the vast literature on time-of-use electricity pricing. Though time-of-use pricing has only recently seen broader implementation by utilities, papers describing its efficiency extend back to at least the 1940s. The pivotal work Boiteux (1960) describing the advantages of peak load pricing was originally published in the *Revue générale de l'électricité*, though it was not translated into English until 1960. Other early works include Houthhaker (1951), Hirshleifer (1958), and Steiner (1957), which described the issue of electricity pricing in the presence of time-dependent load. These papers were followed by others like Williamson (1966), Aigner and Leamer (1984), and Pressman (1970), which built on the foundation for capacity constraints and optimal electricity pricing with further theoretical solutions. In broad terms, these authors recognized that utility companies face a problem of needing significantly more capacity during small periods of the day, which then goes unused for most hours. Under time-independent pricing, such as the common "block" pricing schemes, consumers who use less electricity during peak periods also effectively subsidize their neighbors, as they do not contribute to the peak load problem but face prices that account for it. Being able to charge customers based on the timing of their consumption thus allows utilities to account for the added costs of their demand.

While these advantages have been known for decades, the main difficulty was the ability to implement it. Public utilities around the US began experimenting with peak pricing schemes throughout the 1970s and 1980s, with some of these experiments being discussed in Train and Mehrez (1994) **BRIEF DESCRIPTION**. More contemporaneous time-of-use papers such as **WOLAK, ALLCOTT, JESSOE + RAPSON, ITO, ETC** have also documented other experiments in time-of-use pricing that introduce modifications intended to help with the salience of pricing or other components of demand.

Other papers like Ito et al. (2023) and Fowlie et al. (2021) have also modeled the social benefits and costs of switching consumers from one pricing scheme to another using additional experimental evidence. Fowlie et al. (2021) in particular thoroughly details the differences between opt-in and opt-out plan switching for consumers, concluding that defaulting consumers into a pricing switch is more effective at inducing desired reductions in peak demand than allowing consumers to opt in on their own, in large part due to issues with consumer awareness.

Enrich et al. (2024) is also highly relevant, documenting a similar time-of-use rollout program in Spain. Similarly to this paper, the public utilities were required to default their consumers into time-of-use pricing by a government authority; where this paper differs is in the plan switch implementation. First, most Spanish consumers were on a flat tariff by default rather than increasing-block pricing. Second, the switch occurred for all consumers at the same time. Lastly, the Spanish government appears to have advertised the plan switch more aggressively than in California [1]. As a result, the authors find an immediate and lasting impact on electricity demand from the switch, with consumers reducing their consumption by 5.7% during the "mid-peak" period and 8.9% during the peak period.

Outside of time-of-use pricing, this paper is also related to the broader literature on electricity demand and elasticity, which includes notable works such as Ito (2014), Ito et al. (2023), Buchsbaum (2023), Borenstein (2009), and Reiss and White (2005). This literature centers on estimation of consumer responses to price changes or other shocks.

# 3 Data

## 3.1 Data Acquisition

Data was obtained from Pacific Gas & Electric (PG&E) in California under the state's Energy Data Request Program. The initial dataset was comprised of 300,000 house-years, which amounted to 75,000 households' worth of data for four years, from 2018 through 2021. A random sample was chosen from each zip code in their service area that represented a fixed percentage of their customers in that zip. Zips with fewer than 100 active customers were excluded.

To be eligible, the household must be zoned as a single-family home and must have been an active PG&E customer at that address for the entire four years. I cannot address whether these consumers have different preferences than customers in multifamily homes or who change homes more frequently, though it is easier to compare behavior across homes because many apartment buildings are "master metered," meaning I would not be able to observe an individual customer's behavior. The data are also anonymized to the zip code level, so I cannot observe house characteristics or customer demographics.

[1] While not described in the paper itself, there was broader coverage of the transition, including explanations of optimal usage in the country's largest newspaper *El País*. See https://elpais.com/economia/2021-05-24/la-nueva-factura-de-la-luz-abaratara-al-menos-un-34-el-recibo-de-19-millones-de-consumidores.html?rel=listapoyo

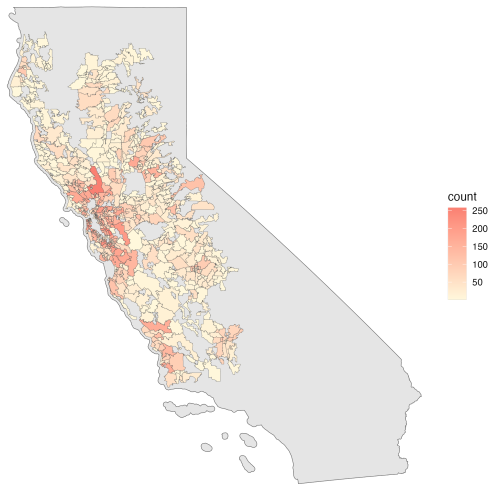


Figure 1: The number of households by zip code, removing alternative plans, solar, EVs, and the top and bottom percentiles of usage.

PG&E provided the data in sets of one-hour increments over the four years. For each customer, I also observe their monthly bill amount and total usage from 2018 through the end of 2022, plus any modifiers to their costs, such as participation in a subsidy program or solar interconnection. Customers have an assortment of plans that they may select during the course of the sample, and I observe any changes in their plan during the sample via a record indicating the beginning and end of their service agreement.

## 3.2 Electric Rate Transition

In PG&E's service, customers can select from two types of rates- time-invariant "block" pricing and "time-of-use" (TOU) pricing. Time-invariant pricing is the predominant electricity plan type in the United States[2], but utility companies have begun to transition to TOU pricing as the default for their customers as "smart" meters, which allow for measuring real-time consumption, have become more widely available [3]. Under block pricing, consumers face a uniform tariff rate that increases at set usage thresholds. Under TOU pricing, consumers face a constant price during "off-peak" hours, but the price increases at "peak" hours of the day, which typically correspond with times of high aggregate consumption across the utility's service area. Some of PG&E's TOU plans eliminate the additional "penalty" for high monthly usage, but others do not. In PG&E's service, customers can select from two types of rates- "block" pricing and "time-of-use" (TOU) pricing. Block pricing is the predominant electricity

[2]According to Faruqui and Tang (2023), in 2021 only 8.7% of US households were on a TOU plan. While I have not seen specific estimates for the US market, block pricing and flat tariffs likely comprise the majority of the remaining plans.

[3]Note that "smart" meters here pertain to grid-connected devices that allow for the utility company to constantly check real-time consumption, and not "smart" thermostats that allow for consumers to manage their in-home temperature, though the latter can connect to the former.

plan type in the United States[4], but utility companies have begun to transition to TOU pricing as the default for their customers as "smart" meters, which allow for measuring real-time consumption, have become more widely available [5]. Under block pricing, consumers face a uniform tariff rate that increases at set usage thresholds. Under TOU pricing, consumers face a constant price during "off-peak" hours, but the price increases at "peak" hours of the day, which typically correspond with times of high aggregate consumption across the utility's service area. Some of PG&E's TOU plans eliminate the additional "penalty" for high monthly usage, but others do not.

In the latter half of my sample, PG&E begins to transition nearly all of its customers to TOU pricing from the original block price at the direction of the state. Based on contemporaneous documentation, PG&E had anticipated switching consumers beginning in October of 2020, but this was likely delayed due to Covid [6]. While a small number of consumers do transition to the new plans before the end of 2020, in my sample, the first "wave" of consumers do not appear to change plans until April of 2021 [7]. Rollout is done on a county-by-county basis, with the last group switching in April of 2022. Crucially, customers had the option to opt out of the transition and either stay on their original rate or choose one of the alternative TOU rates. Consumers were given the option to notify PG&E up until the month of their county's transition, and could do so online, where they also had the ability to compare rate plans for their usage history and decide what their optimal rate plan should be. According to available documents, customers received emails up to four months prior to the transition notifying them of the change. Additionally, the company provided "risk-free bill protection" that would reimburse customers on the TOU plan for any additional cost over the block pricing plan for their first 12 months on the TOU plan.

| Wave | Old Wave Number | Area | Wave Date |
|---|---|---|---|
| 1 | 4 | North Coast | Apr-21 |
| 2 | 6 | Oakland | May-21 |
| 3 | 7 | Far North Coast | Jun-21 |
| 4 | 8 | San Francisco | Jul-21 |
| 5 | 9 | San Mateo | Sep-21 |
| 6 | 10 | Southern Coast | Oct-21 |
| 7 | 3 | North Central | Feb-22 |
| 8 | 5 | Sonoma Valley | Mar-22 |
| 9 | 2 | Central Valley | Apr-22 |

Table 1: Listed dates based on observed transition month in the sample.

Some consumers are on alternative rate plans that they opt into, such as specialized rates for

[4]See Faruqui and Tang (2023)

[5]Note that "smart" meters here pertain to grid-connected devices that allow for the utility company to constantly check real-time consumption, and not "smart" thermostats that allow for consumers to manage their in-home temperature, though the latter can connect to the former.

[6]See https://www.pge.com/assets/pge/docs/account/billing-and-assistance/TOU-Transition-FAQs.pdf

[7]See https://www.pgecurrents.com/articles/3050-support-statewide-initiatives-pg-e-move-residential-customers-time-use-rate-plan-starting-april for an announcement of the updated counties and waves.

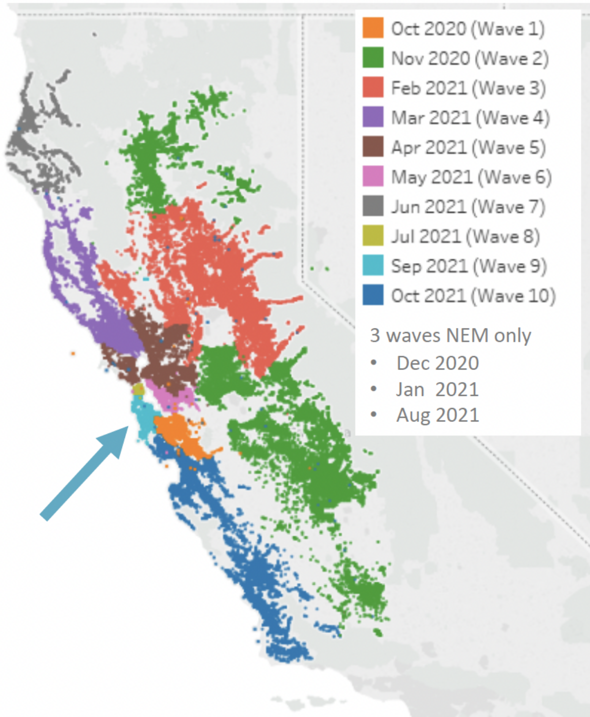


Figure 2: Initial draft of the rollout for PG&E's TOU-C transition program, per their official documentation. Listed dates are for the original plan and not the actual dates.

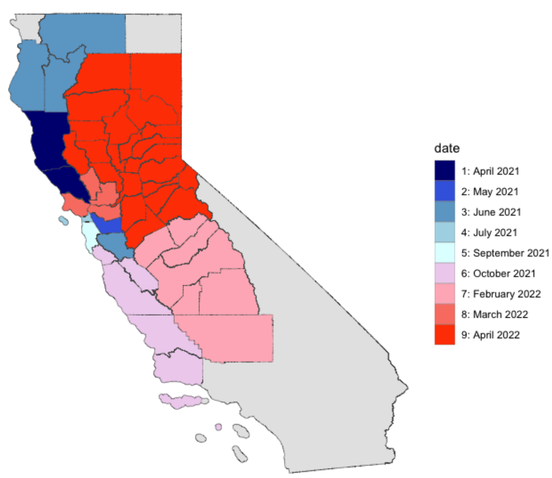


Figure 3: Actual transition dates by county as seen in the data.

electric vehicles or other TOU plans, but the vast majority are not. The new default, "TOU-C", features peak pricing periods from 4PM to 9PM every day of the year, including holidays and weekends. As with block pricing, consumers also face increased tariff rates when they exceed their climate zone's monthly allotment; the penalty is uniform for both the peak and off-peak, so both rates are raised by the same amount. Additionally, there are now rate seasons; peak periods are about 5% higher than off-peak periods during the winter (October-May) but about 15% higher than off-peak in the summer (June-September). This is presumably to account for anticipated increases in electricity consumption from air conditioning; more than 90% of the households in my sample have gas heating and thus do not use as much electricity in the winter.

As alluded to above, consumers in California are divided into "climate zones" that dictate their allotment of electricity at the lowest price tier each month. Since PG&E's service area has a wide variation in climate, customers in areas that face similar weather conditions are grouped, and the region's "allowance" of consumption at the lowest price is calibrated to match the daily usage of households between the 50th and 60th percentiles [8]. This allotment is then multiplied by the number of days in the billing cycle to obtain the total billing cycle allotment; for example, a daily allowance of 20 kWh for a 32-day billing cycle yields 640 kWh. This applies to the cumulative consumption during the billing cycle and does not reset at the beginning of the day. Baseline allowances change in accordance with the winter/summer cycles above, and consumers on both the block and TOU plans face the same allowance within their respective climate zones. Consumers with gas heating have much lower allowances in the winter than consumers with electric heating. The variation across zones can be substantial, and consumers that are quite close geographically can face drastically different climates. For example, the amount of electricity that Boonville consumers in California's mountainous north can use without incurring an increased cost in the summer of 2021 is 10.3 kWh for living in zone X, while those in the beach town of Manchester an hour away can only use 6.8 kWh. In the city of Bakersfield to the far south, where summertime temperatures regularly exceed 100 degrees Fahrenheit, the baseline allotment during this same time period was 20.2 kWh. Figure 4 shows a map of these zones in 1990, and Figure 5 shows a comparison of how baselines change across seasons. The zone borders and allowances are updated infrequently. Borders were adjusted in 2020 but largely stayed the same; allowances are updated every three years but also do not tend to change much in magnitude.

## 3.3 Prices

Prices during the sample period are relatively stable for the lower tiers of block pricing, but vary widely for both the third block pricing tier and both of the TOU price periods. Figure 6 shows a comparison between the block price and TOU price over the entirety of my sample. The most severe change in price occurs for the highest block price tier in June of 2020; this price cut was ordered by governor Gavin Newsom to combat concerns that Californians' electricity consumption would skyrocket because they were staying inside during the Covid pandemic [9]. However, I find that in practice, the percentage of households hitting this price tier did not change significantly. The "jumps" in TOU prices reflect price increases during the summer, with rates within the TOU price tiers being significantly higher than their respective tier of block pricing. During the winter periods, however, TOU rate tiers are actually lower than the block tier.

Figures 7 and 8 plot examples of comparisons between the block pricing and new default

[8] See https://www.pge.com/en/account/rate-plans/how-rates-work/baseline-allowance.html, under "Allowances are determined as follows".

[9] See Advice Letter 5831E, https://www.pge.com/tariffs/assets/pdf/adviceletter/ELEC_5831-E.pdf

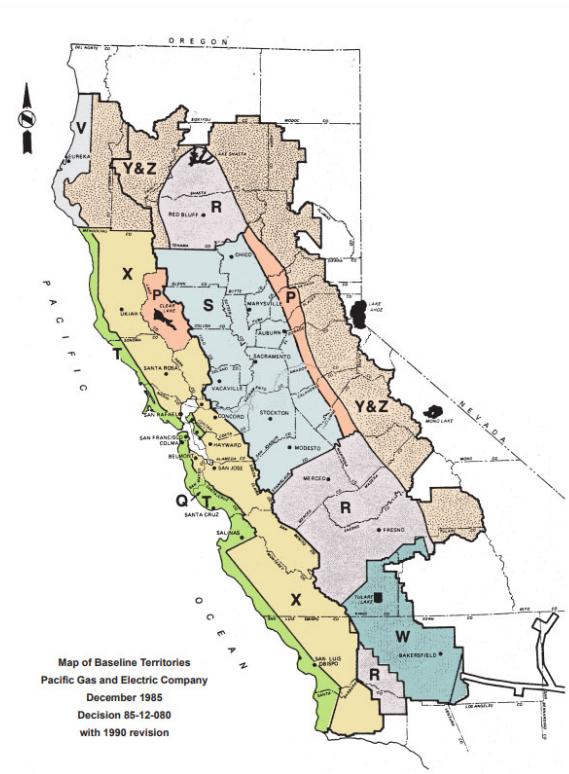


Figure 4: Climate zones for PG&E's service area starting in 1990.

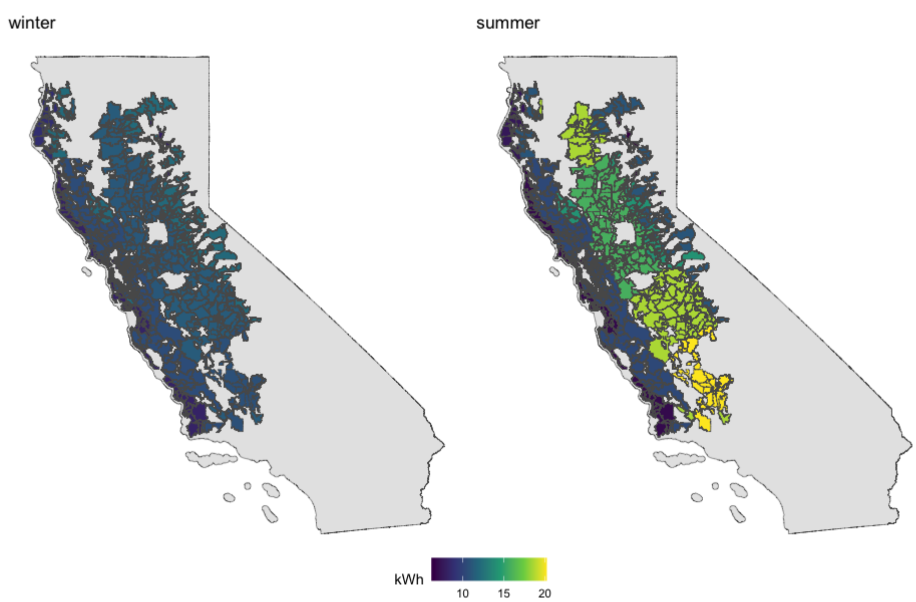


Figure 5: Baselines by season. Scale indicates the estimated average daily consumption for the climate zone.

TOU plan in April and June of 2021 to illustrate how prices changed for consumers. April is the first month of the transition program and June is the third. Prices did not necessarily

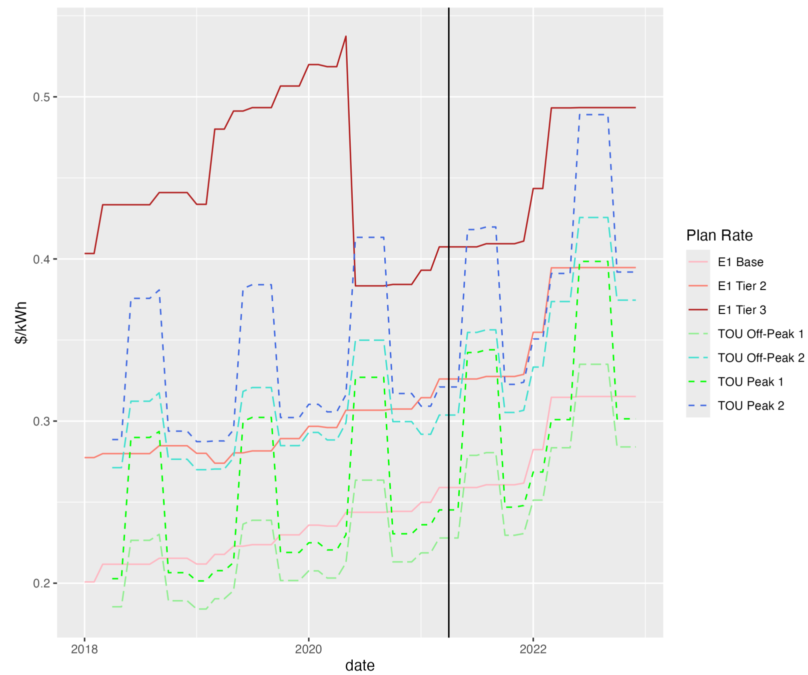


Figure 6: Pricing for TOU and block (E1) plans over time. The black line indicates the first month of the TOU transition rollout. "Peak 1" and "Off-Peak 1" refer to the first tier of the TOU plan, while "Peak 2" and "Off-Peak 2" refer to the second tier.

increase for consumers due to seasonal differentiation in addition to the aforementioned time-of-day differentiation. In the winter months of 2021, prices are better for all consumers relative to the block plan at all tiers of usage, with the most savings for consumers at the high end of consumption. However, during the summer, prices are strictly worse for consumers in the first two tiers; consumers that breach the third usage tier only face higher prices for their peak period consumption.

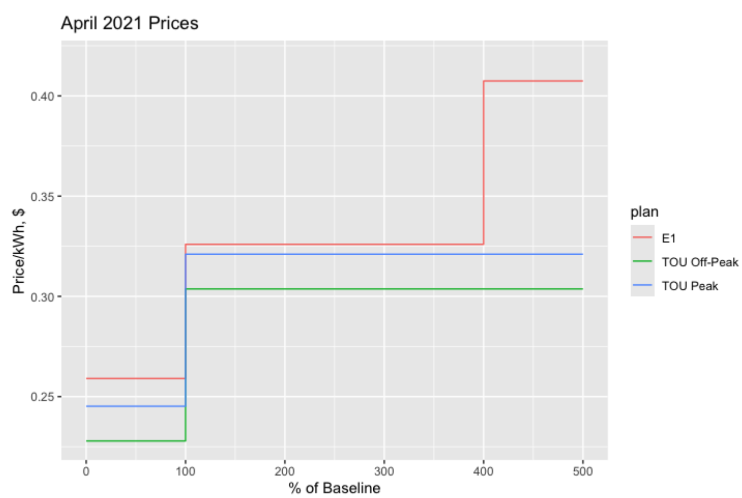


Figure 7: Price comparison, first month of transition (April 2021).

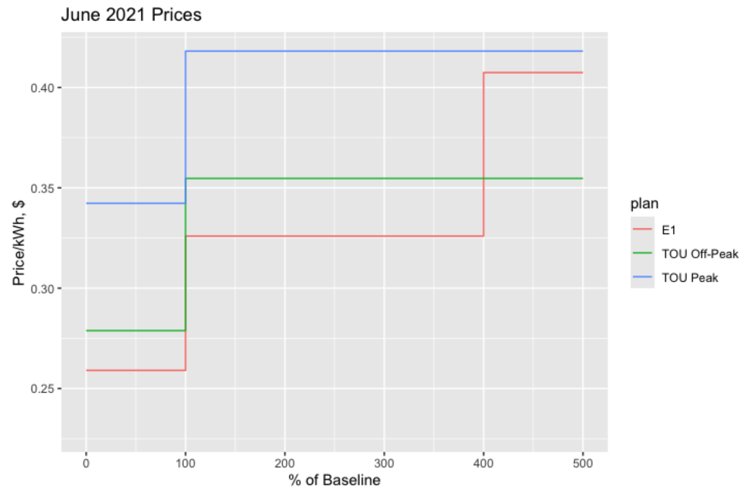


Figure 8: Price comparison, third month of transition (June 2021).

### 3.4 Summary Statistics

From the raw dataset, I remove customers that are ever on an electric vehicle plan, subsidy program (CARE and FERA), or have solar. I also remove any customer that ever records an entire month with less than 15 kWh or more than 3600 kWh. Finally, I remove households that switch to TOU-C earlier or later than their county's wave. This leaves 33,072 households for the analysis.

Select summary statistics are presented in table 2 for the first month in the dataset, and the last month in 3. Waves are sub-divided into households that stayed on block pricing or switched to TOU pricing. Across waves, it is apparent that there are stark differences in consumption patterns; these are mostly driven by differences in climate. In comparing the two, it appears that in the pre-transition period, staying households use approximately the same amount of electricity as switching households, with no decisive trend between waves. However, in the post-transition period, switching households used more electricity on average in every wave.

The opt-out rates for seven of the nine waves are well below half. It is worth noting that the two outlier waves were delayed from the revised transition schedule that I have found available online [10] and thus it is plausible that customers had more time to opt out. Nonetheless, most consumers were transitioned to the new rate plans. It is important to note that some consumers were exempt from the transition and did not need to opt out: those with subsidized plans, electric vehicle plans, have a "medical" baseline to accommodate electricity-heavy medical equipment, or are already on a different TOU plan. However, given that I have removed these customers save for the medical baseline [11], they should not impact the estimated switching rate. PG&E's "FAQ" for the TOU program also mentions that customers in "hot climate zones" were exempt from the transition; however, I do not find evidence of this in the data. See 10

[10] See https://www.businesswire.com/news/home/20210125005821/en/

[11] I do not have an indicator in the data for consumers on a medical baseline; however, these customers are likely filtered out due to very high electricity usage or high rates of error when re-constructing their bills from the hourly level. Medical baseline eligibility requires that the customer use specific equipment such as an electric wheelchair or life support, which also likely represents a small portion of the sample population.

for a comparison of switching rates by climate zone, and 9 for switching rates by wave. While customers in the hottest climate zones—P, R, and W—do have lower switch rates than the more temperate regions, it does not appear that customers in any specific climate zone were completely exempt from the rate transition program. Thus, customers being automatically exempt based on geography does not seem to be a plausible explanation for why the switch rates in the latter waves are conspicuously low.

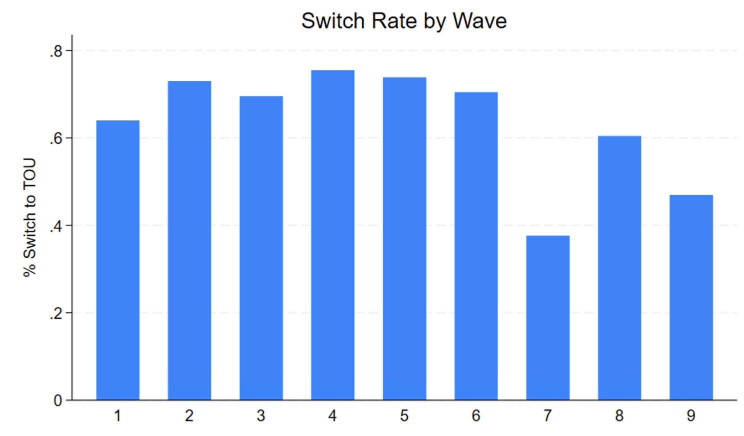


Figure 9: Percentage of households that switched by December 2022, by wave.

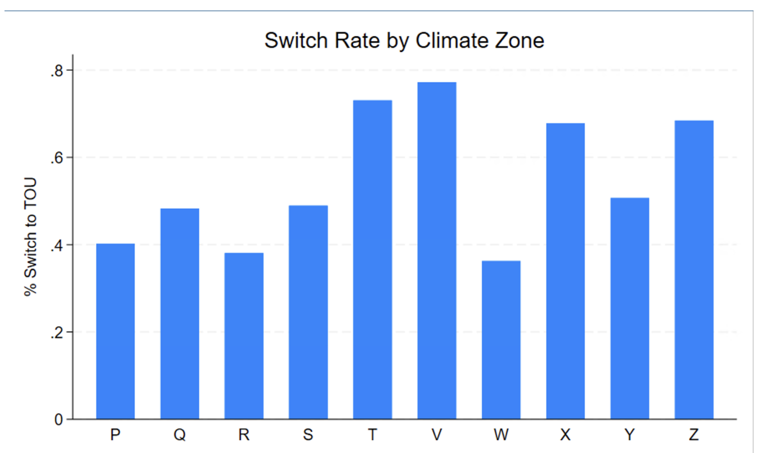


Figure 10: Percentage of households that switched by December 2022, by climate zone.

# 4 Impact on Consumption

With the above descriptive facts established, I intend to study whether the program led to noticeable changes in consumer behavior in the post-transition period. The desired outcome of the transition as described by the California Public Utilities Commission (CPUC) and PG&E is to promote more consumption during periods when California's energy production is more renewable. Currently, California has a large excess of renewable energy production relative to demand during daylight hours, but must rely on natural gas to produce its energy

| | Stay kWh | | | | | | Switch kWh | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Wave** | **N** | **Mean** | **S.D.** | **Median** | **25th** | **75th** | **N** | **Mean** | **S.D.** | **Median** | **25th** | **75th** |
| 1 | 678 | 503.1 | 289.3 | 447.5 | 312.0 | 638.0 | 1,220 | 497.8 | 337.5 | 421.0 | 285.5 | 609.5 |
| 2 | 1,054 | 442.1 | 221.1 | 408.0 | 295.0 | 536.0 | 2,852 | 443.6 | 238.2 | 403.0 | 281.0 | 549.0 |
| 3 | 1,339 | 512.2 | 268.3 | 451.0 | 338.0 | 625.0 | 3,014 | 522.5 | 297.1 | 460.0 | 331.0 | 636.0 |
| 4 | 356 | 415.3 | 252.5 | 362.5 | 250.5 | 530.5 | 1,115 | 410.5 | 242.2 | 372.0 | 248.0 | 522.0 |
| 5 | 634 | 496.9 | 289.6 | 438.0 | 312.0 | 601.0 | 1,803 | 511.0 | 297.1 | 450.0 | 322.0 | 619.0 |
| 6 | 1,034 | 451.7 | 297.2 | 397.5 | 257.0 | 575.0 | 2,477 | 457.2 | 298.3 | 394.0 | 264.0 | 569.0 |
| 7 | 1,475 | 528.0 | 328.0 | 458.0 | 316.0 | 664.0 | 865 | 526.6 | 320.8 | 479.0 | 305.0 | 659.0 |
| 8 | 2,283 | 518.1 | 266.1 | 471.0 | 339.0 | 633.0 | 3,517 | 531.0 | 300.1 | 470.0 | 330.0 | 657.0 |
| 9 | 2,718 | 557.3 | 337.1 | 498.0 | 328.0 | 700.0 | 2,459 | 561.1 | 366.7 | 489.0 | 307.0 | 719.0 |

Table 2: Select summary statistics by wave for the month of January, 2018.

| | Stay kWh | | | | | | Switch kWh | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Wave** | **N** | **Mean** | **S.D.** | **Median** | **25th** | **75th** | **N** | **Mean** | **S.D.** | **Median** | **25th** | **75th** |
| 1 | 629 | 566.3 | 358.7 | 501.0 | 339.0 | 719.0 | 1,105 | 575.2 | 414.3 | 476.0 | 315.0 | 727.0 |
| 2 | 946 | 496.8 | 262.8 | 451.0 | 326.0 | 613.0 | 2,554 | 515.0 | 300.1 | 458.0 | 319.0 | 649.0 |
| 3 | 1,211 | 572.0 | 324.0 | 501.0 | 369.0 | 681.0 | 2,730 | 585.2 | 358.1 | 506.5 | 353.0 | 735.0 |
| 4 | 313 | 458.3 | 289.5 | 420.0 | 256.0 | 572.0 | 998 | 477.3 | 297.8 | 416.0 | 288.0 | 601.0 |
| 5 | 576 | 529.4 | 289.5 | 467.5 | 331.0 | 676.0 | 1618.00 | 573.7 | 357.0 | 497.0 | 343.0 | 704.0 |
| 6 | 954 | 508.1 | 361.6 | 432.0 | 282.0 | 619.0 | 2,250 | 518.0 | 369.7 | 433.0 | 287.0 | 646.0 |
| 7 | 1,336 | 592.5 | 393.1 | 504.5 | 340.0 | 745.0 | 800 | 600.4 | 400.4 | 530.0 | 321.5 | 774.5 |
| 8 | 2,089 | 583.8 | 333.3 | 519.0 | 370.0 | 708.0 | 3,217 | 601.5 | 347.5 | 537.0 | 364.0 | 753.0 |
| 9 | 2,520 | 627.8 | 416.9 | 539.5 | 352.0 | 802.0 | 2,228 | 636.9 | 453.0 | 537.0 | 332.0 | 813.5 |

Table 3: Select summary statistics by wave for the month of December, 2022.

in the evenings when renewable production wanes. While this aim is admirable, it relies on consumers responding to the plan switch in the desired manner.

There are multiple possible ways in which consumers may have responded to the plan switch. First, they may have reduced their consumption during peak hours, but how consumption during off-peak hours may have changed is unclear. For example, consumers may have increased their off-peak consumption and thus their total consumption is relatively unchanged. They may also have not substituted towards off-peak consumption at all if they cannot substitute their consumption between the periods due to schedule restrictions. Alternatively, consumers may have kept their peak consumption unchanged and substituted away from off-peak consumption if their elasticity for it is sufficiently low. These possibilities are all dependent on how substitutable the two periods are, and their respective elasticities. To assess these potential outcomes, I estimate several different regression specifications that are commonly employed in the program evaluation literature.

To assess the outcome in each specification, I use variables that are commensurate with the potential consumer response above. This includes total demand, billed amounts, and peak share as a percentage of total demand. For substitution across time periods, I also run a separate set of regressions for consumption in each hour.

## 4.1 Difference-in-Differences

First, I begin with a traditional difference-in-differences approach. Assuming that selection out of the program is random, "staying" consumers should exhibit similar pre-trends to "switching" consumers in the pre-period, but differ afterwards due to the change in prices. Given that staying consumers have no incentive to change their consumption, they should exhibit little post-transition change. Thus, the difference between the two should be identifiable as the effect of the transition. The model estimated will be

$$Y_{ijt} = \beta_0 + \tau post_{jt} + \gamma_i + \Delta post_{jt} \times treated_{ij} + \theta_j + \tau_t + \epsilon_{ijt}$$

where $Y_{ijt}$ is the outcome of interest, $post_{jt}$ is an indicator of whether consumer $i$'s wave $j$ is in the post-transition period $t$, $treated_{ij}$ an indicator of the consumers in wave $j$ being treated, and $post_{jt} \times treated_{ij}$ the average treatment effect of the program on the consumers that have switched. $\theta$ and $\tau$ represent fixed effects for the consumer's wave-month and year-month, respectively, to address heterogeneity across geographies and seasons. $\gamma_i$ is a household fixed effect, which replaces the traditional indicator for being treated in the program. A comparison table with the alternative specification can be found in the Appendix; the results are largely similar.

**Note to self:** Ran the shown results using eventstudy_seasonal.do and peakdid.do

| | **log(kWh)** | **log(bill \$)** | **log(peak kWh)** | **Peak %** |
|---|---|---|---|---|
| Post x Switch | -0.007 | -0.014 | -0.019 | -0.005 |
| | (0.003) | (0.003) | (0.005) | (0.001) |
| Post | 0.000 | -0.010 | -0.010 | -0.001 |
| | (0.005) | (0.004) | (0.007) | (0.001) |
| Constant | 6.077 | 4.771 | 4.774 | 0.279 |
| | (0.001) | (0.001) | (0.001) | (0.000) |
| N | 1,483,143 | 1,483,143 | 1,163,937 | 1,163,937 |
| R2 | 0.796 | 0.804 | 0.78 | 0.556 |
| Wave x Month FE | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes |
| HH FE | Yes | Yes | Yes | Yes |
| Cluster | Zip | Zip | Zip | Zip |

Table 4: Difference-in-difference estimates, pooling across seasons. Post-period is defined as being relative to the customer's county. "Date" fixed effects are month-year, and "wave-month" fixed effects are the calendar month interacted with the household's transition wave. $log(kWh)$ represents the log of the entire billing period's consumption, while $log(peakkWh)$ represents consumption only on the peak period. Observations cover 2018 through 2022 in columns 1 and 2, and 2018 through 2021 in columns 3 and 4 due to data constraints.

The results in Table 4 indicate that consumption decreases across the board. This implies that consumers are both metering their usage in response to the program and also substituting a small portion of their peak consumption towards the off-peak period. However, it is also necessary to consider whether there are different responses, given the new seasonal variation in prices.

## 4.2 Seasonal Division

While the difference-in-differences results indicate that the program had the intended effect of decreasing overall consumption, it also appears to have decreased peak consumption by only around 2 percentage points, which represents only a slight movement toward the goal of lowering aggregate demand during peak hours. This may be due to a number of factors; for example, consumers may be particularly demand-inelastic for peak consumption and are unwilling to change their habits, or they may be more willing to adjust their off-peak consumption in order to preserve the same level of peak consumption.

Another potential confounder is the stark differences in pricing across seasonal periods. Since prices generally decreased during the winter months and increased in the summer months, the previous regression specification may be conflating increases in winter consumption and decreases in summer consumption.

To adjust for this, I simply split the previous specification into two sets by using only summer or winter months. The results in Tables 5 and 6 show the differences between the two seasons. Total bill consumption and peak consumption both appear to decrease by about a percentage point in the summer, and while peak percentage has a statistically significant decrease in the post period, its magnitude is still very close to zero. In the winter, there is no discernible effect on total or peak consumption, and peak percentage declines by even less than in the summer. Bill costs adjust as expected—decreasing in the winter while increasing in the summer—but this is expected due to the price changes, especially given that consumption does not change by much.

Finally, I note that since the model estimates peak percentage is essentially unchanged amongst switching households in the post-transition period, the magnitude on the difference-in-differences coefficient for total and peak consumption are quite similar, implying that the impact on household consumption is almost entirely due to changes in demand during the peak period, and that off-peak consumption is mostly unchanged. Since we have a panel and it is plausible that the treatment effect of the plan switch is heterogeneous across months, I also employ an event study design in the next section to see how this impacts the estimates.

## 4.3 Event Study

I next estimate an event study approach that allows for heterogeneous effects in each period, both pre-transition and post. There are multiple reasons why this may be the case. First, there is a strong element of seasonality in electricity demand, and prices also now vary by season, so it is plausible that the effect of the transition program is not the same from one month to the next. Second, it is possible that consumers did not respond immediately to the program. Due to the opt-out nature of the program, many customers may not have been aware of the change, and may not have noticed the adjusted prices until some time later. This may mean that we are incorrectly estimating the true effect of the program if the first several months show a muted response. As with the difference-in-differences above, the estimated equation will also use

| Summer Only | log(kWh) | log(bill $) | log(peak kWh) | Peak % |
|---|---|---|---|---|
| Post x Switch | -0.010 | 0.066 | -0.012 | -0.004 |
| | (0.003) | (0.004) | (0.006) | (0.001) |
| Post | -0.006 | 0.000 | -0.024 | -0.002 |
| | (0.004) | (0.005) | (0.006) | (0.001) |
| Constant | 6.144 | 4.837 | 4.875 | 0.290 |
| | (0.001) | (0.001) | (0.001) | (0.000) |
| N | 511,500 | 511,500 | 399,726 | 399,726 |
| R2 | 0.878 | 0.873 | 0.876 | 0.727 |
| Wave x Month FE | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes |
| HH FE | Yes | Yes | Yes | Yes |
| Cluster | Zip | Zip | Zip | Zip |

Table 5: DiD results using only summer months.

| Winter Only | log(kWh) | log(bill $) | log(peak kWh) | Peak % |
|---|---|---|---|---|
| Post x Switch | 0.000 | -0.059 | -0.005 | -0.002 |
| | (0.003) | (0.003) | (0.005) | (0.001) |
| Post | 0.000 | -0.020 | -0.011 | -0.001 |
| | (0.007) | (0.005) | (0.010) | (0.001) |
| Constant | 6.042 | 4.737 | 4.721 | 0.273 |
| | (0.002) | (0.001) | (0.001) | (0.000) |
| N | 971,623 | 971,623 | 764,173 | 764,173 |
| R2 | 0.801 | 0.818 | 0.786 | 0.583 |
| Wave x Month FE | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes |
| HH FE | Yes | Yes | Yes | Yes |
| Cluster | Zip | Zip | Zip | Zip |

Table 6: DiD results using only winter months.

opt-out consumers as control:

$$Y_{ijt} = \beta_0 + \sum_{\tau=-12}^{12} \beta_\tau \mathbf{1}\{\tau = t\} + \sum_{\tau'=-12}^{12} \beta_{\tau'} \mathbf{1}\{\tau = t\} \times treated + \theta_{jt} + \gamma_i + \tau_t + \epsilon_{ijt}$$

where $Y_{ijt}$ is the outcome of interest for household $i$ in wave $j$ during period $t$, and $\beta_\tau$ are period fixed effects relative to the consumer's own transition period. $\theta$ is a set of wave-specific fixed effects interacted with the month, year, and switching status of the household, $\gamma$ household fixed effects, and $\tau$ a set of wave-month interacted effects. Given that I have more than 12 months' worth of post-transition data for only certain waves, I elect to condense all

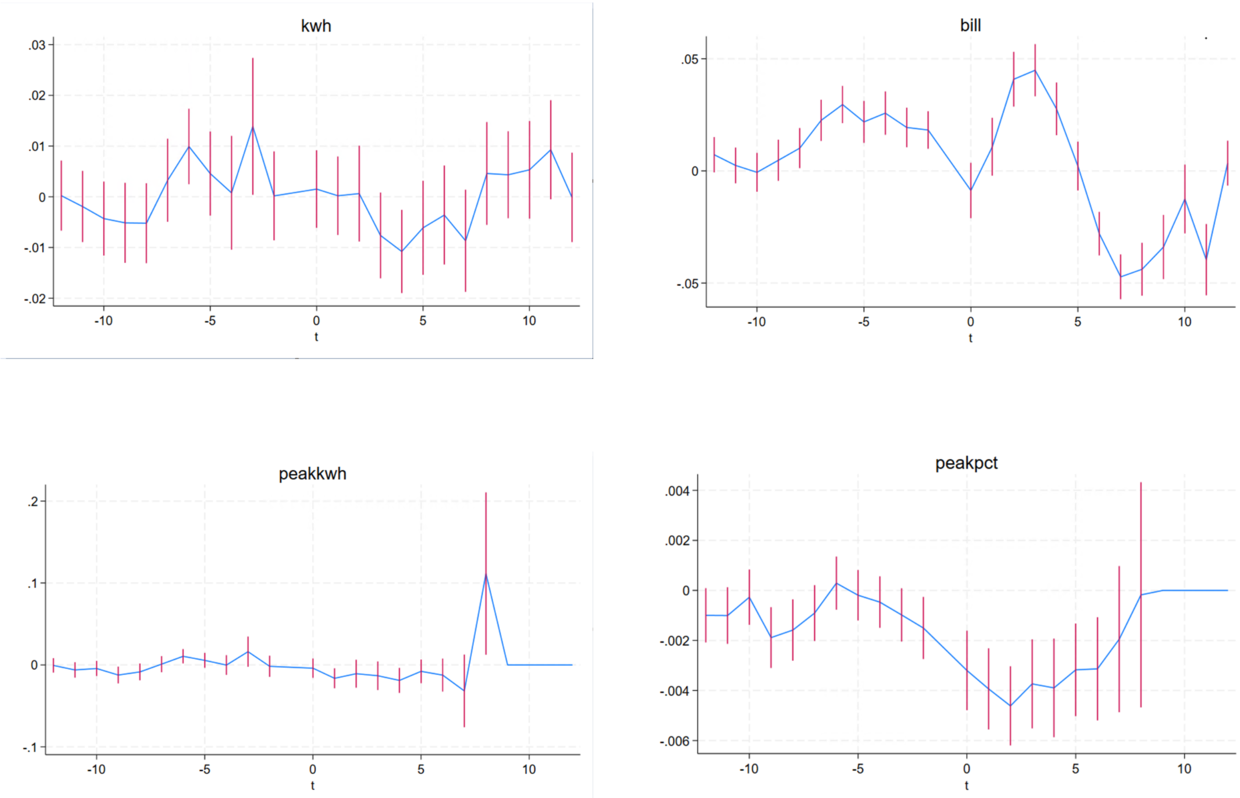


Figure 11: Event studies using a seasonal interaction.

observations outside of the 12-month window. The results are shown in Figure 11. In these plots, I include the same set of fixed effects as in the difference-in-differences: household-specific effects, wave-month effects, and wave-month-year effects. The results do not appear to show a clear picture of consumers changing their behavior in a set way. It is possible that incorporating an additional seasonal effect that we could isolate the summer-specific changes from the overall effect of changing to TOU, which I explore next.

Given that seasonality does appear to be an important component of consumer response in the previous section, I also incorporate the pricing season into the regression via indicators for winter or summer months. It is also worth considering that consumers may have heterogeneous responses to the prices they face in the immediate post-rollout period in addition to the aforementioned period-dependent heterogeneity. That is, month $t$ of the program may show a different consumer demand impact if $t$ occurs during the summer versus the winter. Three of the county groups in PG&E's service area transitioned during summer months, so it is plausible that the lower prices in winter and higher prices in summer, relative to the original block plan, have offsetting effects. This turns the above equation into

$$Y_{ijt} = \beta_0 + \sum_{\tau=-12}^{12} \beta_\tau \mathbf{1}\{\tau = t\} + \sum_{\tau'=-12}^{12} \beta_{\tau'} \mathbf{1}\{\tau = t\} \times treated + \theta_j + \epsilon_{ijt}$$

The results are captured in Figure 12. There are no obvious pre-trends in the data, and the first plot indicates that consumers did not change their consumption in a consistent and statisti-

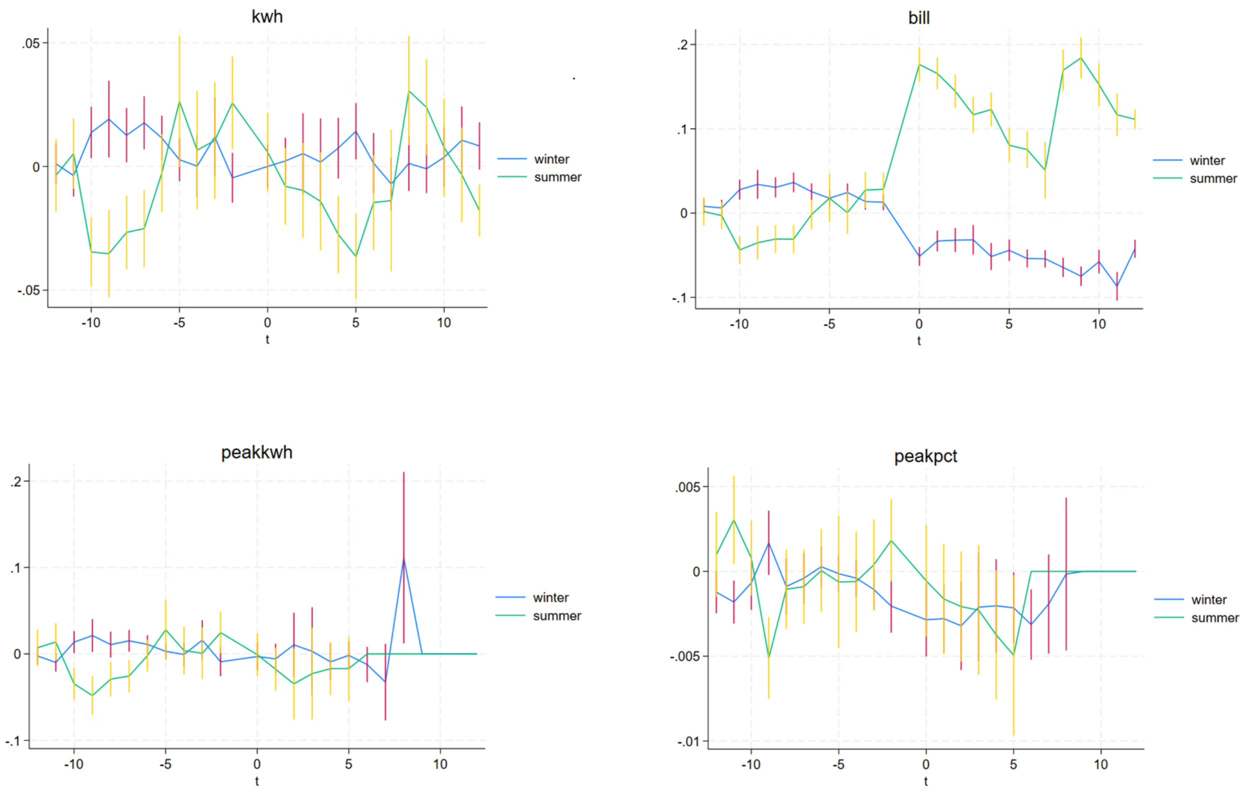


Figure 12: Event studies using a seasonal interaction.

cally significant manner. However, bills did decrease in the winter and increase in the summer as a result, which is to be expected if consumption did not change. Peak-hour usage also does not appear to have changed much, save for a three-month spike that may be attributable to a heat wave or other weather-related event. Lastly, peak usage appears to have increased as a percentage of total usage. This may indicate that even though consumers' overall consumption did not change, they may have increased the proportion of consumption on peak hours. I explore this possibility further in section 4.6 **INSERT SECTION**.

## 4.4 Treatment Effects Estimators

Given the noisiness of the event study, I next employ a matching estimator approach in order to match households based on the similarity of their pre-rollout consumption within their own wave. PG&E mentions in their documentation that households were able to view a cost comparison of the block pricing plan versus the TOU plan based on their previous bills before making the decision to opt out. It is possible that the households deciding to opt out may have thus anticipated increases in their future bills, with this expectation derived from what they could see in their account portal.

Using the billing and hourly data, I recreate this decision by calculating each household's true billing amount in the pre-rollout period and compare it to their "counterfactual" bill using TOU pricing. For most households, I calculate that they face slightly lower bills in any given month, though households whose pre-transition period encompasses summer months have a higher probability of facing higher bills. Households that had a negative-cost pre-rollout period appear to be more likely to have opted out of the TOU plan, lending credence to this idea. Figure 13 shows the densities for one of the variables calculated for this exercise; we can see that the two types have a similar general shape to their density, but the non-switching households have more mass on the negative costs portion, indicating that a larger portion of these households would have seen a net negative value to switching to TOU when making the decision to opt out. Households that had a negative value but still opted in may not have checked the PG&E's online tool may not have been aware at all of the pre-transition notifications, or may have estimated that the cost savings during the winter months would offset the additional costs during the summer months. Figure 14 shows the results of running a probit conditional on each wave; it implies that non-switching households have a lower probability of switching based on these pre-rollout costs. However, we see that the probit still estimated a substantial number of non-switching households have a high probability of doing so, so there may be additional variables to consider and test.

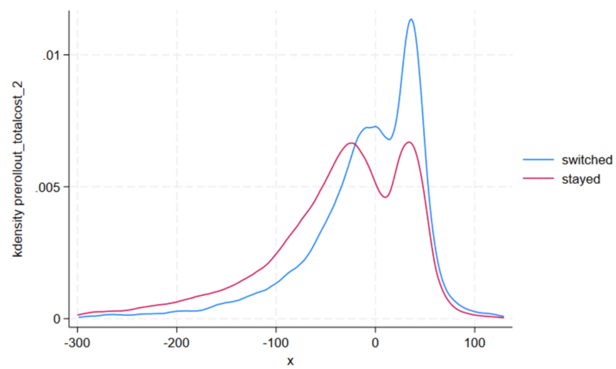


Figure 13: Density of pre-rollout costs by household switching type. Costs shown uses the total net monthly cost difference for block minus TOU pricing of the period between 5 and 8 months before the household's transition period.

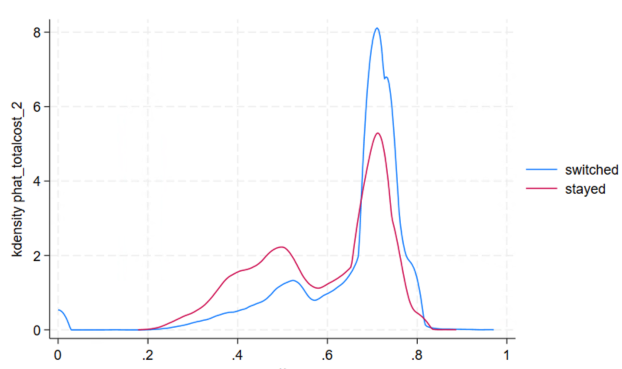


Figure 14: Density of estimated Probit probabilities by household switching type. Probabilities are estimated separately for each transition wave using pre-rollout net costs.

From here, I match households based on this pre-rollout cost difference, and then run two different treatment effects estimators. The dependent variable in this case is the post-transition difference in consumption,

$$\Delta y = y_1 - y_0$$

using both total consumption and peak consumption.

First, I estimate an inverse probability-weighted treatment effects estimator. The results indicate that the baseline households experience an average of $-3.6$ less usage in the post period, while the treated households reduced their consumption by $-4.15$. Swapping for the peak difference, I find that non-switching households used 77 kWh less in the post period, and switching households use 3 kWh less than that; however, this seems like it may be an issue with extreme values in the distribution, so I will have to re-calculate.

Next, I use a propensity score matching approach with the same variables. Under this specification, I estimate that switching households had an ATE of the difference between their pre- and post-transition consumption of $-3.32$ kWh, and $-4.65$ kWh for their peak consumption.

**NOTE: add some discussion on accuracy to the bill reconstruction section in the appendix**

## 4.5 Hourly Impact

As a final check, it is worth taking advantage of the high-frequency data to see how consumers may have adjusted their consumption by substituting across hourly periods. Using peak-percentage in the above sections shows whether demand shifted from peak to off-peak, or vice versa, but we can use the hourly data to assess whether these changes were uniform across all sub-periods or if they were more heavily concentrated in some hours over others. Figures 15, 16, and 17 show three different event studies. In the first, I have calculated a "near-peak" period as being the two-hour intervals before and after the peak period. In the second and third, I estimate the ratio of usage early in the peak period, from 4pm to 6pm, to the two hours beforehand, and the same for the final three hours of the peak period and the two hours afterward. The results do not show much change in these three variables during the program rollout.

- Add: spaghetti plot by hour

## 4.6 Impact of Bill Protection

As previously mentioned, PG&E also promised "bill protection" for consumers that switched into the TOU program.

- Add: summary statistics of bill credits/losses, kernel density, etc
- Add: regression for only the period *after* 12 months to see if people began to change behaviors. Should only be applied as an event study to the first 4 waves.

If consumers' adaptation to the new plan was being stunted by the bill protection program, I would expect that their behavior would begin to shift starting in the 12th month after their transition begins. To test this, I ran the previous event studies using an event window of $-12$ months from the end of bill protection, which is the same as the transition date, up through

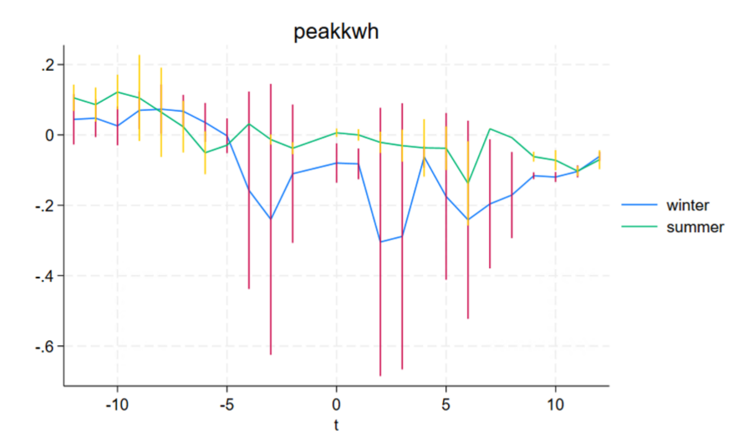


Figure 15: Logged near-peak kWh using an event study design. “Near-peak” is defined as the two-hour period before and after the peak period, so 2-4pm and 9-11pm.

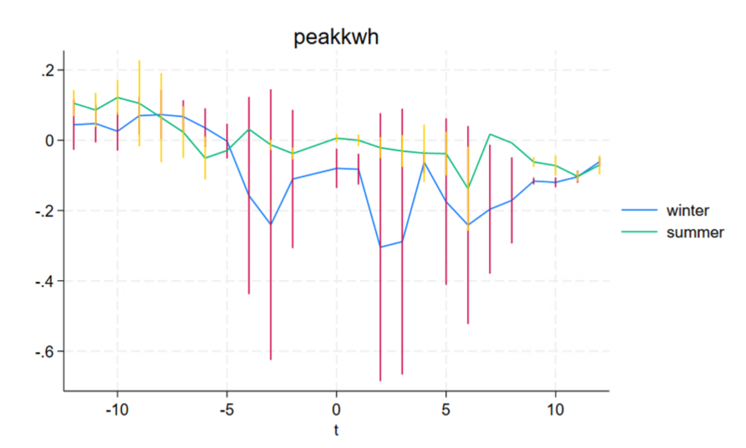


Figure 16: The ratio of usage from 4 to 6pm over 2 to 4pm.

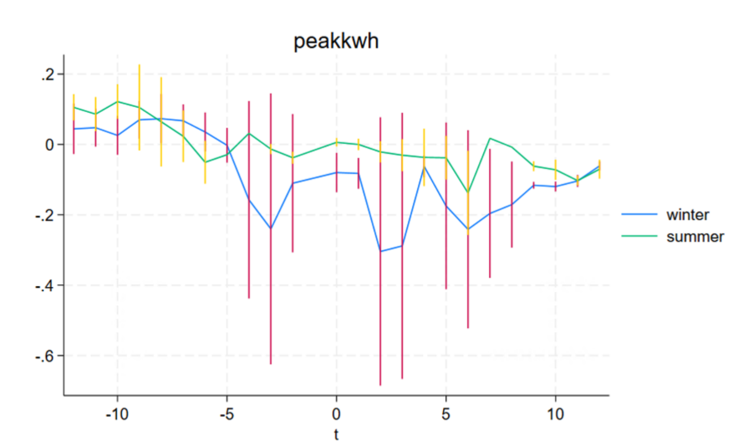


Figure 17: The ratio of usage from 6 to 9pm over 9 to 11pm.

the period six months after the end of the billing protection plan. Since some of the waves in the dataset don't have a full year of available data, I restrict this estimation to the first four waves, which ran from April 2021 through July 2021. However, I do not find evidence that these consumers' habits changed after the expiration of the bill protection plan, either.

# 5 Program Selection

Given that the program is opt-out without any restrictions on the customer, adverse selection is a plausible concern for measuring the impact of the plan change on treated customers. Customers whose consumption typically falls into the first two price tiers potentially face much higher prices in the summers under TOU pricing, while consumers with particularly high consumption may actually benefit. Referring back to Figures 7 and 8, a consumer in the third tier of pricing faces higher prices in the summer for their consumption between 100% and 400% of baseline, but gets a "discount" on their consumption past that due to the elimination of the third price tier under the TOU plan. While this seems to run counter to the idea of using TOU prices to encourage energy conservation, in practice, I estimate that less than 5% of bills in a given month tend to hit the third price tier. Moreover, given that the consumer pays higher prices for all their usage between 100 and 400% of baseline, the amount of electricity required to get total bill "savings" relative to block pricing would be extremely high.

A further complication is the "risk-free bill protection" that PG&E promised as part of the program rollout. As mentioned above, the utility said it would reimburse customers on TOU pricing if their monthly bill was higher on TOU than it would have been on block pricing for the first 12 months of the program. While I was not able to confirm how or when PG&E disbursed these payments, it is plausible that this additional program was enough of an incentive to mollify customers concerned about the change in price structure.

Finally, it is also imperative that I check for selection on other possible criteria. The assumption that consumers may opt out over concerns for their bills hinges on the assumption that consumers even check their monthly bills in the first place. Many consumers likely autopay their bill each month or manually pay the amount owed without comparing their costs to previous months. As discussed elsewhere in the literature, such as Borenstein (2009), the delay between consumption and subsequent payment may lead to consumers being largely unaware of how their habits impact their final bill costs.

## 5.1 Selection on Price

## 5.2 Selection on Plan Reimbursement

## 5.3 Selection on Other Factors

# 6 Results

## 6.1 Difference-in-Differences

Table 7 displays results for four key variables

| | **log(kWh)** | **log(Bill $)** | **Peak %** | **log(Peak kWh)** |
|---|---|---|---|---|
| Switched x Post | -0.006 | -0.013 | -0.004 | -0.025 |
| | (0.003) | (0.003) | (0.000) | (0.005) |
| Switched | -0.024 | 0.005 | -0.006 | -0.154 |
| | (0.001) | (0.001) | (0.000) | (0.002) |
| Post | 0.026 | 0.018 | 0.005 | 0.043 |
| | (0.003) | (0.004) | (0.000) | (0.005) |
| Constant | 6.033 | 4.699 | 0.279 | 4.863 |
| | (0.001) | (0.001) | (0.000) | (0.002) |
| N | 1,326,033 | 1,325,971 | 548,336 | 548,336 |
| R2 | 0.052 | 0.084 | 0.053 | 0.124 |
| Wave FE | Yes | Yes | Yes | Yes |
| Yr x Mon FE | Yes | Yes | Yes | Yes |

Table 7: Columns 1-2 use true billing numbers; columns 3 and 4 use estimated values from interval data.

### 6.2 Event Study

### 6.3 Staggered Event Study

### 6.4 Matching Estimator

## References

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# 7 Appendix

## 7.1 Covid and Electricity Demand

It bears mentioning that the Covid pandemic straddles the middle section of my data sample. In California, a "stay home" order was officially put in place by the governor on March 19, 2020, and lifted January 25, 2021. During this nearly year-long order, customers are supposed to have stayed in the home, save for designated activities like time outside, purchasing groceries, or work if the consumer was from certain industries. In general, this should have had the effect of increasing households' electricity consumption beyond what it otherwise would have been. Figure 18 plots the coefficients for each hour in a year-over-year regression in 2019 versus 2020, while 19 shows the same for 2020 to 2021. The shocks to daily consumption in each hour beginning in March of 2020 is rather stark. However, these shocks gradually began to dissipate by the end of the year. Note that in the 2020 to 2021 plot, January and February appear to show an acceleration in usage, but these two months were unaffected by Covid in the previous year, so consumption during work hours is still slightly elevated above normal levels.

Fortunately for the TOU program, the Covid order expired more than two months before the first counties began to transition to the new plan. Given that I can also account for the Covid period by using appropriate fixed effects, I do not consider this a threat to the identification of the program's impact.

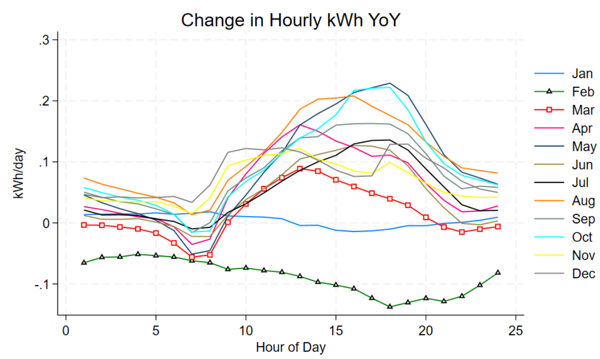


Figure 18: Year-over-Year difference in consumption from 2019 to 2020 by hour.

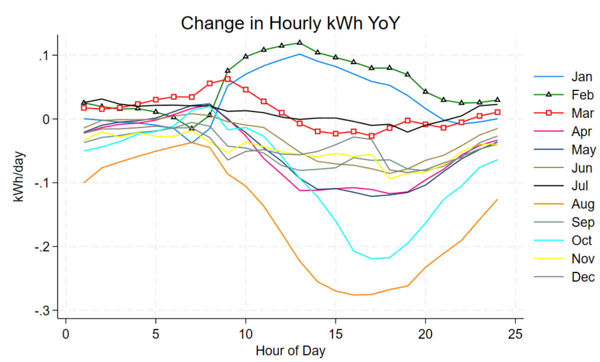


Figure 19: Year-over-Year difference in consumption from 2020 to 2021 by hour.

## 7.2 Sample Construction

As previously mentioned, I removed all accounts that ever were on a subsidized rate or alternative payment plan, ever reported being on a solar plan, or ever were on an electric vehicle rate. I find that a small percentage of bills report implausibly high or low numbers—less than 1% in either case[12]—and so I truncate the dataset by removing the top and bottom percentile for both total kWh usage and billed dollar amounts, relative to each wave. I only remove single observations that violate either of these rules, and keep the household's other bills.

Using PG&E's historical tariff rates, I hand-collected the rates for the major plans in my sample from 2018 through 2022. This included the "E1" block plan and "TOU-C" plan that became the default during the rate transition program, as well as the TOU "A", "B", and "D" rates, which all use slight variations in price and peak hours, and a more niche time-of-use plan called "E6". I then aggregated the hourly data to the daily and monthly level, and attempted to reconstruct the household's bill using the same billing dates and plan rates. I find that in approximately **X%** of bills, I am within 10% of the dollar amount reported in the monthly billing dataset[13]. This implies that there are some hidden bill components which I may not be

[12] As an example, some bills purportedly show consumption in the tens of thousands of kWh in a single billing cycle. Others report usage of less than 1kWh per day, approximately the amount needed to power a conventional refrigerator.

[13] Per discussions with PG&E, they do not recommend that researchers attempt to do this due to the potential for high rates of error. However, this is necessary in my case in order to understand the changes in hourly consumption

able to observe, or that billing credits from previous over- or under-payment may be carried forward as well. PG&E has a daily metering rate of approximately $0.30 that is applied to the customer's bill as a reported "minimum" cost each day if their consumption does not exceed that cost, but this does not seem to be the source of the error.

The error rates for the block pricing plan are generally lower than those for the TOU plans **INSERT GRAPH OF ERROR RATES**. One plausible source of error for TOU plans is that after 2021, I do not observe hourly consumption, so in months where the consumer's bill switches seasons or costs I cannot observe what percentage of their consumption is on either cost. To account for this, I simply weight their consumption in the peak and off-peak periods by the number of days on either cost schedule. This improves the error rate for months where there are seasonal cost switches but does not eliminate it.

## 7.3 Robustness: Difference-in-Differences

Table 8 is intended to show how the results change relative to Section 4.1 when using a singular "switch" indicator for households that switched plans, akin to a treatment indicator in traditional difference-in-differences settings, rather than household fixed effects. The results are by and large the same, with the main differences being that this specification predicts a slightly larger decrease in both total and peak usage. However, as seen in Tables 6 and 5, these are likely not accurate estimates given that there is a high degree of seasonality in consumer demand.

| | **log(kWh)** | **log(bill $)** | **log(peak kWh)** | **Peak %** |
|---|---|---|---|---|
| Post x Switch | -0.010 | -0.016 | -0.025 | -0.005 |
| | (0.004) | (0.004) | (0.011) | (0.001) |
| Switch | -0.023 | 0.003 | -0.052 | -0.008 |
| | (0.008) | (0.008) | (0.009) | (0.001) |
| Post | 0.002 | -0.008 | -0.005 | 0.000 |
| | (0.005) | (0.005) | (0.009) | (0.001) |
| Constant | 6.092 | 4.769 | 4.808 | 0.284 |
| | (0.009) | (0.009) | (0.010) | (0.001) |
| N | 1,483,153 | 1,483,153 | 1,163,942 | 1,163,942 |
| R2 | 0.115 | 0.13 | 0.14 | 0.102 |
| Wave x Month FE | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes |
| Cluster | Zip | Zip | Zip | Zip |

Table 8: Difference-in-difference estimates, pooling across seasons. Post-period is defined as being relative to the customer's county. "Date" fixed effects are month-year, and "wave-month" fixed effects are the calendar month interacted with the household's transition wave.

As an additional specification, I also estimate this model while including interactions for

and costs between the two programs.

the season, which can be seen in Table 9. The advantage of this specification is to include the entire sample while also allowing for the separate estimation of the seasonal effects on the dependent variable. Compared to Table 4 and the separate seasonal specifications in Tables 5 and 6, this specification indicates that peak usage in the winter amongst switching households increased by a net 1.7 percentage points, while decreasing in the summer by 6.7 percentage points. This also estimates that total usage by switching households during the summer season after the transition declined by a net 4.6 percentage points, though it slightly increased in winter months.

| **No Season** | **log(kWh)** | **log(bill $)** | **log(peak kWh)** | **Peak %** |
|---|---|---|---|---|
| Post x Switch | 0.017 | -0.046 | 0.017 | 0.000 |
| | (0.003) | (0.003) | (0.006) | (0.001) |
| Post | -0.011 | -0.029 | -0.027 | -0.003 |
| | (0.007) | (0.005) | (0.010) | (0.001) |
| Post x Switch x Summer | -0.063 | 0.081 | -0.084 | -0.010 |
| | (0.005) | (0.005) | (0.009) | (0.001) |
| Post x Summer | 0.030 | 0.050 | 0.042 | 0.005 |
| | (0.007) | (0.006) | (0.011) | (0.001) |
| Constant | 6.077 | 4.771 | 4.774 | 0.278 |
| | (0.001) | (0.001) | (0.001) | (0.000) |
| N | 1,483,143 | 1,483,143 | 1,163,937 | 1,163,937 |
| R2 | 0.796 | 0.805 | 0.780 | 0.556 |
| Wave x Month FE | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes |
| HH FE | Yes | Yes | Yes | Yes |
| Cluster | Zip | Zip | Zip | Zip |

Table 9: ”Summer” takes value 1 if the month is a summer month per the TOU-C plan.

In addition to the four main variables that I focus on in the main analysis—total kWh, peak kWh, peak percentage, and bill cost—I also wanted to test whether there is substitution between the peak period and the hours surrounding it. To do this, I split the peak period, which spans from 4PM to 9PM, into a two-hour (4PM - 6PM) and three-hour (6PM - 9PM) window, and compared the demand in these two sub-periods to the two-hour off-peak periods surrounding the peak, i.e. 2PM - 4PM and 9PM - 11PM. If consumers are switching their usage in the peak period towards the off-peak because they want to save on the higher peak costs, then the ratio of the off-peak period to the peak period should increase. If instead they are substituting towards the peak period and reducing off-peak consumption, then the ratio should decrease. I decided to use the two adjacent sub-periods because consumers

## 7.4 Robustness: Average kWh

One possible alternative dependent variable to explore is average kWh per day by taking total monthly demand and dividing by the length of the bill cycle. This can help account for differences in the lengths of months, particularly February. An example is shown in Figure 20. Compared to the plots in 11, this does not appear to drastically affect the trends in the data, though it does make some of the standard errors a little smaller.

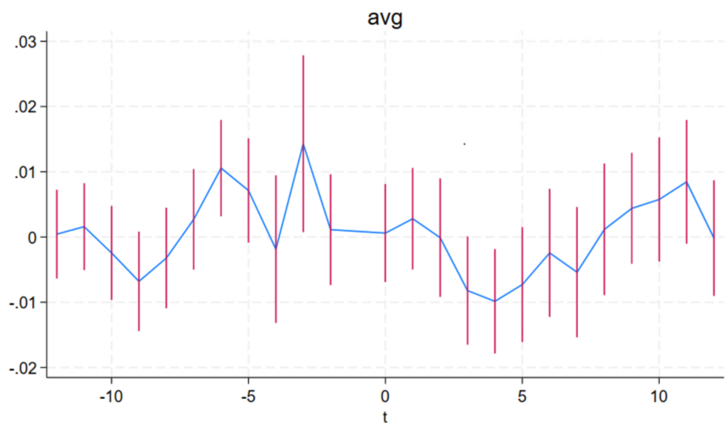


Figure 20: Logged average kWh using a standard event study design.

## 7.5 Robustness: Staggered Event Study

To address the possibility that the non-treated households are not a comparable control for the treated, I also employ a "staggered" event study design in which the later-treated households are used as control for the earlier-treated. This serves two functions. First, if selection into the program is such that households opting out are sufficiently distinct from those being opted in—due to being more attentive, using more electricity, or other reasons—then they may not be a reliable predictor of the behavior of switching households. If household $i$ is treated in period $t$, and $j$ is treated in $t+n$, then $j$ can serve as a control up until period $j$ because we would anticipate that their behavior will not have been altered by the program yet [14]

The estimating equation is similar to the above, sans the indicator for treatment due to the sub-sample being restricted to only households that eventually switch:

$$Y_{ijt} = \beta_0 + \sum_{s=1,2} \sum_{\tau'=-12}^{12} \beta_{\tau'} \mathbf{1}\{\tau = t\} \times season_s + \theta_{jm} + \gamma_i + \epsilon_{ijt}$$

Instead of three-way fixed effects, I instead use household fixed effects with an interacted wave-month fixed effect. The latter captures seasonality specific to the counties themselves. I cannot incorporate month-year fixed effects as these are collinear with the event study coefficients of interest.

The results are shown in Figures 21, 22, 23, and 24. Compared with the previous event study, the results are less clear and the standard errors notably larger, even for the bill cost. This is likely due to the smaller number of observations available in each period after eliminating the households that opt out of the program.

[14] This is only the case when we expect that $j$ is not influenced by $i$. Given that all households in the same county group are treated simultaneously, it seems reasonable to conclude that demand in households from other counties is not pre-emptively impacted by others.

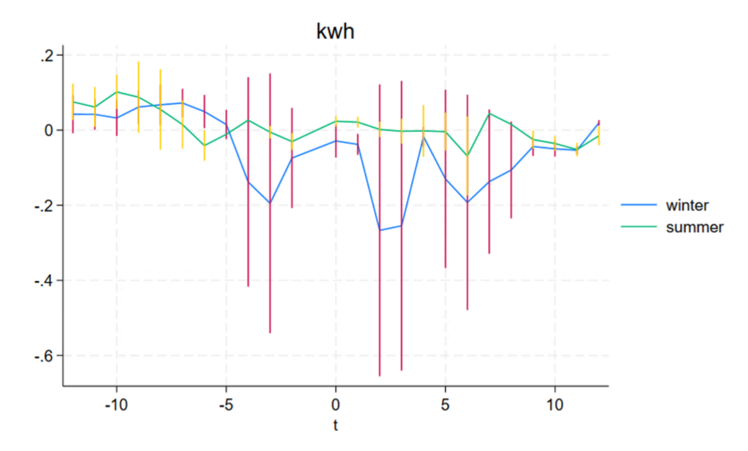


Figure 21: Logged total kWh using a staggered event study design.

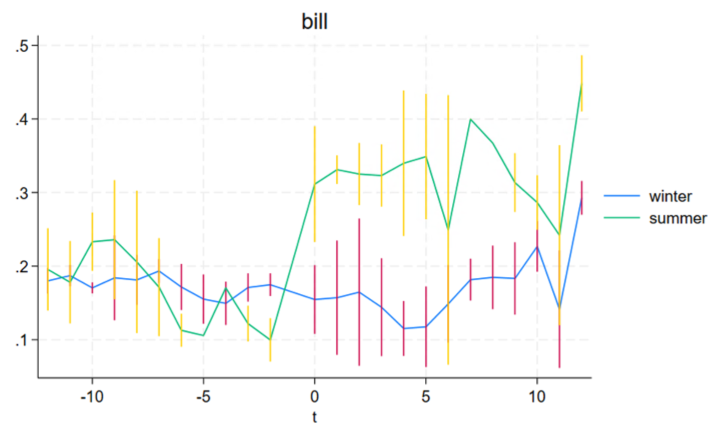


Figure 22: Logged total bill cost using a staggered event study design.

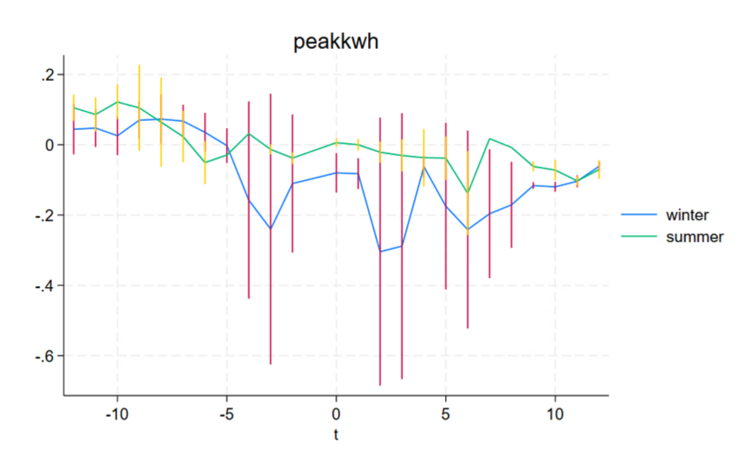


Figure 23: Logged peak kWh using a staggered event study design.

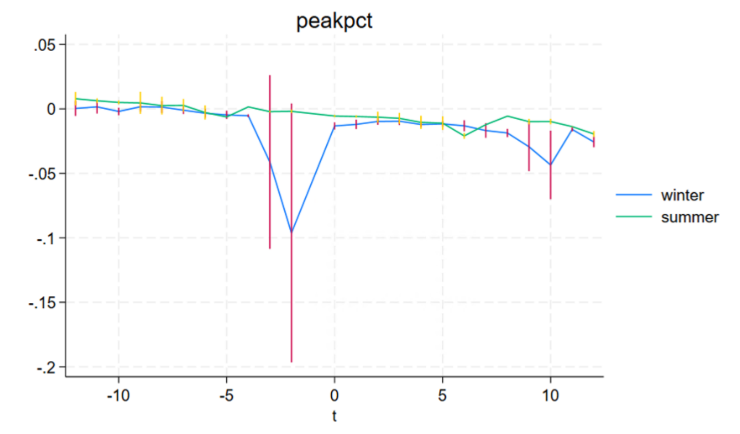


Figure 24: Percent of bill usage during peak hours using a staggered event study design.