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Heterogeneity in Own-Price Residential Customer Demand Elasticities for Electricity under Time-of-Use Rates: Evidence from a Randomized-Control Trial in the United States

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Title: Heterogeneity in Own-Price Residential Customer Demand Elasticities for Electricity under Time-of-Use Rates: Evidence from a Randomized-Control Trial in the United States

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Category: Energy markets and pricing

Highlights:

- Residential demand is price-elastic in and surrounding the peak time-of-use
- Critical peak days produce an increase in the own-price elasticity under a time-of-use rate
- Ownership and use of AC is predicted to increase the own-price elasticity
- Defaulted customers have an elasticity that is 25% of their voluntary counterparts

Abstract: Regulators, policymakers, and stakeholders in several states have raised concerns about the price elasticity of residential customers' electricity demand, especially as related to different customer subpopulations, management of critical end-uses, and enrollment approaches. This analysis sought to quantify the diversity of residential customer price elasticity in a time-of-use rate across these different dimensions using data generated from a utility pricing experiment. Customers were found to be more elastic during the peak period of critical peak days, who were predicted to own and use air conditioning, and who volunteered for time-of-use (TOU) rates (but those defaulted on were 25% as elastic).

Keywords: Demand response, pricing, time of use, elasticity, air conditioning

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1. Introduction

The earliest rendition of demand response in the electricity sector came at the dawn of the industry in the form of time-based rates that were heavily debated (Hausman and Neufeld, 1984). However, because the cost of metering to capture electricity consumption at the necessary level of time differentiation was very high, offering such time-based rates to customers and achieving the desired level of demand response was simply not cost-effective. In 1978, the U.S. Congress tried to spur the electric power industry to pursue time-based pricing through The Public Utility Regulatory Policies Act (PURPA). This legislation contained standards calling for states to consider adopting time-of-use rates to reflect the cost of service more accurately by charging prices that encouraged customers to shift consumption from more expensive peak to less expensive off-peak periods. In response to PURPA, many states implemented TOU rates for residential customers on a pilot basis to evaluate their cost-effectiveness. During the 1980s, evaluations of these pilot programs (e.g., Aigner, 1985; Caves et al., 1984a; Caves and Christensen, 1980; Caves et al., 1984b, 1987; Faruqui and Malko, 1983; Patrick, 1990) found that residential customers can and do respond to TOU rates. However, the costs of new meters capable of measuring consumption by time of day still presented a sizable barrier to the cost-effective implementation of TOU rates on a larger scale.

With recent utility investments in Advanced Metering Infrastructure (AMI) that include interval meters, state regulators are once again considering the proper role of time-based rates for their residential customers. As rationale, most US utilities included the financial benefits associated with customer response to time-based rates in their business case (DOE, 2020). Many regulators are keenly interested in capturing those claimed benefits to maximize the cost-effectiveness from these sizable infrastructure investments. However, only a few states are moving forward with either a more dedicated commitment to effective utility marketing of redesigned customer-friendly voluntary TOU rates (e.g., NYDPS, 2015) or transitioning their residential customers to a default time-of-use rate (e.g., COPUC, 2016; CPUC, 2015; MADPU, 2014), due in part to the results of high-quality rate pilots. Utilities and regulators in many other states have not yet followed suit, due to a myriad of concerns. Many focus on customer response capabilities, especially as they relate to different customer subpopulations, management of critical end-uses, and enrollment approaches (e.g., voluntary vs. default), which affect customers' ability to manage potential adverse bill impacts.

Although there have been many residential pricing pilots in the United States over the past 15 years summarized extensively in EPRI (2008), EPRI (2012), Faruqui and Palmer (2012), and Cappers and Scheer (2016); only a handful derived elasticity estimates from unbiased and randomized experimental conditions (EPRI, 2011; George et al., 2018; Potter et al., 2014).[1] Furthermore, none attempted or (or indeed were able) to examine the heterogeneity of estimated

[1] There also exists elasticity evaluations of residential TOU pricing pilots utilizing rigorous experimental designs outside of the United States (e.g., Di Cosmo et al., 2012; Henley and Peirson, 1994). In contrast, Filippini (1995, 2011), for example, estimated elasticities from broad based adoption of residential TOU rates in Switzerland but not under experimental conditions.

elasticities that results from the combined diversity of load response across different customer types, operating conditions, and especially enrollment approaches (i.e., voluntary vs. default).[2]

Our analysis seeks to fill this void in the recent literature by delving deep into the heterogeneity of estimated demand elasticities for US residential customers taking service on a TOU rate under rigorous and unbiased experimental conditions, in order to provide regulators, policymakers, and stakeholders with a more comprehensive understanding of customer capabilities. We hope that these results can contribute to a more robust and informed debate about the proper role of time-based rates for residential customers in the US and internationally, where time-of-use rates are applicable, valuable, and relevant. This analysis is not focused on applying new and novel evaluation techniques; instead, it seeks to apply well-established analytical methods to a novel dataset in order to provide new and robust insights into the diversity of estimated own-price elasticities by:

- Hour of the day;
- Type of day (e.g., peak usage days);
- Predicted central air conditioning ownership and use; and
- Enrollment approach (e.g., default vs. voluntary).

Section 2 discusses the data sources for this analysis. Section 3 contains details on the methodology employed in the elasticity estimation process. Section 4 presents the numerical results, while Section 5 provides a discussion of those results. In Section 6, we provide some concluding thoughts on the implications of this analysis.

2. Data sources

We had access to a pricing study at Sacramento Municipal Utility District (SMUD), which provided sufficient participation, demographic, metering, and survey data to derive elasticity estimates.[3] Our dataset included hourly electricity use for 92,089 customers (53,245 customers for the voluntary rate, and 38,844 customers for the default rate) over three summers (260 days).

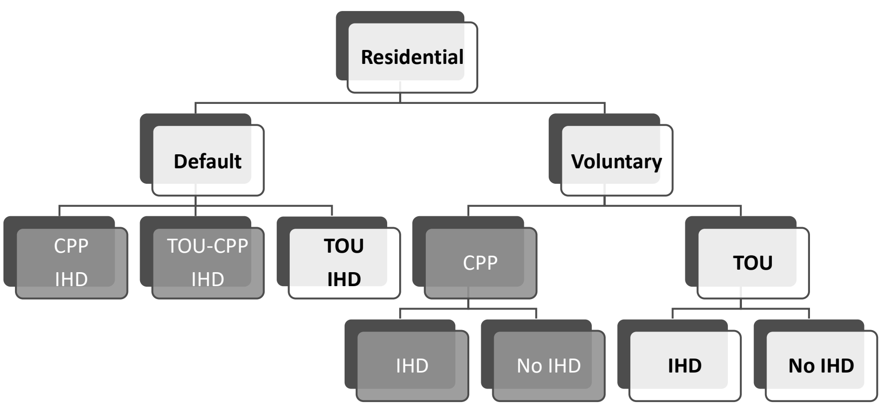
The SMUD study's main goals were to understand better how the enrollment approach (voluntary vs. default) affected enrollment rates, drop-out rates, and electricity demand impacts of different time-based rate and in-home display (IHD) treatment arms (see Figure 1). The study employed a randomized encouragement design (RED), whereby SMUD randomly assigned pre-qualified residential customers to one of the treatment arms and then offered them that treatment

[2] Reiss and White (2005) were one of the first to illustrate the existence of significant heterogeneity in residential customers' demand elasticity under non-linear pricing programs, but did so using data derived from broad implementation of rates in California utilities and not from pilots implemented under rigorous experimental conditions. Cappers et al. (2018) and White and Sintov (2020) estimated on-peak energy use reduction for vulnerable and non-vulnerable customers experimentally exposed to a TOU rate in several US utilities, but did not estimate price elasticities. George et al. (2018) derived arc elasticities from estimates of usage changes by vulnerable and non-vulnerable residential customers in response to experimentally administered TOU rates in all three California investor-owned utilities. Fowlie et al. (2021) estimated load impacts, but not demand elasticities, for residential customers of a US municipal utility, which differed by enrollment approach into a rigorous experimental TOU pricing pilot.

[3] For more details about SMUD's consumer behavior study, see Jimenez et al. (2013), Cappers et al. (2013a), or Potter et al. (2014).

arm (i.e., voluntary) to opt in to or notified them that they would receive that treatment arm unless they opted out (i.e., default). Treatment arms included three rate designs all in effect during the summer months (June through September) of 2012 and 2013: (1) a two-period TOU rate with a three-hour (4-7 p.m.) peak period, (2) critical peak pricing (CPP) overlaid on an underlying inclining block rate, and (3) CPP overlaid on the TOU rate. The TOU rate, which is the focus of this analysis, had an on-peak price of $0.27/kWh between hour-ending (HE) 17-19 on summer weekdays, excluding holidays, and an off-peak price for all other hours that differed by blocks of consumption in that billing period (see Table 1).

For this analysis, only the customers exposed to a TOU rate, including enrollment approaches and treatments with or without an IHD offer, were analyzed. However, it should be noted that for purposes of estimation here that the two voluntary treatment arms were combined: TOU rate with an offer of an IHD and TOU rate without an offer of an IHD. The marginal load impact estimate associated with the existence of the offer of an IHD in this pricing pilot was not statistically significant (Potter et al., 2014), so combining the two treatment groups was expected to produce consistent and unbiased estimates for all study participants exposed to the TOU rate.



Note: Those treatment arms not depicted in gray were analyzed in this analysis.

Figure 1. SMUD's consumer behavior study experimental design

Table 1. SMUD's CBS summer 2012 & 2013 rate design (¢/kWh)[4]

[4] Table 1 shows the rates charged to SMUD's general population of customers on the TOU treatment rates. SMUD also included customers enrolled in the low-income rate, referred to as EAPR (Energy Assistance Program). These customers faced a lower fixed charge than non-EAPR customers, and were given a discount of 35% applied to electricity use charges for base use, and a discount of 30% applied to non-base use up to 600kWh, above which no

Period	TOU rate in ¢/kWh (Treatment)	Inclining-block rate in ¢/kWh (Control)[5]
Off-Peak Base (< 700 kWh)	8.46	10.16 (2012) / 9.55 (2013)
Off-Peak Base-Plus (> 700 kWh)	16.60	18.30 (2012) / 17.71 (2013)
Peak	27.00	N/A

3. Methodology

This section describes the methodology employed to derive elasticity estimates.

3.1 Own-price elasticity estimating equations

We leverage the power of the randomized controlled experimental design[6] to estimate hourly own-price demand elasticities for both voluntary and default TOU rate treatments. We use a log-log linear regression model because it is a simple specification with as few assumptions imposed on the functional form of demand estimation as possible, including whether or not substitution of electricity occurs between the peak and off-peak periods. This model is convenient because the regression coefficient can be interpreted directly as the own-price elasticity of demand and is constant at all prices and usage levels.[7]

To estimate own-price demand elasticities for the average treated customer exposed to a TOU rate in the context of SMUD's pricing pilot with a RED design, we use a difference-in-differences instrumental variable (IV) regression, which in this case is also called two-stage least squares (2SLS); see Cappers et al. (2016) for a detailed explanation. We use the randomized *encouragement* for the household to adopt the TOU rate (encouraged is being asked to change to the pilot rate) as the instrument for a household's enrollment in the pilot and taking the TOU rate (i.e., being treated). Thus, the encouraged price change that a household would have experienced by accepting the offer to be placed on the rate is an instrument for the treated price change a household did experience by being placed on the offered rate. Through this regression, we estimate the following set of equations:

Stage 1:

(1) $TreatedChangeLogPr_{it} = \varphi_i + \omega_t + \vartheta EncouragedChangeLogPr_{it} + e_{it}$

---

discount was applied. This same discount structure applied to both time-based treatment rates and inclining block flat rates.

[5] SMUD altered the standard rate between the summers of 2012 and 2013; however, they chose to not change the rate for customers in the study.

[6] Recent analysis by Davis et al. (2013) and Baylis et al. (2016) showed that traditional evaluation techniques applied in pricing pilots utilizing quasi-experimental designs may produce biased load impact results vis-à-vis those derived from pilots utilizing randomized control trials.

[7] Perhaps because the log-log linear regression model is simplistic, requires few structural assumptions, and results in clear and easily interpretable elasticity estimates, it has been used widely in the empirical estimation of demand equations for products ranging from agricultural and food commodities and other consumer goods to energy (Cappers et al., 2013).

Stage 2:

(2) $ln(y_{it}) = \gamma_i + \tau_t + \beta \widehat{TreatedChangeLogPr_{it}} + \varepsilon_{it}$

Where

- y_{it} captures electricity consumption for household *i* in hour *t*;
- $TreatedChangeLogPr_{it} = Treated_{it} * [ln(PriceTreat_{it}) - \ln(PriceControl_{it})]$;
- $EncouragedChangeLogPr_{it} = Encouraged_{it} * [ln(PriceTreat_{it}) - \ln(PriceControl_{it})]$;
- $TreatedChangeLogPr_{it}$ is instrumented using $EncouragedChangeLogPr_{it}$, resulting in the variable predicted by the first stage, $Treated\widehat{Change}LogPr_{it}$;
- $Treated_{it}$ is an indicator variable equal to one for all observations starting on June 1, 2012 and thereafter if household *i* was enrolled in treatment on day *t*, zero otherwise;
- $Encouraged_{it}$ is an indicator variable equal to one for all observations starting on June 1, 2012 and thereafter if household *i* had been previously encouraged to accept treatment on day *t*, zero otherwise;
- $PriceTreat_{it}$ and $PriceControl_{it}$ are the price of electricity charged to customers in the treatment group and control group, respectively, at time *t* during the study;
- φ_i and γ_i are household fixed effects; and
- ω_t and τ_t are hour-of-sample fixed effects; and e_{it} and ε_{it} are errors clustered for customer *i* and time *t.*

The coefficient of interest is β, which is the estimated own-price elasticity. A detailed discussion about elasticity model specifications and simple average treatment effects can be found in Cappers et al. (2013).

3.2 Opportunities for heterogeneity in elasticity estimates

Customer response to a TOU rate likely differs along a number of dimensions. For example, many customers have weather-sensitive loads that may increase peak period load or limit the degree of shifting in response to a TOU rate on certain days. Accordingly, it is worth trying to understand the degree to which a customer is more or less elastic under the following conditions:

- From an enrollment standpoint – Is the average residential customer more or less elastic under a voluntary or default enrollment approach to TOU rates?
- From a temporal standpoint – Is the average residential customer more or less elastic under a TOU rate on critical peak days vs. non-critical peak days?
- From a usage standpoint – Is the average residential customer who uses air conditioning (AC) more or less responsive to TOU rates than one who does not use AC?

To examine the heterogeneity for each of these segments, we estimate the own-price elasticities specific to each segment as well as every combination of segments (such as critical peak days for customers on the voluntary TOU rate who are likely to use AC).

For the temporal heterogeneity, we define **critical peak** days as those for which emergency conditions might warrant peak demand reductions. Such days are typically the hottest business days of the summer (i.e., excluding weekends and holidays). In this analysis, we assign a critical peak delineation to a day if SMUD had declared a critical peak event for one of the other experimental cells in its study during the two treatment summers (i.e., critical peak pricing) as well as proxy-CPP days during the pre-treatment summer (defined as weekdays with a maximum hourly dry-bulb temperature greater than or equal to the mean maximum hourly dry-bulb temperature of called CPP days during the treatment period, which was 96° F). There are 36 critical peak days during the study, 12 from the pre-treatment summer and 23 for the two treatment summers.

To define the heterogeneity in AC use, we apply an algorithm developed by Borgeson (2013) that estimates whether or not a customer appears to own and use air conditioning by modeling customer energy demand as a piece-wise continuous function of daily average outside temperature. This model contains one change-point (CP), corresponding to the threshold cooling temperature at which an air conditioner would be turned on inside the household (i.e., a combination of the thermostat set point within the household, the outside temperature, and the thermal insulation properties of the house shell). Specifically, this algorithm estimates, for each customer, the following equation:

$$(3)\quad y_{id} = \beta_0 + \beta_{i,tout-}(CP - tout_d) \quad + \beta_{i,tout+}(tout_d - CP) \quad + \varepsilon_{i,d}$$

Where:

- y_{idt} is metered electricity consumption for customer i on day d;
- CP is the change-point temperature where the slope of the piece-wise linear spline is set to change;
- $tout_{id}$ is the daily average outdoor temperature on day d;
- $\beta_{i,tout-}$ is the slope coefficient for customer i's first segment of the piece-wise linear spline;
- $\beta_{i,tout+}$ is the slope coefficient for customer i's second segment of the piece-wise linear spline; and
- ε_{it} is error clustered for customer i and day d.

The estimation approach is a gridded search of change point temperatures, starting at 62° F and increasing in increments of 1° F, applied until arriving at the set of CP, $\beta_{i,tout-}$, and $\beta_{i,tout+}$ that produces the minimum of the sum of squared residuals. We apply bootstrapping to quantify the standard errors in the change points for each household. Then we develop a distribution of change points and upper slope coefficients to derive a customer-specific prediction of air conditioning ownership and usage. Following this algorithm, we code customers for which the estimated upper slope is weakly positive, with a cutoff of $\beta_{i,tout+} > 0.25$, as "likely to use AC", and those lower than this cutoff as "AC use unlikely or unknown." We then estimate the elasticities for those two subsets of customers using the instrumental variables equation defined above. For the voluntary rate, 37,845 customers were labeled by this algorithm as likely, and 6,913 as unlikely; for the default rate, 27,671 were likely, and 5,030 were unlikely.

4. Empirical results

This section presents results for the estimated elasticities, including the heterogeneous estimates across various different dimensions.[8]

4.1 Base elasticity estimates

Average estimated own-price demand elasticities for each hour of the day are shown in Figure 2 for participants who volunteered to take service under the TOU rate. Customers in our sample exhibit a statistically significant ($p < 0.05$) own-price elasticity of demand to the TOU rate during HE 16 through HE 20, which include both the peak period (HE 17 – HE 19), the hour leading up as well as right after it. During the peak period, when prices are higher for treated customers than control customers, the simple average of the estimated elasticities is -0.23, with a range between -0.22 and -0.25. In the off-peak period, when prices are lower for treated customers than control customers, the estimated elasticities are 0.35 in HE 16 and 0.41 in HE 20. In no other hours in the day do customers exhibit statistically significant elasticity.

Estimates of own-price elasticities for customers defaulted onto the TOU rate were statistically significant in HE 17-HE 20, as shown in Figure 3. The simple average hourly own-price elasticity across the entire peak period is -0.07, with a similarly narrow range between -0.06 and -0.08. In HE 20, the first hour after the peak period, customers exhibit a statistically significant positive own-price elasticity of 0.11.

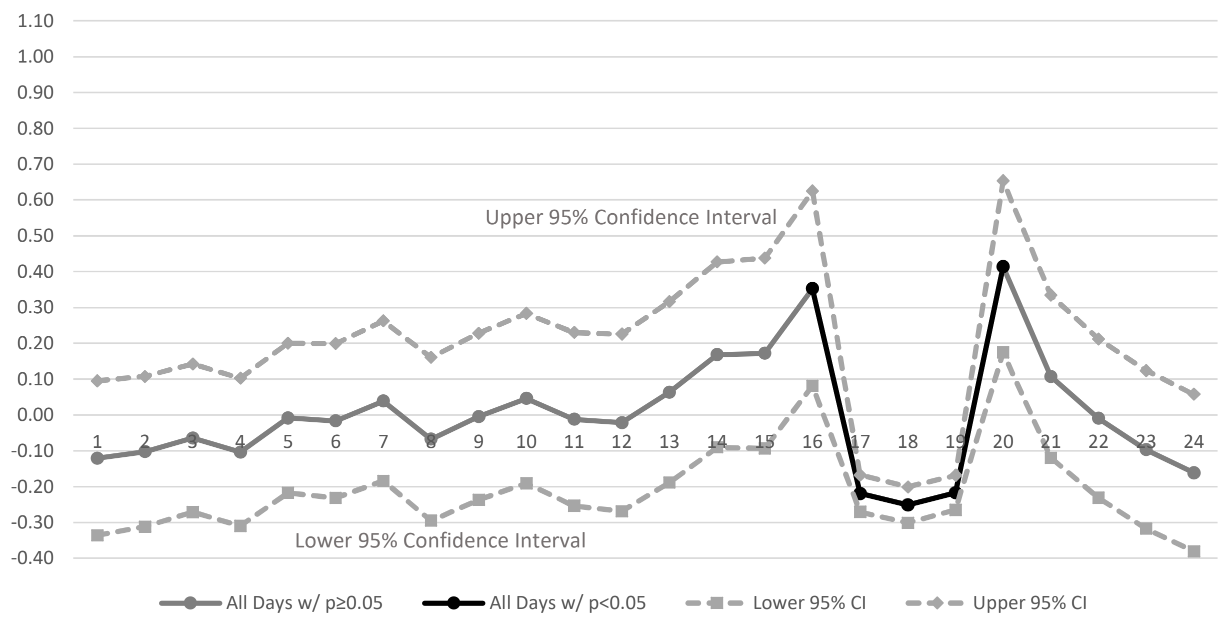


Figure 2. Hourly estimated own-price demand elasticities for the voluntary TOU rate across all days and customers in the sample

[8] The full econometric model results can be found in the Appendix.

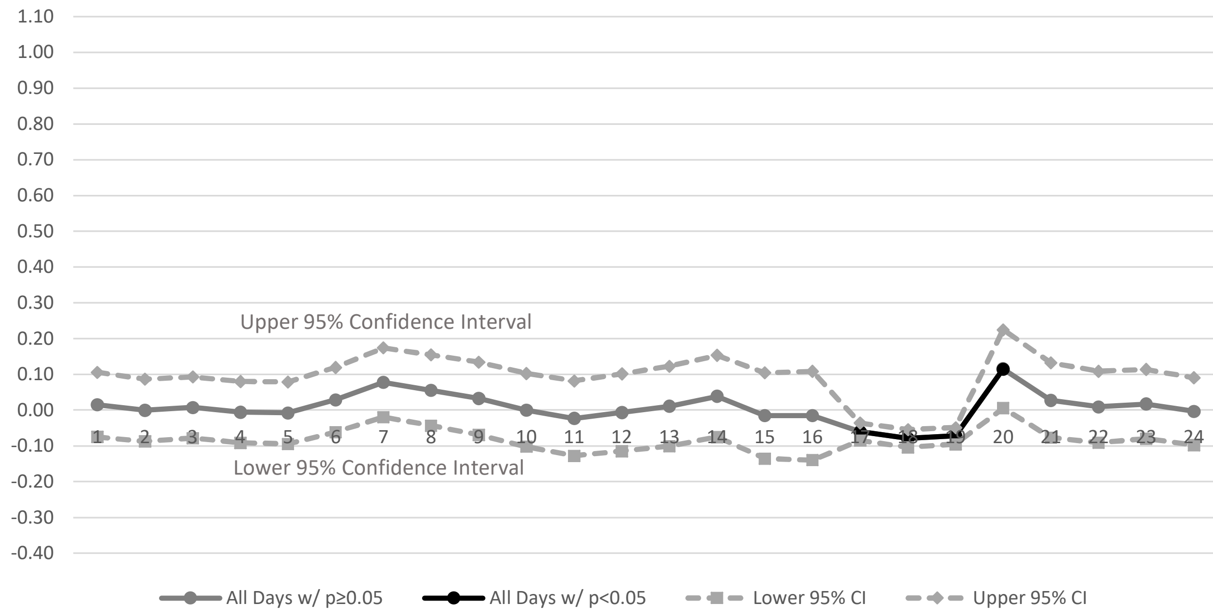


Figure 3. Hourly estimated own-price demand elasticities for the default TOU rate across all days and customers in the sample

4.2 Temporal heterogeneity in elasticity estimates

Next, we segmented the data based according to a critical peak (i.e., hot) day or not and estimated elasticities for these two different types of days. As seen in Figure 4, own-price demand elasticities for customers on a voluntary TOU rate are statistically significant during the peak period hours (HE 17-HE 19), regardless of day type. However, own-price elasticities during that time on critical peak days, when the maximum daily temperature was frequently well over 90° F, was roughly 30% to 50% higher than on days not identified with a critical peak designation. The average customer in the study exhibited an own-price elasticity of -0.30 between HE 17 and HE 19 (i.e., peak period) on critical peak days but was estimated to be -0.22 on non-critical peak days during those same hours. Customers also exhibited statistically significant own-price demand elasticities in a few off-peak hours, but only those directly surrounding the peak period: HE 15, HE 16, and HE 20 on critical peak days and in HE 16 and HE 20 on non-critical peak days.

Figure 5 shows estimated hourly own-price demand elasticities across critical peak days and non-critical peak days for those customers who defaulted to the TOU rate, with the statistically significant estimates darkened. Regardless of day type, these customers exhibited a statistically significant own-price elasticity from HE 17-HE 20 (-0.09 on critical peak days and -0.07 on non-critical peak days). Although the estimated own-price elasticity was statistically significant in the hour after the peak period ended (HE 20) on both day types, it is positive with estimates of 0.16 on critical peak days and 0.11 on non-critical peak days. In no other hours did defaulted customers exhibit any statistically significant elasticity to the TOU rate.

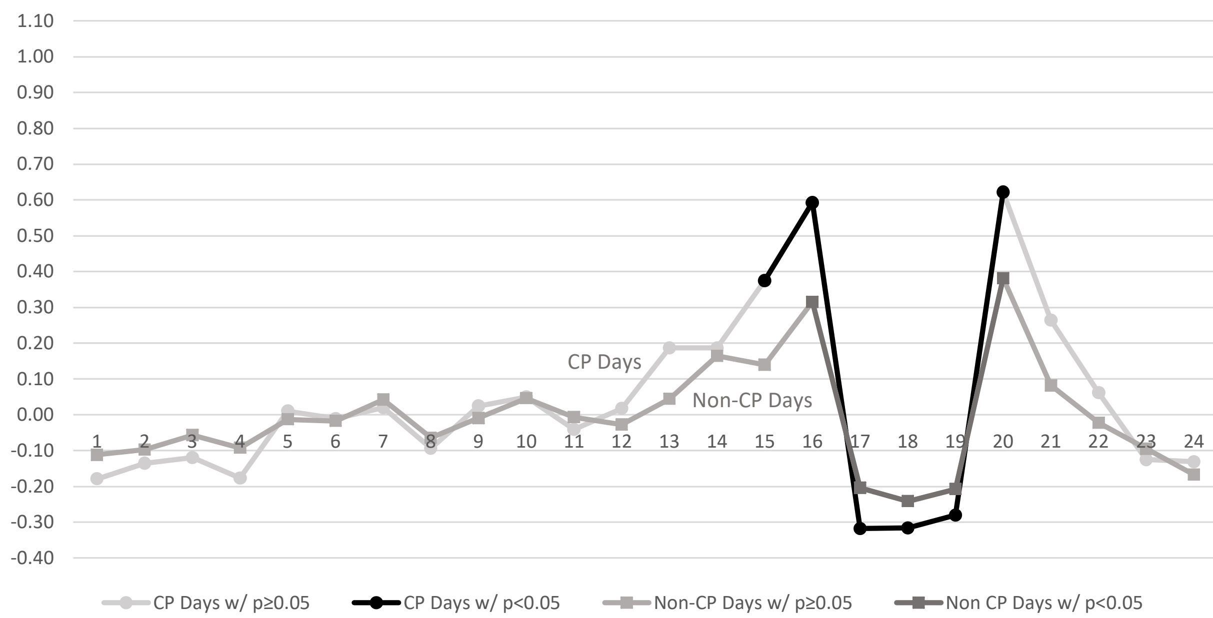


Figure 4. Hourly estimated own-price demand elasticities for the voluntary TOU rate segmented by critical peak days

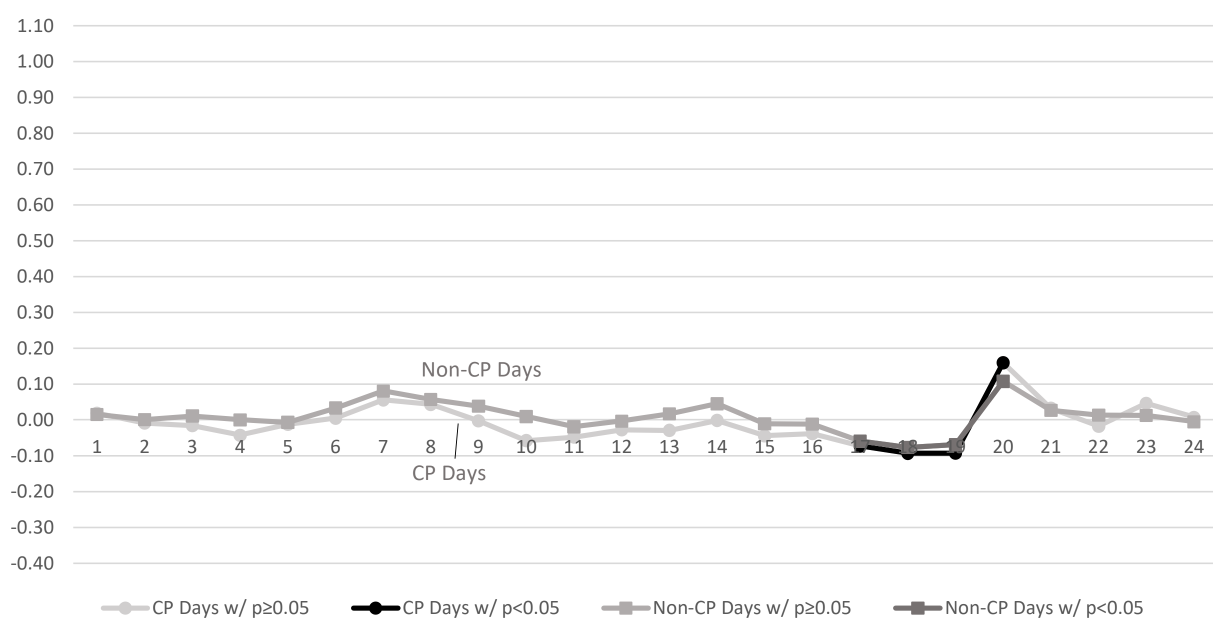


Figure 5. Hourly estimated own-price demand elasticities for the default TOU rate segmented by critical peak days

4.3 Usage Heterogeneity in Elasticity Estimates

The high temperatures frequently experienced in SMUD's service territory have resulted in high penetration of air conditioning (Potter et al., 2014). Given how large AC loads are, they present an opportunity for customers to reduce their usage in response to the higher peak period TOU rate. Customers may prepare for higher internal household temperatures during the peak period by implementing pre-cooling activities ahead of time or exhibit increased overall electricity use in the hours just after the peak period as the AC system works to cool the house back down.

Figure 6 clearly shows that volunteers to the TOU rate who were predicted to own and use air conditioning were more elastic than those customers who were unlikely to own and use AC during the peak period (i.e., HE 17-HE 19). In these three hours, customers expected to use AC exhibit an average elasticity of -0.25, while those non-expected to use AC show an average elasticity of -0.19. However, in the hour before and after the peak period, customers predicted to use AC are about half as elastic (average of 0.36) as their counterparts (average of 0.71); all of these elasticities are statistically significant at the 5% level. In all other hours of the day (except for HE 24 for those predicted to use AC), customers do not exhibit any statistically significant elasticity, regardless of the expected use of AC or not.

In contrast, only those defaulted customers predicted to own and use AC exhibited any statistically significant elasticity across all days, occurring only from HE 17 to HE 20 (see Figure 7). Customers who were not predicted to own and operate air conditioning did not exhibit any statistically significant elasticity in any hour at the 5% level in response to the TOU rate.[9]

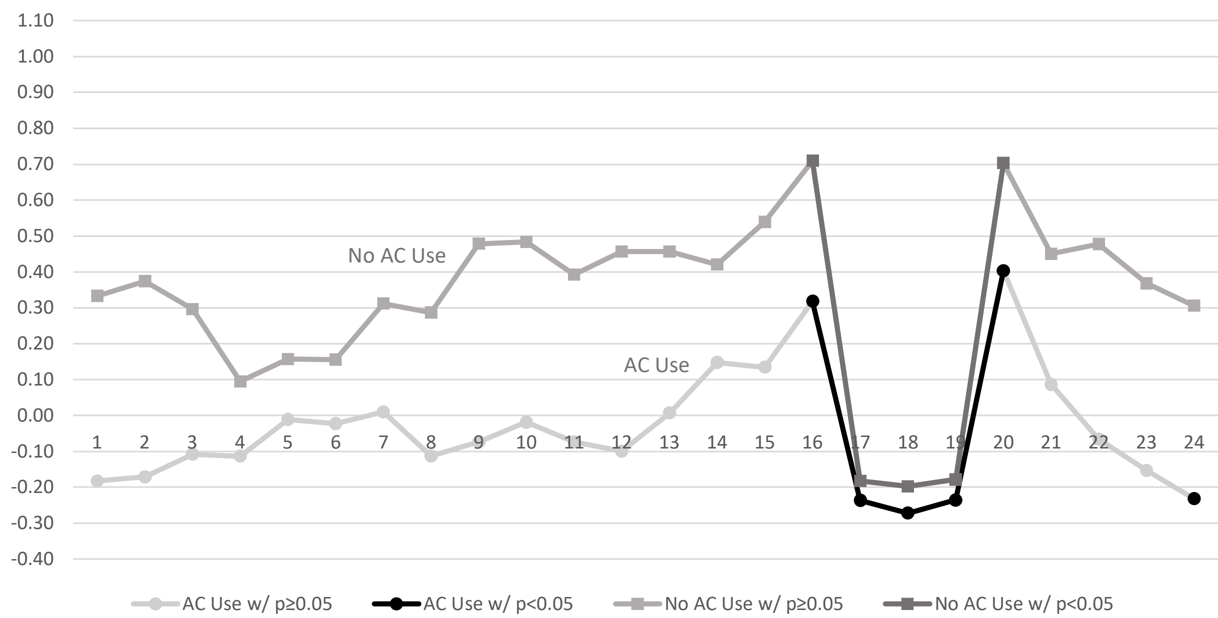


Figure 6. Hourly estimated own-price demand elasticities for the voluntary TOU rate segmented by likelihood of AC ownership and use

[9] If the level of significance were dropped to 10% there would have been statistically significant elasticities in HE 18 and HE 19.

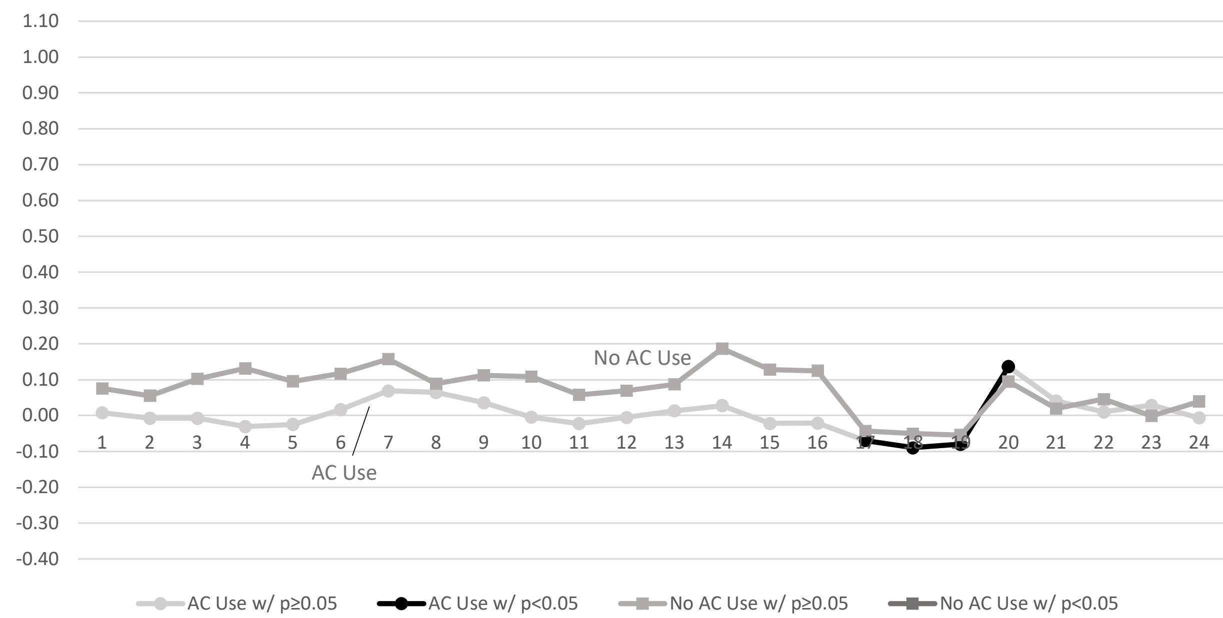


Figure 7. Hourly estimated own-price demand elasticities for the default TOU rate segmented by likelihood of AC ownership and use

4.4 Temporal and usage heterogeneity in elasticity estimates

Air conditioning use is likely to be more prevalent when temperatures are high, which creates more opportunity for price response to a TOU rate by increasing the setpoint or turning the AC off entirely, both of which were actions study participants indicated they undertook (Potter et al., 2014).

As shown in Figure 8, those volunteers for the TOU rate who were predicted to own and use AC exhibited a 30% larger estimated elasticity during the peak period (HE 17-HE 19) than those who were not expected to own or use AC (-0.33 vs. -0.25, respectively). Although both sets of customers exhibited statistically significant own-price elasticity estimates at the 5% level from HE 16 through HE 20, it is those who were not predicted to own and use AC that continued to be elastic through HE 21 and HE 22 (elasticity estimates of ~0.79 in both hours).[10]

A similar, but less striking, trend is observed of those who defaulted to the TOU rate, as shown in Figure 9. Of those hours with statistically significant own-price elasticity estimates, customers predicted to own and operate their AC were slightly more elastic than their non-AC using counterparts in HE 17 and HE 18, with a modest reversal in HE 19. The simple average own-price elasticity for non-AC users during the peak period is nearly the same for those who were not predicted to own and operate air conditioning (i.e., -0.09 vs. -0.09). However, the estimated elasticity in HE17 for the former group is only statistically significant at the 10% level.

[10] It is worth noting that these non-AC users exhibit statistically significant elasticities, at the 10% level from HE 13 through HE 24 (excluding HE 14).

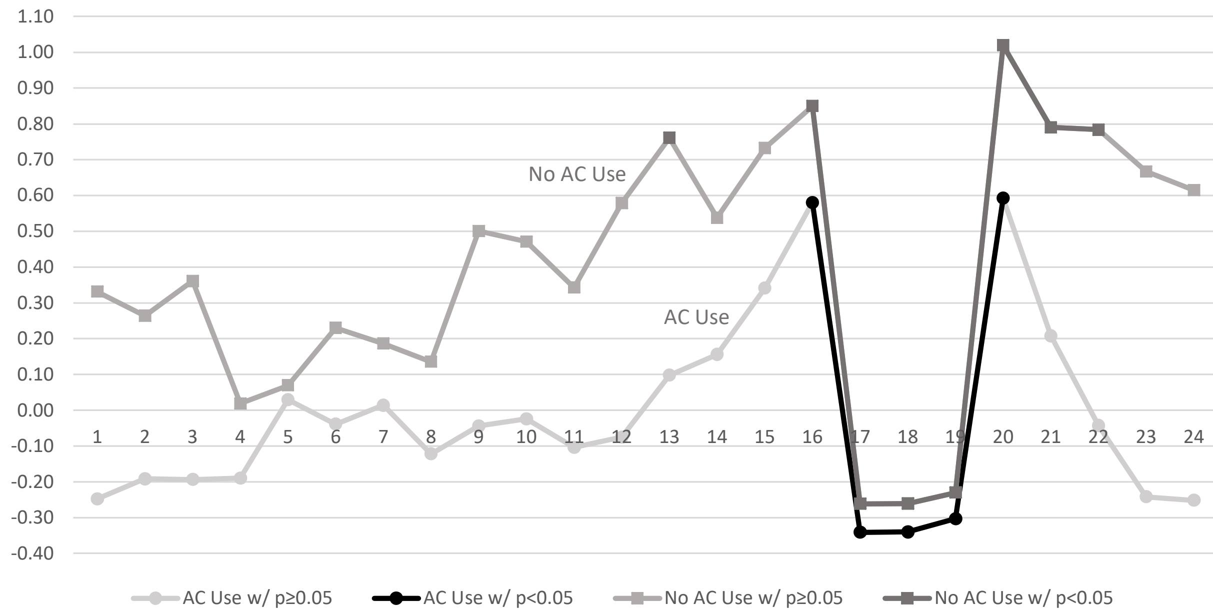


Figure 8. Hourly estimated own-price demand elasticities for the voluntary TOU rate segmented by likelihood of AC ownership and use on critical peak days only

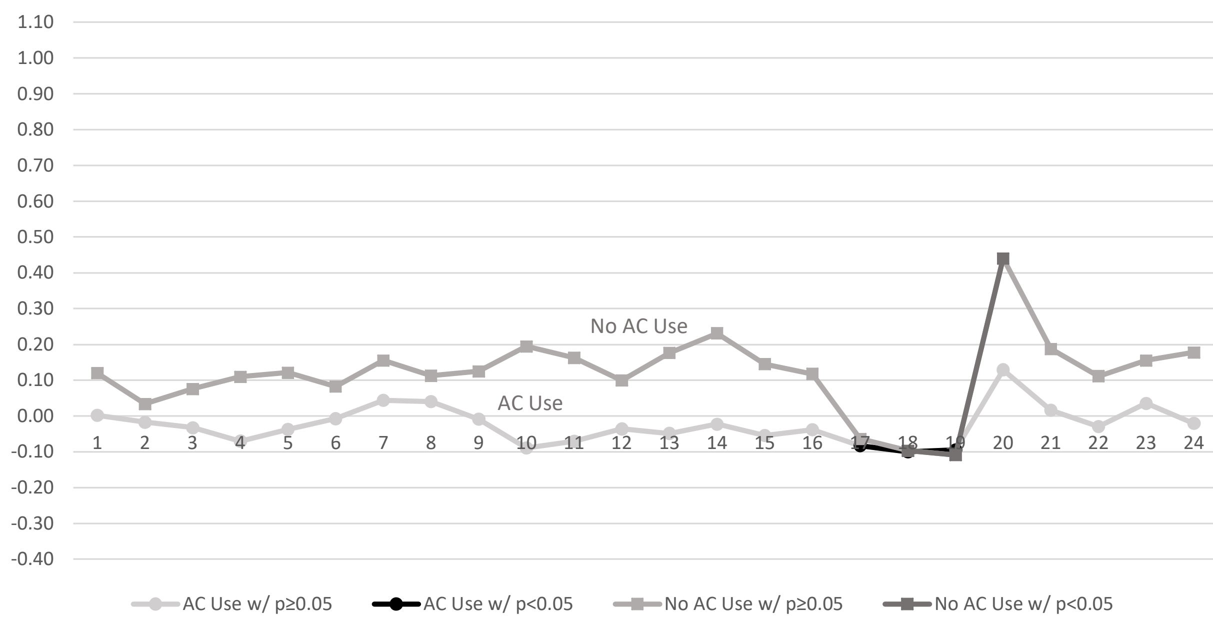


Figure 9. Hourly estimated own-price demand elasticities for the default TOU rate segmented by likelihood of AC ownership and use on critical peak days only

5. Discussion

In this study, our analysis consistently revealed statistically significant negative estimates of the elasticity of electricity demand in the peak period (e.g., HE 17 – HE 19). This finding was nearly universally true across all cross-sections analyzed: voluntary vs. default enrollment;

critical peak vs. non-critical peak days; and prediction of AC ownership vs non-ownership. Residential customers appeared to dependably reduce their electricity consumption in direct response to the higher peak period price, producing simple average peak period own-price elasticities between -0.19 and -0.33 under a voluntary enrollment approach and between -0.05 and -0.09 under a default enrollment approach. Within the peak period, the hour-by-hour variation in estimated elasticities was relatively modest. Across all of the different analytical groupings, the variance was 0.0005 or less. This relative consistency of elasticity may be due to the short length of the peak period where customers only needed to maintain whatever actions they undertook in response to the price for three hours.

Although the majority of the off-peak period elasticities were not statistically significant, some subset of customers seemed frequently inclined to undertake some load reduction efforts in anticipation of the peak period (i.e., HE 16) and maintain those activities beyond the end of the peak period (i.e., HE 20). Such efforts appeared to be more pronounced on critical peak days and exhibited more systematically by those predicted not to own and operate AC. In all cases, these few statistically significant positive elasticities were counterintuitive. Further exploration of what may have caused such results was beyond the scope of our analysis.

This analysis does suggest the potential value in deriving customer characteristics by analyzing readily available interval meter data to help create more refined but comprehensive subsets of customers. Our analysis using ownership and air conditioning usage as an example, illustrates how customers predicted to have this characteristic are categorically different and more elastic than their counterparts not predicted to have it. Given the expense associated with survey collection efforts as well as the limited coverage such approaches often result in (i.e., response rates that are less than 20%), analysis of interval meter data could present a more cost-effective way to comprehensively target market customers under a voluntary setting, as well as to identify customers who might potentially be unwilling or unable to manage their usage under a transition to default TOU rate. If undertaken, such activities might alleviate concerns and allow more jurisdictions to pursue voluntary or default TOU rate offerings vigorously.

6. Conclusions

The elasticity estimates derived from this analysis provide a more heterogeneous view of customer response to price on a temporal, cross-sectional, and enrollment approach basis.

Our analysis shows that in a narrowly defined TOU rate (i.e., 3 hour peak period) with a meaningful peak to off-peak price ratio of 1.6 - 3.4 (depending on the block), customers are generally elastic only during the peak period as well as the single hour before and after it. Only in very rare cases were the estimated own-price elasticity statistically significant in other hours of the day. In addition, the average customer appears to be more elastic during the peak period of critical peak days, when temperatures were extremely high, than during the peak period on all days of the summer. Most of the hourly elasticity patterns that emerged for volunteers to the TOU rate where likewise observed for their default counterparts, but of roughly an order of magnitude difference.

7. References:

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8. Appendices

The full results from all regressions, with the estimated coefficients and standard errors, are presented below.

Elasticity Estimates

All days; all households

	Voluntary					Default				
Hour	coefficient	*p-value*	*std error*	N households	N days	coefficient	*p-value*	*std error*	N households	N days
0	**-0.1207**	*0.2724*	*0.1100*	53245	260	**0.0153**	*0.7394*	*0.0460*	38844	260
1	**-0.1024**	*0.3391*	*0.1071*	53245	260	**-0.0003**	*0.9948*	*0.0443*	38844	260
2	**-0.0647**	*0.5399*	*0.1055*	53245	260	**0.0073**	*0.8674*	*0.0437*	38844	260
3	**-0.1037**	*0.3236*	*0.1051*	53245	260	**-0.0056**	*0.8980*	*0.0438*	38844	260
4	**-0.0086**	*0.9353*	*0.1065*	53245	260	**-0.0079**	*0.8588*	*0.0442*	38844	260
5	**-0.0164**	*0.8813*	*0.1099*	53245	260	**0.0290**	*0.5295*	*0.0461*	38844	260
6	**0.0392**	*0.7307*	*0.1139*	53245	260	**0.0772**	*0.1174*	*0.0493*	38844	260
7	**-0.0675**	*0.5616*	*0.1164*	53245	260	**0.0554**	*0.2729*	*0.0506*	38844	260
8	**-0.0047**	*0.9686*	*0.1187*	53245	260	**0.0327**	*0.5286*	*0.0518*	38844	260
9	**0.0461**	*0.7030*	*0.1209*	53245	260	**0.0003**	*0.9962*	*0.0522*	38844	260
10	**-0.0120**	*0.9222*	*0.1234*	53245	260	**-0.0230**	*0.6666*	*0.0535*	38844	260
11	**-0.0217**	*0.8634*	*0.1261*	53245	260	**-0.0066**	*0.9046*	*0.0551*	38844	260
12	**0.0636**	*0.6217*	*0.1288*	53245	260	**0.0109**	*0.8479*	*0.0570*	38844	260
13	**0.1680**	*0.2033*	*0.1320*	53245	260	**0.0389**	*0.5048*	*0.0583*	38844	260
14	**0.1721**	*0.2042*	*0.1356*	53245	260	**-0.0154**	*0.8011*	*0.0612*	38844	260
15	**0.3529**	*0.0110*	*0.1387*	53245	260	**-0.0157**	*0.8043*	*0.0633*	38844	260
16	**-0.2194**	*0.0000*	*0.0263*	53245	260	**-0.0606**	*0.0000*	*0.0125*	38844	260
17	**-0.2513**	*0.0000*	*0.0256*	53245	260	**-0.0792**	*0.0000*	*0.0126*	38844	260
18	**-0.2171**	*0.0000*	*0.0245*	53245	260	**-0.0721**	*0.0000*	*0.0119*	38844	260
19	**0.4138**	*0.0007*	*0.1223*	53245	260	**0.1151**	*0.0394*	*0.0559*	38844	260
20	**0.1071**	*0.3551*	*0.1158*	53245	260	**0.0277**	*0.6036*	*0.0534*	38844	260
21	**-0.0098**	*0.9309*	*0.1130*	53245	260	**0.0089**	*0.8618*	*0.0509*	38844	260
22	**-0.0971**	*0.3889*	*0.1127*	53245	260	**0.0170**	*0.7307*	*0.0494*	38844	260
23	**-0.1616**	*0.1487*	*0.1119*	53245	260	**-0.0034**	*0.9427*	*0.0480*	38844	260

All days; households with AC use likely

	Voluntary					Default				
Hour	coefficient	*p-value*	*std error*	N households	N days	coefficient	*p-value*	*std error*	N households	N days
0	**-0.1823**	*0.1210*	*0.1176*	37845	35	**0.0075**	*0.8787*	*0.0494*	27671	35
1	**-0.1710**	*0.1358*	*0.1146*	37845	35	**-0.0075**	*0.8757*	*0.0479*	27671	35
2	**-0.1081**	*0.3395*	*0.1132*	37845	35	**-0.0076**	*0.8723*	*0.0475*	27671	35
3	**-0.1134**	*0.3142*	*0.1127*	37845	35	**-0.0308**	*0.5160*	*0.0474*	27671	35
4	**-0.0112**	*0.9218*	*0.1144*	37845	35	**-0.0250**	*0.5997*	*0.0476*	27671	35
5	**-0.0232**	*0.8442*	*0.1181*	37845	35	**0.0164**	*0.7410*	*0.0496*	27671	35
6	**0.0099**	*0.9356*	*0.1219*	37845	35	**0.0688**	*0.2003*	*0.0537*	27671	35
7	**-0.1129**	*0.3666*	*0.1250*	37845	35	**0.0644**	*0.2400*	*0.0548*	27671	35
8	**-0.0736**	*0.5661*	*0.1283*	37845	35	**0.0357**	*0.5271*	*0.0564*	27671	35
9	**-0.0186**	*0.8871*	*0.1312*	37845	35	**-0.0047**	*0.9346*	*0.0568*	27671	35
10	**-0.0734**	*0.5851*	*0.1345*	37845	35	**-0.0226**	*0.6985*	*0.0583*	27671	35

11	**-0.0997**	*0.4688*	*0.1376*	37845	35	**-0.0050**	*0.9334*	*0.0600*	27671	35
12	**0.0070**	*0.9604*	*0.1405*	37845	35	**0.0128**	*0.8364*	*0.0620*	27671	35
13	**0.1474**	*0.3071*	*0.1443*	37845	35	**0.0278**	*0.6630*	*0.0637*	27671	35
14	**0.1345**	*0.3639*	*0.1482*	37845	35	**-0.0222**	*0.7421*	*0.0674*	27671	35
15	**0.3181**	*0.0349*	*0.1508*	37845	35	**-0.0213**	*0.7598*	*0.0697*	27671	35
16	**-0.2368**	*0.0000*	*0.0284*	37845	35	**-0.0697**	*0.0000*	*0.0137*	27671	35
17	**-0.2723**	*0.0000*	*0.0275*	37845	35	**-0.0900**	*0.0000*	*0.0137*	27671	35
18	**-0.2356**	*0.0000*	*0.0261*	37845	35	**-0.0801**	*0.0000*	*0.0128*	27671	35
19	**0.4036**	*0.0018*	*0.1291*	37845	35	**0.1366**	*0.0211*	*0.0592*	27671	35
20	**0.0861**	*0.4778*	*0.1213*	37845	35	**0.0406**	*0.4672*	*0.0558*	27671	35
21	**-0.0658**	*0.5785*	*0.1184*	37845	35	**0.0103**	*0.8462*	*0.0533*	27671	35
22	**-0.1533**	*0.1981*	*0.1191*	37845	35	**0.0288**	*0.5810*	*0.0521*	27671	35
23	**-0.2323**	*0.0511*	*0.1191*	37845	35	**-0.0064**	*0.8998*	*0.0510*	27671	35

All days; households with AC use unlikely or unknown

	Voluntary					Default				
Hour	**coefficient**	***p-value***	***std error***	**N households**	**N days**	**coefficient**	***p-value***	***std error***		
0	**0.3329**	*0.2414*	*0.2842*	6913	225	**0.0755**	*0.5158*	*0.1162*	5030	225
1	**0.3738**	*0.1758*	*0.2762*	6913	225	**0.0554**	*0.6075*	*0.1078*	5030	225
2	**0.2963**	*0.2722*	*0.2699*	6913	225	**0.1026**	*0.3292*	*0.1052*	5030	225
3	**0.0948**	*0.7247*	*0.2691*	6913	225	**0.1313**	*0.2200*	*0.1070*	5030	225
4	**0.1571**	*0.5618*	*0.2707*	6913	225	**0.0956**	*0.3850*	*0.1100*	5030	225
5	**0.1554**	*0.5794*	*0.2804*	6913	225	**0.1167**	*0.3182*	*0.1169*	5030	225
6	**0.3118**	*0.2947*	*0.2975*	6913	225	**0.1579**	*0.1902*	*0.1205*	5030	225
7	**0.2866**	*0.3401*	*0.3004*	6913	225	**0.0888**	*0.4906*	*0.1288*	5030	225
8	**0.4788**	*0.1083*	*0.2982*	6913	225	**0.1123**	*0.3898*	*0.1306*	5030	225
9	**0.4835**	*0.1027*	*0.2963*	6913	225	**0.1087**	*0.4070*	*0.1310*	5030	225
10	**0.3928**	*0.1848*	*0.2962*	6913	225	**0.0577**	*0.6647*	*0.1331*	5030	225
11	**0.4566**	*0.1270*	*0.2992*	6913	225	**0.0692**	*0.6138*	*0.1371*	5030	225
12	**0.4568**	*0.1334*	*0.3044*	6913	225	**0.0871**	*0.5377*	*0.1413*	5030	225
13	**0.4209**	*0.1679*	*0.3052*	6913	225	**0.1871**	*0.1897*	*0.1427*	5030	225
14	**0.5392**	*0.0827*	*0.3107*	6913	225	**0.1280**	*0.3754*	*0.1443*	5030	225
15	**0.7094**	*0.0284*	*0.3238*	6913	225	**0.1248**	*0.3995*	*0.1481*	5030	225
16	**-0.1826**	*0.0034*	*0.0624*	6913	225	**-0.0431**	*0.1345*	*0.0288*	5030	225
17	**-0.1980**	*0.0015*	*0.0623*	6913	225	**-0.0507**	*0.0935*	*0.0302*	5030	225
18	**-0.1788**	*0.0036*	*0.0615*	6913	225	**-0.0544**	*0.0679*	*0.0298*	5030	225
19	**0.7033**	*0.0264*	*0.3167*	6913	225	**0.0948**	*0.5138*	*0.1452*	5030	225
20	**0.4505**	*0.1459*	*0.3098*	6913	225	**0.0193**	*0.8935*	*0.1441*	5030	225
21	**0.4771**	*0.1164*	*0.3038*	6913	225	**0.0459**	*0.7381*	*0.1372*	5030	225
22	**0.3677**	*0.2178*	*0.2984*	6913	225	**-0.0010**	*0.9938*	*0.1301*	5030	225
23	**0.3056**	*0.2944*	*0.2915*	6913	225	**0.0392**	*0.7536*	*0.1250*	5030	225

Critical Peak days; all households

	Voluntary					Default				
Hour	**coefficient**	***p-value***	***std error***	**N households**	**N days**	**coefficient**	***p-value***	***std error***	**N households**	**N days**

0	**-0.1789**	*0.1921*	*0.1371*	53245	260	**0.0188**	*0.7472*	*0.0583*	38844	260
1	**-0.1355**	*0.3023*	*0.1313*	53245	260	**-0.0092**	*0.8669*	*0.0550*	38844	260
2	**-0.1198**	*0.3459*	*0.1271*	53245	260	**-0.0161**	*0.7671*	*0.0545*	38844	260
3	**-0.1768**	*0.1575*	*0.1251*	53245	260	**-0.0428**	*0.4174*	*0.0528*	38844	260
4	**0.0104**	*0.9338*	*0.1254*	53245	260	**-0.0122**	*0.8159*	*0.0523*	38844	260
5	**-0.0108**	*0.9329*	*0.1286*	53245	260	**0.0051**	*0.9250*	*0.0538*	38844	260
6	**0.0200**	*0.8808*	*0.1334*	53245	260	**0.0560**	*0.3342*	*0.0580*	38844	260
7	**-0.0935**	*0.4989*	*0.1383*	53245	260	**0.0428**	*0.4773*	*0.0603*	38844	260
8	**0.0245**	*0.8637*	*0.1426*	53245	260	**-0.0030**	*0.9622*	*0.0623*	38844	260
9	**0.0498**	*0.7359*	*0.1477*	53245	260	**-0.0577**	*0.3672*	*0.0640*	38844	260
10	**-0.0411**	*0.7907*	*0.1547*	53245	260	**-0.0476**	*0.4776*	*0.0670*	38844	260
11	**0.0176**	*0.9134*	*0.1616*	53245	260	**-0.0276**	*0.6969*	*0.0709*	38844	260
12	**0.1870**	*0.2684*	*0.1689*	53245	260	**-0.0294**	*0.6940*	*0.0747*	38844	260
13	**0.1870**	*0.2869*	*0.1756*	53245	260	**-0.0015**	*0.9842*	*0.0773*	38844	260
14	**0.3750**	*0.0391*	*0.1818*	53245	260	**-0.0441**	*0.5808*	*0.0799*	38844	260
15	**0.5929**	*0.0012*	*0.1835*	53245	260	**-0.0383**	*0.6386*	*0.0816*	38844	260
16	**-0.3178**	*0.0000*	*0.0345*	53245	260	**-0.0729**	*0.0000*	*0.0158*	38844	260
17	**-0.3161**	*0.0000*	*0.0333*	53245	260	**-0.0929**	*0.0000*	*0.0159*	38844	260
18	**-0.2804**	*0.0000*	*0.0318*	53245	260	**-0.0924**	*0.0000*	*0.0152*	38844	260
19	**0.6217**	*0.0001*	*0.1586*	53245	260	**0.1596**	*0.0265*	*0.0720*	38844	260
20	**0.2644**	*0.0802*	*0.1511*	53245	260	**0.0325**	*0.6330*	*0.0680*	38844	260
21	**0.0619**	*0.6722*	*0.1462*	53245	260	**-0.0172**	*0.7951*	*0.0661*	38844	260
22	**-0.1250**	*0.3870*	*0.1445*	53245	260	**0.0466**	*0.4682*	*0.0642*	38844	260
23	**-0.1314**	*0.3568*	*0.1425*	53245	260	**0.0076**	*0.9044*	*0.0631*	38844	260

Critical Peak days; households with AC use likely

	Voluntary					Default				
Hour	**coefficient**	***p-value***	***std error***	**N households**	**N days**	**coefficient**	***p-value***	***std error***	**N households**	**N days**
0	**-0.2477**	*0.0943*	*0.1481*	37845	35	**0.0017**	*0.9786*	*0.0635*	27671	35
1	**-0.1916**	*0.1767*	*0.1418*	37845	35	**-0.0171**	*0.7752*	*0.0598*	27671	35
2	**-0.1936**	*0.1585*	*0.1373*	37845	35	**-0.0328**	*0.5829*	*0.0598*	27671	35
3	**-0.1893**	*0.1608*	*0.1350*	37845	35	**-0.0704**	*0.2247*	*0.0580*	27671	35
4	**0.0296**	*0.8273*	*0.1355*	37845	35	**-0.0372**	*0.5140*	*0.0571*	27671	35
5	**-0.0392**	*0.7774*	*0.1386*	37845	35	**-0.0071**	*0.9024*	*0.0581*	27671	35
6	**0.0140**	*0.9222*	*0.1437*	37845	35	**0.0441**	*0.4856*	*0.0633*	27671	35
7	**-0.1218**	*0.4147*	*0.1494*	37845	35	**0.0403**	*0.5425*	*0.0661*	27671	35
8	**-0.0441**	*0.7760*	*0.1550*	37845	35	**-0.0091**	*0.8943*	*0.0682*	27671	35
9	**-0.0238**	*0.8827*	*0.1616*	37845	35	**-0.0890**	*0.2072*	*0.0706*	27671	35
10	**-0.1035**	*0.5423*	*0.1699*	37845	35	**-0.0708**	*0.3384*	*0.0739*	27671	35
11	**-0.0749**	*0.6731*	*0.1776*	37845	35	**-0.0357**	*0.6486*	*0.0782*	27671	35
12	**0.0977**	*0.5978*	*0.1853*	37845	35	**-0.0484**	*0.5564*	*0.0822*	27671	35
13	**0.1559**	*0.4180*	*0.1925*	37845	35	**-0.0227**	*0.7901*	*0.0852*	27671	35
14	**0.3413**	*0.0850*	*0.1982*	37845	35	**-0.0547**	*0.5318*	*0.0875*	27671	35
15	**0.5802**	*0.0034*	*0.1981*	37845	35	**-0.0383**	*0.6645*	*0.0884*	27671	35
16	**-0.3410**	*0.0000*	*0.0369*	37845	35	**-0.0826**	*0.0000*	*0.0170*	27671	35
17	**-0.3398**	*0.0000*	*0.0352*	37845	35	**-0.0995**	*0.0000*	*0.0169*	27671	35

Hour	coefficient	p-value	std error	N households	N days	coefficient	p-value	std error	N households	N days
18	**-0.3030**	*0.0000*	*0.0333*	37845	35	**-0.0951**	*0.0000*	*0.0159*	27671	35
19	**0.5922**	*0.0003*	*0.1654*	37845	35	**0.1292**	*0.0848*	*0.0750*	27671	35
20	**0.2080**	*0.1862*	*0.1573*	37845	35	**0.0162**	*0.8173*	*0.0703*	27671	35
21	**-0.0429**	*0.7794*	*0.1530*	37845	35	**-0.0293**	*0.6738*	*0.0696*	27671	35
22	**-0.2416**	*0.1145*	*0.1531*	37845	35	**0.0353**	*0.6040*	*0.0681*	27671	35
23	**-0.2517**	*0.0997*	*0.1529*	37845	35	**-0.0209**	*0.7582*	*0.0679*	27671	35

Critical Peak days; households with AC use unlikely or unknown

	Voluntary					Default				
Hour	**coefficient**	***p-value***	***std error***	**N households**	**N days**	**coefficient**	***p-value***	***std error***	**N households**	**N days**
0	**0.3313**	*0.3296*	*0.3398*	6913	225	**0.1199**	*0.3862*	*0.1384*	5030	225
1	**0.2639**	*0.4174*	*0.3255*	6913	225	**0.0339**	*0.7951*	*0.1305*	5030	225
2	**0.3608**	*0.2544*	*0.3166*	6913	225	**0.0753**	*0.5483*	*0.1254*	5030	225
3	**0.0187**	*0.9520*	*0.3111*	6913	225	**0.1096**	*0.3685*	*0.1219*	5030	225
4	**0.0692**	*0.8240*	*0.3110*	6913	225	**0.1211**	*0.3306*	*0.1245*	5030	225
5	**0.2299**	*0.4769*	*0.3232*	6913	225	**0.0822**	*0.5377*	*0.1333*	5030	225
6	**0.1867**	*0.5823*	*0.3394*	6913	225	**0.1550**	*0.2698*	*0.1405*	5030	225
7	**0.1358**	*0.6967*	*0.3484*	6913	225	**0.1125**	*0.4412*	*0.1460*	5030	225
8	**0.5007**	*0.1499*	*0.3477*	6913	225	**0.1249**	*0.4101*	*0.1516*	5030	225
9	**0.4709**	*0.1765*	*0.3484*	6913	225	**0.1945**	*0.2007*	*0.1520*	5030	225
10	**0.3429**	*0.3356*	*0.3561*	6913	225	**0.1627**	*0.3066*	*0.1592*	5030	225
11	**0.5785**	*0.1167*	*0.3688*	6913	225	**0.0994**	*0.5455*	*0.1645*	5030	225
12	**0.7609**	*0.0482*	*0.3851*	6913	225	**0.1762**	*0.3166*	*0.1759*	5030	225
13	**0.5379**	*0.1725*	*0.3943*	6913	225	**0.2310**	*0.1968*	*0.1790*	5030	225
14	**0.7321**	*0.0761*	*0.4127*	6913	225	**0.1448**	*0.4364*	*0.1861*	5030	225
15	**0.8497**	*0.0489*	*0.4314*	6913	225	**0.1178**	*0.5537*	*0.1989*	5030	225
16	**-0.2617**	*0.0015*	*0.0825*	6913	225	**-0.0637**	*0.1010*	*0.0388*	5030	225
17	**-0.2606**	*0.0017*	*0.0833*	6913	225	**-0.0967**	*0.0203*	*0.0417*	5030	225
18	**-0.2299**	*0.0051*	*0.0821*	6913	225	**-0.1089**	*0.0082*	*0.0412*	5030	225
19	**1.0197**	*0.0160*	*0.4234*	6913	225	**0.4402**	*0.0289*	*0.2015*	5030	225
20	**0.7907**	*0.0528*	*0.4083*	6913	225	**0.1877**	*0.3264*	*0.1913*	5030	225
21	**0.7836**	*0.0467*	*0.3940*	6913	225	**0.1115**	*0.5265*	*0.1760*	5030	225
22	**0.6668**	*0.0784*	*0.3789*	6913	225	**0.1551**	*0.3568*	*0.1683*	5030	225
23	**0.6153**	*0.0873*	*0.3598*	6913	225	**0.1776**	*0.2648*	*0.1592*	5030	225

Non-Critical Peak days; all households

	Voluntary					Default				
Hour	**coefficient**	***p-value***	***std error***	**N households**	**N days**	**coefficient**	***p-value***	***std error***	**N households**	**N days**
0	**-0.1121**	*0.3079*	*0.1100*	53245	260	**0.0150**	*0.7433*	*0.0459*	38844	260
1	**-0.0974**	*0.3633*	*0.1072*	53245	260	**0.0010**	*0.9823*	*0.0443*	38844	260
2	**-0.0567**	*0.5917*	*0.1056*	53245	260	**0.0110**	*0.8008*	*0.0436*	38844	260
3	**-0.0924**	*0.3802*	*0.1053*	53245	260	**0.0007**	*0.9880*	*0.0438*	38844	260
4	**-0.0126**	*0.9061*	*0.1067*	53245	260	**-0.0068**	*0.8779*	*0.0442*	38844	260
5	**-0.0173**	*0.8755*	*0.1101*	53245	260	**0.0333**	*0.4715*	*0.0462*	38844	260
6	**0.0423**	*0.7116*	*0.1144*	53245	260	**0.0808**	*0.1019*	*0.0494*	38844	260

7	-0.0642	0.5824	0.1168	53245	260	0.0573	0.2582	0.0506	38844	260
8	-0.0093	0.9377	0.1192	53245	260	0.0382	0.4624	0.0519	38844	260
9	0.0461	0.7038	0.1213	53245	260	0.0096	0.8548	0.0523	38844	260
10	-0.0065	0.9583	0.1235	53245	260	-0.0189	0.7241	0.0536	38844	260
11	-0.0275	0.8272	0.1259	53245	260	-0.0033	0.9526	0.0549	38844	260
12	0.0446	0.7281	0.1283	53245	260	0.0173	0.7599	0.0565	38844	260
13	0.1645	0.2104	0.1313	53245	260	0.0453	0.4330	0.0578	38844	260
14	0.1396	0.3000	0.1347	53245	260	-0.0105	0.8627	0.0608	38844	260
15	0.3155	0.0223	0.1380	53245	260	-0.0115	0.8554	0.0630	38844	260
16	-0.2043	0.0000	0.0262	53245	260	-0.0588	0.0000	0.0124	38844	260
17	-0.2414	0.0000	0.0256	53245	260	-0.0772	0.0000	0.0125	38844	260
18	-0.2076	0.0000	0.0245	53245	260	-0.0691	0.0000	0.0119	38844	260
19	0.3814	0.0019	0.1225	53245	260	0.1080	0.0530	0.0558	38844	260
20	0.0818	0.4807	0.1160	53245	260	0.0268	0.6155	0.0533	38844	260
21	-0.0225	0.8425	0.1132	53245	260	0.0132	0.7950	0.0506	38844	260
22	-0.0950	0.4000	0.1128	53245	260	0.0126	0.7979	0.0491	38844	260
23	-0.1673	0.1353	0.1120	53245	260	-0.0049	0.9176	0.0476	38844	260

Non-Critical Peak days; households with AC use likely

	Voluntary					Default				
Hour	coefficient	p-value	std error	N households	N days	coefficient	p-value	std error	N households	N days
0	-0.1735	0.1400	0.1176	37845	35	0.0083	0.8659	0.0491	27671	35
1	-0.1688	0.1413	0.1147	37845	35	-0.0064	0.8939	0.0477	27671	35
2	-0.0957	0.3986	0.1134	37845	35	-0.0039	0.9348	0.0472	27671	35
3	-0.1018	0.3675	0.1129	37845	35	-0.0243	0.6079	0.0473	27671	35
4	-0.0182	0.8742	0.1147	37845	35	-0.0227	0.6325	0.0475	27671	35
5	-0.0211	0.8585	0.1184	37845	35	0.0204	0.6807	0.0497	27671	35
6	0.0090	0.9417	0.1224	37845	35	0.0729	0.1754	0.0538	27671	35
7	-0.1124	0.3702	0.1254	37845	35	0.0679	0.2157	0.0548	27671	35
8	-0.0783	0.5431	0.1287	37845	35	0.0424	0.4531	0.0565	27671	35
9	-0.0176	0.8937	0.1316	37845	35	0.0085	0.8816	0.0569	27671	35
10	-0.0678	0.6145	0.1346	37845	35	-0.0152	0.7950	0.0583	27671	35
11	-0.1036	0.4514	0.1375	37845	35	-0.0007	0.9913	0.0598	27671	35
12	-0.0079	0.9550	0.1401	37845	35	0.0220	0.7200	0.0615	27671	35
13	0.1448	0.3139	0.1438	37845	35	0.0353	0.5764	0.0632	27671	35
14	0.1004	0.4964	0.1476	37845	35	-0.0172	0.7978	0.0670	27671	35
15	0.2763	0.0664	0.1505	37845	35	-0.0184	0.7919	0.0696	27671	35
16	-0.2207	0.0000	0.0284	37845	35	-0.0679	0.0000	0.0137	27671	35
17	-0.2620	0.0000	0.0276	37845	35	-0.0887	0.0000	0.0137	27671	35
18	-0.2253	0.0000	0.0262	37845	35	-0.0778	0.0000	0.0128	27671	35
19	0.3732	0.0041	0.1300	37845	35	0.1374	0.0207	0.0594	27671	35
20	0.0656	0.5905	0.1220	37845	35	0.0439	0.4326	0.0559	27671	35
21	-0.0719	0.5458	0.1190	37845	35	0.0166	0.7551	0.0531	27671	35
22	-0.1426	0.2326	0.1195	37845	35	0.0278	0.5914	0.0518	27671	35
23	-0.2310	0.0528	0.1193	37845	35	-0.0041	0.9348	0.0504	27671	35

Non-Critical Peak days; households with AC use unlikely or unknown

	Voluntary					Default				
Hour	**coefficient**	***p-value***	***std error***	**N households**	**N days**	**coefficient**	***p-value***	***std error***	**N households**	**N days**
0	**0.3369**	*0.2357*	*0.2841*	6913	225	**0.0699**	*0.5531*	*0.1179*	5030	225
1	**0.3935**	*0.1547*	*0.2765*	6913	225	**0.0589**	*0.5889*	*0.1089*	5030	225
2	**0.2880**	*0.2858*	*0.2698*	6913	225	**0.1072**	*0.3133*	*0.1064*	5030	225
3	**0.1074**	*0.6903*	*0.2694*	6913	225	**0.1352**	*0.2123*	*0.1084*	5030	225
4	**0.1693**	*0.5328*	*0.2714*	6913	225	**0.0920**	*0.4079*	*0.1112*	5030	225
5	**0.1459**	*0.6037*	*0.2811*	6913	225	**0.1233**	*0.2933*	*0.1174*	5030	225
6	**0.3332**	*0.2654*	*0.2992*	6913	225	**0.1590**	*0.1889*	*0.1210*	5030	225
7	**0.3102**	*0.3045*	*0.3021*	6913	225	**0.0857**	*0.5088*	*0.1296*	5030	225
8	**0.4744**	*0.1139*	*0.3001*	6913	225	**0.1109**	*0.3962*	*0.1307*	5030	225
9	**0.4862**	*0.1032*	*0.2984*	6913	225	**0.0965**	*0.4642*	*0.1318*	5030	225
10	**0.3995**	*0.1795*	*0.2976*	6913	225	**0.0426**	*0.7503*	*0.1340*	5030	225
11	**0.4382**	*0.1437*	*0.2997*	6913	225	**0.0653**	*0.6349*	*0.1375*	5030	225
12	**0.4108**	*0.1757*	*0.3033*	6913	225	**0.0734**	*0.6023*	*0.1409*	5030	225
13	**0.4026**	*0.1842*	*0.3032*	6913	225	**0.1810**	*0.2026*	*0.1420*	5030	225
14	**0.5091**	*0.0978*	*0.3075*	6913	225	**0.1258**	*0.3799*	*0.1432*	5030	225
15	**0.6873**	*0.0319*	*0.3202*	6913	225	**0.1261**	*0.3884*	*0.1462*	5030	225
16	**-0.1703**	*0.0058*	*0.0618*	6913	225	**-0.0399**	*0.1624*	*0.0285*	5030	225
17	**-0.1885**	*0.0023*	*0.0618*	6913	225	**-0.0436**	*0.1418*	*0.0297*	5030	225
18	**-0.1709**	*0.0050*	*0.0610*	6913	225	**-0.0460**	*0.1170*	*0.0293*	5030	225
19	**0.6570**	*0.0368*	*0.3147*	6913	225	**0.0407**	*0.7760*	*0.1431*	5030	225
20	**0.3985**	*0.1962*	*0.3083*	6913	225	**-0.0071**	*0.9605*	*0.1428*	5030	225
21	**0.4314**	*0.1540*	*0.3026*	6913	225	**0.0356**	*0.7950*	*0.1369*	5030	225
22	**0.3220**	*0.2792*	*0.2976*	6913	225	**-0.0252**	*0.8461*	*0.1298*	5030	225
23	**0.2573**	*0.3768*	*0.2912*	6913	225	**0.0180**	*0.8854*	*0.1249*	5030	225