The Environmental and Social Benefits of Dynamic Pricing*

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Abstract

This paper estimates the impact of dynamic pricing on utility operating costs and emissions using household-level electricity consumption data from a randomized control trial. We find that household responses to treatment results in savings for the utility, but the emissions impacts are ambiguous. While dynamic pricing has been touted as a means to control generation costs and pollution, price-induced reallocation of electricity consumption within a day may actually increase net emissions depending on the source-generation mix of a region. Our findings highlight the unintended overall and distributional consequences of time-varying pricing schemes.

JEL: D12, L11, L94, Q53, Q58

Keywords: Dynamic Pricing; Randomized Experiment; Load Shifting; Air Pollution

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1 Introduction

The increasing prevalence of time-varying pricing for residential electricity reflects growing interest in market-based demand side management among both regulators and utilities.[1] Proponents of dynamic pricing argue that time-varying electricity rates help consumers better manage their energy consumption while reducing utility production costs (Public Utilities Commission of the State of California, 2016). Additionally, these price schemes, by reducing energy demand, may improve air quality and yield significant health benefits since electricity generation is a major source of both global and local air pollutants. Electricity production accounted for 27 percent of U.S. greenhouse gas emissions in 2018, primarily Carbon Dioxide (CO_2).[2] Power plants are also major sources of Sulfur Dioxide (SO_2) and Nitrogen Oxides (NO_x), which impose considerable health costs (Burtraw and Mansur, 1999; Deschenes et al., 2017; Chan et al., 2018).[3]

The magnitudes of production cost savings and environmental benefits, however, are likely to vary significantly with the design of the dynamic pricing program and by geography. Cost savings depend importantly on consumer price elasticity, and various features of program design have been shown to moderate household response to price changes (Jessoe and Rapson, 2014; Harding and Lamarche, 2016; Harding and Sexton, 2017; Fowlie et al., 2017). Geographic variation in local population, temperature/atmospheric conditions, and source of power generation can also alter the marginal damage of emissions (Graff-Zivin et al., 2014; Holland et al., 2016). In addition, there is concern from regulators that allowing the market to completely determine prices could be risky.[4] Skeptics also raise distributional concerns about the costs imposed by TOU rates, citing evidence from pilot programs that low-income customers are less price-elastic and thus less able to respond to periods of high

[1]The California Public Utilities Commission has ordered the state's three investor-owned utilities to transition most of their customers to time of use (TOU) electricity rates beginning in 2019. Nearly seven million households will face the new rate structures (Roth, 2019). Similarly, major utilities such as ComEd, which serves approximately 3.5 million customers, are in various stages of implementing TOU rates (Thill, 2019).

[2]Source: https://www.epa.gov/ghgemissions.

[3]SO_2 contributes to smog and acid rain, and NO_x, combined with Volatile Organic Compounds (VOCs), heat, and sunlight, creates ozone. Both are also important sources of particulate matter (PM).

[4]Winter storms that affected parts of Texas in 2021 yielded public outcry as electricity rates climbed to $9/kWh in some areas (McDonnell Nieto del Rio et al., 2021).

electricity prices (Alexander, 2010).[5] Given the active discussion about time-varying pricing among utilities and regulators, it is therefore crucial to understand the impacts of dynamic pricing on emissions and generation costs.

This paper evaluates the causal effect of time-varying electricity rates on short term operating costs and emissions. We investigate these impacts using high frequency observations of household electricity consumption from a randomized control trial (RCT) for dynamic pricing, data on utility generation costs, and data on grid-level, power plant emissions of SO_2, NO_x, and CO_2. Specifically, we evaluate the behavioral response of households who are randomly assigned to face higher electricity rates during peak-demand hours and given a programmable communicating thermostat (PCT) relative to households in a control group who remained on a standard block tariff without any form of automation technology. The PCT in conjunction with an app and website provide information on current prices and quantities of electricity, but also enables households to automate their responses to price changes. The behavioral responses of treated households are then evaluated in terms of their emissions impact and operating cost savings for the utility conducting the experiment using estimates of marginal emissions and marginal generation costs.

We find that households indeed respond to higher prices, with average energy savings ranging from 22 to 46 percent depending on the peak to off-peak price ratio. Moreover, households, with the aid of automation technology, shift consumption from peak to off-peak hours, but do not engage in strategic pre-cooling before periods of elevated prices. These results are similar to and complement Harding and Lamarche (2016), which analyzes a different treatment in the same experimental program. This is an important finding because peak demand hours, when marginal production costs are highest, coincide with the lowest marginal rate of emissions in the region of the experiment. Such load shifting behavior that reallocates energy use to off-peak hours implies that while the utility may see generation cost savings, the overall benefits of dynamic prices could be tempered by net emissions increases. Our results, when scaling our estimated treatment effects by marginal emissions and marginal production costs, reflect the tradeoff between reducing operating

[5] There are likely to be impacts on other domains. For example, high electricity bills have been associated with increased odds of food insecurity for households below the poverty line, as has been found during seasonally elevated energy costs under traditional flat rates for electricity (Nord and Kantor, 2006).

expenses and pollution.

We find that operating costs fall by roughly 20 cents per household per day in response to the highest peak price increase (about 10 times the non-peak rate). Assuming that 5 million households, which roughly corresponds to the population served by the NERC region containing the experiment, are treated with the current price scheme, our mean treatment effect estimates imply aggregate cost savings of $24.1 million (in 2011 dollars) during the four months of the experiment from June to September of 2011. In contrast to claims of blanket environmental benefits, we find that the emissions impacts are varied: we estimate net decreases in NO_x on average (213 tons during the treatment period), but net increases in SO_2 (561 tons) and CO_2 (119,000 tons).

We present back-of-the-envelope net benefit calculations after monetizing the impact from emissions using $PM_{2.5}$-induced premature mortality for SO_2 and NO_x (both precursors to $PM_{2.5}$), and a range of Social Cost of Carbon (SCC) values for CO_2. Reductions in NO_x emissions increase overall benefits by $1.2 million, but the net benefits of the program are largely tempered by losses from increased SO_2 emissions ($21 million) and CO_2 emissions ($1.4 to $14 million, depending on the SCC used). Overall, we find impacts that range from a net benefit of $2.8 million (SCC=$12/ton) to a net cost of $10.1 million (SCC=$120/ton).

To our knowledge, this is the first paper to use household-level electricity consumption data to demonstrate the impacts of time-varying electricity rates on short term operating costs and emissions associated with power generation. We contribute to recent work using experiments to understand the ways in which energy consumption responds to dynamic electricity pricing (Allcott, 2011; Burkhardt et al., 2019; Faruqui et al., 2013; Jessoe and Rapson, 2014; Harding and Lamarche, 2016; Bollinger et al., 2015; Wolak, 2010; Fowlie et al., 2017).[6] To date, there is limited evidence of *intentional* load shifting. Our findings confirm this result for Variable Peak Price (VPP) price schemes and highlights the importance of unintentional load shifting and default settings associated with automation technology: on the one hand, automation may increase consumer sensitivity to prices and help mitigate generation costs (shown in previous work); on the other hand, it may increase emissions in regions where off-peak marginal emissions are high relative to peak hour marginal emissions.

[6] See Harding and Sexton (2017) for a comprehensive review of this literature.

Furthermore, the overall net benefits we calculate mask considerable heterogeneity in the response to different price levels, which emphasizes the important role for optimal pricing design.

Second, this paper contributes to a growing literature that evaluates the environmental effects of supplying energy to the electricity grid (Holland and Mansur, 2008; Cullen, 2013; Graff-Zivin et al., 2014; Callaway et al., 2018; Holland et al., 2016, 2020). Holland and Mansur (2008) is the first to demonstrate that the emissions impact of real-time electricity pricing is ambiguous; the ambiguity stems from the heterogeneity in the source of power generation and the way in which generating plants meet electricity demand at different parts of the country at different parts of the day.[7] In contrast to Holland and Mansur (2008), which uses quasi-experimental variation from aggregated electricity demand data, this paper identifies environmental impacts as a result of consumer load-shifting behavior induced by random variation from a large-scale RCT.

Third, we add to the body of work investigating the incidence and distributional effects of policies. By increasing emissions at the source of power generation where vulnerable communities are more likely to reside, we demonstrate how a policy aimed at improving economic efficiency may unintentionally burden the disadvantaged. Distributional issues associated with environmental policies are of increasing concern (Banzhaf et al., 2019), including for cap-and-trade programs (Shadbegian et al., 2007; Fowlie et al., 2012), adoption of energy efficient technology (Holland et al., 2019; Levinson, 2019), and federal legislation, e.g. the Clean Air Act Amendments (Bento et al., 2015). Equity concerns may similarly apply to time-varying electricity pricing.

This study provides valuable insights for energy planning, although our conclusions should be extrapolated with caution. The experiment was implemented in a state in the south central region of the US. This region has been experiencing significant changes in terms of how electricity is generated in the last decade, with coal declining and natural gas

[7]That variation in marginal emissions moderates environmental effects has also been shown in the context of electric vehicle adoption (Graff-Zivin et al., 2014), subsidies for wind power (Cullen, 2013), and investments in renewable energy generation and energy efficiency (Callaway et al., 2018). A recent literature also demonstrates how unanticipated natural gas price decreases from the shale boom changed the generation mix of electricity production and impacted carbon emissions (Cullen and Mansur, 2017; Fell and Kaffine, 2018; Linn and Muehlenbachs, 2018; Holladay and LaRiviere, 2017).

and renewable resources such as wind becoming increasingly more important. In addition, the population affected by the randomized control trial, although large, is not necessarily representative of the east and west of the U.S. Moreover, we employ electricity records over the summer, when temperatures are high and the majority of households use air conditioning. We believe that this can explain the shift in consumption at later hours in the day, as well as the relatively high consumption at night. In light of these limitations, the size and design of the experiment offer important evidence that we hope helps policy making by highlighting the issues that need to be taken into account when dealing with the heterogeneity of treatment effects across the US.

Section 2 presents our data sources and preliminary evidence of behavioral responses from the RCT. We also provide evidence that there are no systematic differences between households in the treatment and control groups before the implementation of the program. Section 3 presents models and methods, describing the empirical strategy for estimating residential household electricity demand and the associated impacts on emissions and operating costs. Section 4 reports the results, and Section 5 concludes.

2 Data and Preliminary Evidence

Data on emissions, production costs, and electricity consumption come from the following sources: (1) emissions data are from the Environmental Protection Agency's (EPA) Continuous Emission Monitoring System (CEMS), (2) regional electricity demand comes from Federal Energy Regulatory Commission (FERC), (3) data on electricity production costs are reported by the utility implementing the RCT, and (4) household consumption data are recorded from the RCT. The first two sources of data on emissions and electricity demand are available at the electricity-grid level for each hour; electricity generation costs are available for each hour at each node controlled by the utility; finally, the RCT provides household-level consumption in 15-minute intervals. We first provide an overview of each source of data, and follow with summary statistics and preliminary evidence to motivate our investigation.

2.1 Data Sources

Emissions: The EPA's Continuous Emission Monitoring System (CEMS) provides grid-wide emissions of carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) from all fossil fuel generating plants with at least 25 megawatts of generating capacity (U.S. EPA, 2011). Hourly emissions of each pollutant are reported at the generating unit level. We average hourly emissions from all generating units in the NERC region between 12:01 a.m. July 1, 2011 and 11:59 p.m. September 30, 2011.

Region-wide Electricity Demand: The Federal Energy Regulatory Commission (FERC) mandates that balancing authorities and planning regions report grid electricity demand for each hour of every day via FERC form 714 (FERC, 2011). The sum of hourly demand for the NERC region containing the experiment is computed for each hour. To simplify the relationship between consumption and emissions, the amount of energy traded between regions is assumed to be zero. Identification of grid-wide emissions per marginal megawatt of electricity demand follows from this simplification.

Marginal Generation Costs: The utility that implemented the randomized experiment makes data available data on the marginal costs of electricity generation, or the "locational marginal price" (LMP). The LMP is a measure of the cost to provide an additional megawatt of electricity to the grid. The cost varies between nodes of the grid according to the time of day, distance to the nearest type of generating plant (e.g. coal vs. wind), and the amount of loss or congestion along the physical transmission infrastructure. In addition, the LMP reflects balancing authorities' attempts to vary dispatch order to minimize costs, where cheaper generating units are employed before more expensive ones. LMPs are computed in five-minute increments. We average the LMP over each hour and across all nodes operated by the utility running the experiment.

Household-level Electricity Consumption: Household consumption data are from a large-scale randomized controlled trial (RCT) for a dynamic pricing scheme in the residential market for electricity. Due to a confidentiality agreement, the organization running the trial will be referred to as 'the Utility'. The Utility tested how a new price regime impacted the daily profile of residential electricity consumption. Consumers facing the new price regime were also provided with technologies designed to facilitate information access and price change responses. Household energy use for the months of June through September of 2011 was subsequently monitored with smart meters that report consumption in fifteen minute intervals. We aggregate household-level energy consumption over each hour to match the temporal frequency of emissions and generation costs. In addition to consumption data, measures of household income and age/family structure are available. Households are categorized into 'low,' 'middle,' and 'high' groups, where low income households have yearly earnings below \$30,000, median income households have yearly earnings averaging around \$50,000, and high income households have yearly earnings above \$75,000.[8] In the Online Appendix, we use this information to investigate the impact of dynamic pricing among low- and high-income households.

The price treatment studied in this paper exposed a subset of households (i.e., the treatment group) to a variable peak price (VPP) pricing scheme, where a flat rate of \$0.045 per kilowatt (kW) hour, or simply 4.5¢/kWh, is charged during off peak hours and higher rates are charged during the peak hours of 2 p.m. through 7 p.m. on weekdays (excluding Independence Day and Labor Day). The peak rates, based on generation costs, could be low (4.5¢/kWh), medium (11.3¢/kWh), high (23¢/kWh), or critical (46¢/kWh), and are announced by 5 p.m. on the previous day. Households have multiple observations of consumption at each hour for each price level because there are multiple days of each price type observed throughout the summer. Specifically, there were respectively 52, 24, and 12 medium, high, and critical price days during the treatment period. The remaining households (i.e., the control group) remained on a standard block tariff, which charged 8.4¢/kWh for the first 1400 kW used in a month and 9.68¢/kWh for usage above that level.

To better inform households about the peak price period, members of the treatment group were given automation technology. All treated households were provided with a programmable communicating thermostat (PCT), which allowed households to automate adjustments to interior temperature in response to price changes. Households also had access to a web portal that reported the amount of electricity that was consumed during

[8]Households are also categorized into a family-structure and age group: 'young' households are those under the age of 45 with no children, 'family' households consist of middle-aged families with children, and 'mature' households consist of older empty nest households, who are age 65 or older.

the previous fifteen minute usage interval, as well as the current price of electricity. Control households did not receive any type of technology intervention.

Assignment to treatment was based on a randomization after opt-in design.[9] Assignment to the treatment group was enforced successfully in most cases, although a few households changed treatment status because of technical difficulties. In total, 1,461 households in the RCT are examined in this analysis, 978 of which belonged to the control group and 483 of which belonged to the treatment group. Table 1 presents a breakdown of the sample by household characteristics and treatment status.

Our sample of households is older and has higher income than the national average.[10] However, a comparison of the share of households in each income or family structure category across treatment groups suggests that demographic characteristics are fairly balanced. In subsequent analysis, we take our main treatment effects specification to pre-treatment consumption data to assess balance in baseline energy consumption by treatment status.

2.2 Descriptive Evidence

Figure 1 compares the average hourly consumption of treated with control households for different VPP levels (medium, high, and critical). These raw data reveal several important features of consumer behavior. First, higher prices yield larger reductions in electricity use. The average peak-hour reduction in electricity consumption for treatment groups (relative to the control group) is 0.25 kW under a medium rate, and increases to 0.63 and 0.81 kW under high and critical rates, respectively. Variation in marginal peak prices within households enables us to assess the price responsiveness of individual households.

Second, there is clear visual evidence of load shifting: households facing VPP rates consume less electricity during peak periods, but relatively more during the following hours. Third, while treated households shift consumption to post-peak hours, there is little evidence of strategic pre-cooling, which is consistent with previous work examining consumption of customers of the same utility in a parallel experiment (Harding and Lamarche, 2016).

[9]Based on a pilot study during the previous year, demographics predicted to have low participation rates received additional advertising.

[10]For instance, between 44 to 52 percent of households in the RCT have an annual income above $75,000, compared to 32 percent nationally (based on the 2010 Current Population Survey). See www.census.gov/data/tables/time-series/demo/income-poverty/cps-hinc/hinc-01.2010.html.

Households do not appear to take advantage of low prices during the morning to proactively reduce temperatures before the high peak price in the afternoon. Prior work has found that marginal CO_2 emissions are higher during off-peak hours compared to on-peak hours, particularly for the Eastern interconnection (Graff-Zivin et al., 2014). This reflects the use of coal to meet base-level electricity demand and cleaner natural gas to meet additional demand during peak hours. Taken together with Figure 1, this makes clear how load-shifting as a result of dynamic pricing and automation can reduce the overall net benefits of these programs given the tradeoff between utility generation costs and emissions impacts.

We also note that behavior at the mean masks considerable heterogeneity in price responses across the consumption distribution. Figure 1 also reports the 10th and 90th percentiles of the distribution of electricity usage by hour and treatment status. While the evidence reveals a similar pattern in terms of savings during the peak hours with considerable load shifting, it is interesting to see that medium and high price levels seem to affect low-usage households proportionally more than high-usage households. These heterogeneous effects may imply that dynamic pricing schemes entail important distributional consequences.

2.3 A Falsification Exercise

The RCT employed in our study allows us to examine the differences in electricity usage by treatment status before the implementation of the program, as we have access to the 2010 data for the month of September. The data collected before the implementation of the program does not include information for all households considered in the 2011 sample due to a variety of technical reasons at the time of the pilot implementation.

With these caveats in mind, we employ 2010 data to compare the average hourly consumption of treated with control households as in Figure 1. The left panel of Figure 2 shows hourly usage, and in contrast to the 2011 data, we see similar average consumption behavior between households in the treatment and control group, as expected. To examine systematic differences more rigorously, we estimate a model for the logarithm of electricity usage on a treatment variable indicating whether the household was in the treatment group in 2011 and weather variables, which are described in the next section. We estimate the model by hour and report the effect of the treatment variable on electricity usage in the right panel of Figure 2. We provide point-wise confidence intervals obtained by clustering the standard errors at the household level. We see, as expected, that the estimated treatment effect fluctuates around zero when we consider different hours of the day, including the period from 2 p.m. to 7 p.m. The evidence convincingly shows that the use of dynamic pricing and the enabling technology in 2011 do not lead to energy reductions in 2010. We interpret this as strong evidence in favor pre-treatment balance.

3 Models and Methods

Consider emissions $E_{t,h}$ at hour h on day t by $E_{t,h} = f(v(Y_{t,h}), W_{t,h})$, where $Y_{t,h}$ is electricity consumption at the household level and $W_{t,h}$ is a vector of weather variables. The function $v(\cdot)$ aggregates individual consumption into a region specific measure (e.g., mean load). Consider also that electricity consumption at the household level is $Y_{t,h} = g(P_{t,h}, W_{t,h}, X_{t,h})$, where $P_{t,h}$ denotes the price of electricity and the vector $X_{t,h}$ includes exogenous factors that affect individual consumption but not directly emissions in the region (e.g., income, air conditioning, etc.). The effect of an increase in the price of electricity on emissions is $\Psi_{t,h} := \partial E_{t,h}/\partial P_{t,h} = f_Y \cdot g_P$, where f_Y is the partial derivative of the composite function $f \circ v$ with respect to usage, and g_P is the partial effect of the rate on usage.

Alternatively, the change in emissions due to the change in prices can be obtained simply by evaluating emissions $E_{t,h}$ at two different price levels:

$$\Delta E_{t,h} = f(v(g(P_{t,1}, W_{t,h}, X_{t,h}), W_{t,h}) - f(v(g(P_{t,0}, W_{t,h}, X_{t,h}), W_{t,h}), \tag{3.1}$$

where $P_{t,0}$ denotes a standard rate and $P_{t,1}$ denotes a peak price. Importantly, equation (3.1) states clearly the main identification issue. The change in emission $\Delta E_{t,h}$ cannot be estimated directly using observational data because one cannot simultaneously observe emissions and household consumption at the standard and peak prices at the same hour on the same day. Our empirical strategy is to utilize a reliable RCT to overcome the difficulty of identifying changes on electricity usage from changes in prices.

In order to investigate the effect of dynamic pricing following this simple conceptual framework, we need to estimate f_Y and g_P by modeling the emission and household consumption equations. The next sections present the models and proposed approach to estimate changes in emissions based on a dynamic pricing policy. We first focus on estimating treatment effects, and then obtain changes in electricity usage induced by the policy. Based on these changes, we identify variations in emissions after considering marginal emissions of electric demand.

3.1 Household Level Models

We pursue a modeling approach first suggested by Ramanathan et al. (1997), which was employed by Harding and Lamarche (2016) for the evaluation of a similar (but distinct) dynamic pricing model. We denote electricity usage by $Y_{i,t,h}^k$, where household i is observed at hour h on day t, facing a price level k. As explained before, the price level k can be medium, high or critical for the treated households or the standard rate for the households in the control group. Also, recall that all treated customers face the same price level k on day t. The model includes a treatment indicator and, as standard in the literature, a vector of weather variables. The variable $D_i(k)$ indicates the treatment status of each household i. The variable takes a value of 1 if price level k is announced to the treated households by 5 p.m. the previous day, and 0 for control households. Moreover, we consider temperature and dew point variables, included in the vector $W_{i,t,h}$.

We estimate the average treatment effect of the VPP price scheme on household electricity consumption considering the following model:

$$\log(Y_{i,t,h}^k) = \alpha_h + \beta_h^k D_i(k) + f(W_{i,t,h}) + \epsilon_{i,t,h}^k \tag{3.2}$$

where the response variable is the natural logarithm of electricity consumption $Y_{i,t,h}^k$ and $f(W_{i,t,h})$ flexibly controls for the non-linear relationship between weather and electricity consumption. Specifically, we introduce weather controls in $f(\cdot)$ as a linear combination of temperature and dew point approximated by cubic B-splines. The intercept α_h can be interpreted as a fixed effect for every hour that captures variation in average electricity usage among control households throughout the course of day that is independent of the effect of weather. Finally, the error term, $\epsilon_{i,t,h}$, captures remaining, unobserved determinants of demand and is allowed to be correlated over time for a given household.

The parameters of interest are β_h^k for $h \in \{0, \ldots, 23\}$. We expect β_h^k to be negative from $h = 14$ through $h = 19$ since greater VPP prices occur during those hours, and letting $k \in \{1, 2, 3\}$ index medium, high and critical prices, we expect $\beta_h^1 > \beta_h^2 > \beta_h^3$ when $h \in \{14, \ldots, 19\}$. The parameter $\exp(\beta_h^k) - 1$ represent the percentage change in electricity consumption among treated households facing price k during hour h relative to households facing the standard rate during the same hour.

Consistent estimation of a causal average treatment effect rests on the random assignment of households to the treatment group. The previous evidence reported in Figure 2 strongly suggests that the randomized experiment was successfully carried out, and the policy had a remarkably high degree of compliance among treated participants.[11] Therefore, equation (3.2) is estimated, at each hour h and price level k, by standard semi-parametric methods based on cubic B-splines. The standard errors are clustered at the household level.

While the evidence presented in Figure 1 is descriptive, it does provide tentative evidence that dynamic pricing has a different impact across the distribution of electricity usage. Motivated by these empirical lessons, we estimate quantile treatment effects considering the conditional quantile function corresponding to equation (3.2):

$$Q_{\log(Y_{i,t,h}^k)}(\tau | D_i(k), W_{i,t,h}) = \alpha_h(\tau) + \beta_h^k(\tau) D_i(k) + f(W_{i,t,h}; \tau), \tag{3.3}$$

where $\tau \in (0, 1)$. As before, the parameters of interest are the sequence of $\beta_h^k(\tau)$'s for each hour of the day at a particular peak price level k. The parameter $\beta_h^k(\tau)$ measures the difference between the quantile functions of the treatment and control groups, evaluated at a given quantile τ. They are similar in spirit to the average treatment effect parameter in equation (3.2), but rather than measuring the difference between two conditional mean models, the quantile treatment effect measures the distance between two conditional quantile functions (Koenker, 2005, 2017).

We estimate (3.3) considering semiparametric quantile regression, where the nonparametric function is estimated using B-splines, and evaluate treatment effects at two quantiles, $\tau \in \{0.1, 0.9\}$. We cluster the standard errors at the household level by using the bootstrap

[11] Considering TOU pricing rather than VPP, Harding and Lamarche (2016) investigate the impact of a few households who switched assignments after the initial randomization due to technological incompatibilities with the provided devices. They use the initial assignment as an instrument, finding no significantly different results due to possible non-compliance issues.

(Hagemann, 2017).

3.2 System Level Models

We now turn our attention to our model of emissions. Following previous work (Graff-Zivin et al., 2014), we estimate marginal emissions by regressing hourly emissions from generating units within the NERC region for each day, $E_{t,h}$, on hourly electricity demand on each day, $q_{t,h}$:

$$E_{t,h} = \sum_{h=0}^{23} \gamma_h \left(H_h \cdot q_{t,h}\right) + \sum_{h=0}^{23} \sum_{m=7}^{9} \alpha_{hm} \left(H_h \cdot M_m\right) + \sum_{m=7}^{9} \alpha_m M_m + \sum_{h=0}^{23} \alpha_h H_h + \epsilon_{t,h} \quad (3.4)$$

where α_m and α_h are month- and hour- fixed effects that capture changing electricity use cycles during different parts of the summer, and M_m and H_h are indicator variables for hour of the day and month of the year. The marginal emissions of pollutant $E_{t,h}$ attributable to an increase in grid demand at each hour of the day are given by the sequence $\gamma_0, \ldots, \gamma_{23}$. In the next sections, we consider three power plant emissions: Carbon Dioxide (CO_2), Sulfur Dioxide (SO_2), and Nitrogen Oxides (NO_x).

Since wholesale electricity prices are generally not passed on to consumers, consumer demand does not depend on emissions. The identifying assumption is that the level of demand in the NERC region, $q_{t,h}$, is unaffected by the adoption of VPP rates in the RCT. This assumption is supported by the data as dynamic pricing affected 483 households out of an estimated 5 million households in the region. Grid level consumer electricity demand, $q_{t,h}$, can therefore be treated as exogenous in this context.

Lastly, we define the hourly marginal generation cost as $\delta_h = E(MC_{t,h,j})$. This parameter is the expected value of the cost of supplying one additional megawatt of electricity to a node, or location, in the service area of the Utility. Nodes are denoted by j and we have information on locational marginal price (LMP), or marginal cost (MC), for 42 nodes controlled by the Utility at each hour of the day. The hourly marginal generation cost is estimated by the average of the reported locational marginal price across all nodes and days in the period of analysis.

3.3 Projecting Hourly Changes Under Dynamic Prices

Following closely the conceptual framework discussed above, we now obtain the change in emissions induced by the effect of dynamic pricing on household electricity demand. We also introduce a parameter that captures the impact of dynamic pricing on generation costs.

First, we compute the average number of kilowatts conserved by implementing the dynamic price policy. We apply the percent change in consumption due to VPP k, $\exp(\beta_h^k)-1$, to the expected value of electricity consumption at hour h among households in the control group, $\mu_h^k = E(Y_{t,h}^k)$. Then, the change in consumption during hour h is given by:

$$\Delta Y_h^k = (\exp(\beta_h^k) - 1) \cdot \mu_h^k, \tag{3.5}$$

where ΔY_h^k is measured in kW. Next, we multiply the change in energy consumption for each hour with the marginal emissions rate γ_h estimated from equation (3.4) to compute the associated quantity change in each pollutant, ΔE_h^k. The change in emissions during hour h for VPP k is given by:

$$\Delta E_h^k = \Delta Y_h^k \cdot \gamma_h = (\exp(\beta_h^k) - 1) \cdot \mu_h^k \cdot \gamma_h. \tag{3.6}$$

We similarly define the change in hourly production costs, ΔC_h^k, by multiplying the marginal generation cost in hour h, δ_h, by the hourly level change in consumption for each VPP level k, ΔY_h^k:

$$\Delta C_h^k = \Delta Y_h^k \cdot \delta_h = (\exp(\beta_h^k) - 1) \cdot \mu_h^k \cdot \delta_h. \tag{3.7}$$

The advantage of our approach is that the parameters in equations (3.5), (3.6), and (3.7) are simple to estimate considering the methods introduced in the previous sections. Moreover, the parameter μ_h^k can be estimated by the average hourly consumption among households in the control group (who did not experience price changes and do not have access to a PCT). Although these parameters are defined at the mean level, it is straightforward to accommodate these formulas to estimate the effects at the low and high conditional quantiles of the distribution of electricity usage. For instance, we estimate the change in electricity usage at the τ-th quantile by $\widehat{\Delta Y_h^k}(\tau) = (\exp(\hat{\beta}_h^k(\tau)) - 1) \cdot \hat{\mu}_h^k$.

Finally, the information offered by hourly changes in emissions and production costs might not provide a complete picture of the effects of dynamic pricing. The evidence in Figure 1 suggests that households facing VPP rates consume less electricity during peak periods, but relatively more during the subsequent hours. Therefore, we obtain *daily* net changes in household emissions and generation costs. Consider, for instance, emission E_h^k. We aggregate the hourly changes over all hours of the day for each price level k following the formula:

$$\Delta E^k = \sum_{h=0}^{23} \Delta E_h^k = \sum_{h=0}^{23} (\exp(\beta_h^k) - 1) \cdot \mu_h^k \cdot \gamma_h, \tag{3.8}$$

which is interpreted as the daily average household effect of dynamic pricing on emissions. Generation costs associated with electricity consumption and corresponding impacts at the τ-th quantile of the conditional distribution of electricity consumption are calculated by accommodating (3.8).

Standard errors for these parameters including the one defined in equation (3.8) are obtained using the bootstrap. Specifically, the procedure draws from the original sample of treated and control households from each respective group with replacement. In each draw, considering a bootstrap sample, we are able to obtain bootstrap estimates of the parameters defined above, including the mean of Y_h^k for the control group. It is important that each draw preserves selected households' entire consumption path over the summer in order to account for learning effects, varying consumer engagement with the experiment, and idiosyncratic inter-day correlations from each household's daily schedule. Standard errors and 95% confidence bands are computed using 400 iterations of the bootstrap procedure.

4 Results

This section presents experimental results of the dynamic pricing scheme on emissions and production costs. Before we turn our attention to the benefits and costs of the policy, we present results for the household- and system-level parameters.

4.1 Dynamic Impact of Prices

We begin by estimating average and quantile treatment effects for each price level k, which are computed from the full sample consisting of all weekdays in June, July, August, and September. The results for the mean treatment effect and quantile treatment effect parameters are presented in the Online Appendix (Tables S.1-S.3). At each hour h, these estimates are obtained using 1,461 households observed during 52 medium price days, 24 high price days, or 12 critical price days, corresponding to samples sizes that range between 17,532 to 75,972 observations. We then obtain point estimates for ΔY_h^k and present them in Figure 3. For instance, the change in consumption in the first panel at $h = 14$ is $-0.52 \approx (\exp(-0.21) - 1) \times 2.75$, which is obtained based on the average consumption in kilowatts for the control group as shown in the first panel of Figure 1, and the estimate of the treatment parameter shown in Table S.1.

Figure 3 presents the changes in household electricity consumption measured in kilowatts at each hour of the day. The vertical dotted lines at $h = 14$ and $h = 19$ indicate the peak hours, that is, the hours of the day when the price of electricity increases. The results across columns show estimates based on different price levels, while the results across rows show estimates based on different parts of the consumption distribution. For instance, prices increase from a flat or low rate of \$0.045 during non-peak hours to \$0.113 (i.e., medium price, as shown in the first column), \$0.23 (high), or \$0.46 (critical) during peak hours, representing a price increase of between 2.5 to over 10 times the non-peak rate for the treatment group. Moreover, the average treatment effects are presented in the first row, and the quantile treatment effects estimated at the 0.1 and 0.9 quantiles are presented in the last two rows. All impacts are evaluated at the average consumption among control group households in the corresponding hour.

The treatment effect is characterized by a large reduction in consumption at the very beginning of the peak period that tapers off over the afternoon. The magnitude of the reduction increases with peak price rates, where the largest drop in consumption (at hour 15) increases from -0.6 kilowatts during medium peak prices to -1.8 kilowatts during critical peak prices. The reductions range from 22 to 46 percent, which represent negative price elasticities similar to those found in the recent literature.[12] Moreover, the results suggest

[12] Jessoe and Rapson (2014) consider a difference-in-differences model, in contrast to our approach of estimating treatment effects that are allowed to vary by hour. The variation in the price of electricity is also different and in the range of between 200 to 600 percent with a one-day-ahead notice. Having in mind these differences, our results imply elasticities that range between -0.06 to -0.10, which are slightly larger compared to the estimated elasticity of -0.12 implied by their results.

that low-usage households exhibit the most extreme response to changes in the peak price. The estimated reduction at the 0.1 quantile of the conditional distribution is approximately two times larger than the estimated mean treatment effect. In contrast, households consuming at the 0.9 quantile of the conditional distribution are much less responsive to elevated peak prices.

For all price treatments, we also see clear evidence of load shifting, particularly in the immediate post-peak period between 8 p.m. and 12 a.m. and, to a lesser extent, during the early morning hours from 12 a.m. to 7 a.m. This behavior occurs at the mean as well as the high and low quantiles of the conditional distribution of energy use. These responses are compatible with a household that takes advantage of the programmable communicating thermostat to reallocate cooling hours away from the period of elevated prices. Automation technology reduces consumption at the beginning of the peak period by raising the allowable interior temperature. As homes warm up, thermostats turn on to maintain the new, higher temperature. Thermostats then reset to the default temperature when the peak period ends, prompting an increase in energy consumption to return the household to the initial lower temperature.

4.2 Marginal Emissions and Generation Costs

We next use estimates of marginal emissions and marginal generation costs to evaluate the environmental and economic consequences of load shifting in response to dynamic prices. The first three panels in Figure 4 report estimates for γ_h in equation (3.4) for SO_2, CO_2, and NO_x emissions. The point estimate is interpreted as the marginal emission (in pounds) from a kilowatt increase in electricity demand at hour h. The last figure reports the hourly average locational marginal price (LMP, measured in dollars) to provide a kilowatt of electricity to customers of the Utility.

The daily pattern of marginal emissions is consistent with the literature and reflects the sources of base load power and peak power employed to meet electricity demand. During the late night and early morning, demand across the NERC region is low and mostly powered by coal plants. As demand rises during peak hours, relatively cleaner gas power plants are dispatched to respond to increasing grid demand, which decrease marginal emissions relative to off-peak hours. Moreover, solar power, with zero marginal emissions, is available during the day and further reduces marginal emissions. This pattern suggests that marginal increases in electricity consumption during the afternoon (peak hours) generate fewer additional emissions than during the night. In contrast, average LMP is highest during the afternoon hours. Together, these figures highlight the need to balance environmental and economic objectives in VPP price schemes: load shifting from peak to non-peak hours may reduce total generation costs at the expense of increasing global and local pollutants (in the short-run and without changes in the generation mix or capacity).

To quantify the tradeoff, we multiply the estimated treatment effects for the three different price levels by marginal emissions and marginal costs to recover the hourly change in emissions and production costs. Impacts are plotted in Figures 5 through 8, and Table 2 reports the net impact on emissions and generation costs by summing the average treatment impacts over the course of the day according to equation (3.8).

We begin with sulfur emissions changes reported in Figure 5. It is clear that the confluence of high marginal emissions and significant increases in consumption during the early morning hours results in a statistically significant increase in sulfur emitted during off-peak hours. The load shifting to off-peak hours with higher marginal emissions causes an overall net increase. Following Table 2, daily SO_2 emissions increase between 0.001 and 0.006 pounds per household, depending on the price treatment and household consumption level. The estimated daily increase is largest if one considers the response among low-usage households at the 0.1 quantile of the conditional consumption distribution, particularly for high and critical price treatments.

A similar pattern of statistically significant increases in emissions during off-peak hours is borne out in the estimates for CO_2 (Figure 6) and NO_x (Figure 7). However, whether the net impact on emissions is positive or negative depends on both the price and quantile of household consumption. At the mean, net CO_2 emissions range from an increase of approximately a pound per day per household in response to medium peak prices to a decrease of almost a pound in response to critical peak prices. The net decreases in CO_2 at critical peak prices are driven by households at the lower quantiles of consumption, where critical peak prices lead to a daily reduction in CO_2 emissions of almost 2.4 pounds per household. Daily NO_x emissions fall during high and critical peak price days, ranging from -0.001 to -0.01 pounds per household per day. At medium peak prices, effects range from a small increase of 0.001 to a small decrease of a similar magnitude at the 0.1 quantile, although this result is insignificant at standard levels.

The change in production costs for the Utility (Figure 8) reflects net savings in operating costs associated with peak shaving due to dynamic prices. The Utility reduces the production costs to supply a treated household during the peak hours. While increased demand during off-peak hours results in some cost increases for the Utility, reductions in production costs to supply treated households during the peak hours generally outweigh off-peak cost increases. If we focus our attention on effects significantly different than zero, cost savings range from 4.6 to 41.7 cents per household per day and increase as peak prices shift from medium to critical (Table 2). Reductions in costs are largest if we consider results at the 0.1 quantile, where savings are 33.6 and 41.7 cents per household per day in response to high and critical prices. Savings are generally lower at the 0.9 quantile of consumption, ranging between -8 to -4.6 cents per household per day.

4.3 Measuring Total Impacts

We now employ the experimental estimates to evaluate the effects of an universal adoption of the dynamic pricing scheme in the regulatory region, where it is estimated that 5 million households reside. Our analysis below is based on average treatment effects and results based on quantile treatment effects are presented in the Online Appendix.

Based on the mean estimates presented in Table 2, the production costs associated with supplying power for a single high peak price day would fall by $589,000 if every household in the entire regulatory region received treatment of the dynamic price scheme with a programmable control thermostat. For a critical peak price, savings increase to $982,000 per day. Scaling the daily estimates by the number of each type of VPP day, the total change in production costs during the experiment is $24.1 million.[13]

How do these estimated cost savings compare to the changes in emissions associated with load shifting? We next present back-of-the-envelope calculations to assess the net impacts accounting for emissions. In order to answer the question, we first calculate aggregate changes in emissions (Table 3) and then monetize the impacts (Table 4).

[13] As noted before, there were 52 medium peak price days, 24 high peak price days, and 12 critical peak price days during the experiment.

Panel A of Table 3 reproduces the daily mean treatment effects from Table 2. As for the case of generation costs, Panel B shows changes in emissions considering the number of households residing in the NERC region during weekdays in June, July, August, and September. Scaling the mean treatment effect by the number of each VPP price day and the number of households, our estimates imply an increase in SO_2 emissions of 1.1 million pounds. However, as shown in Panel C, this increase is relatively small in comparison to the average monthly SO_2 emissions in the NERC region. The estimated price-induced increase in monthly SO_2 emissions is 0.66 percent of monthly emissions.[14] Applying similar calculations to the other pollutants, we find increases in CO_2 of 238 million pounds and decreases in NO_x of 0.4 million pounds.

Table 4 presents the total monetized value of emissions (Panel A) and net impacts after factoring production cost savings (Panel B).[15] We recover the dollar value of changes in SO_2 and NO_x (both $PM_{2.5}$ precursors) using sector-specific $PM_{2.5}$ benefits per ton (BPT) from the EPA Benefits Mapping and Analysis Program (EPA, 2018).[16] For evaluating CO_2 impacts, we use a range of Social Cost of Carbon (SCC) values generated by the U.S. Interagency Working Group (IWG, 2010).[17]

The increase in sulfates of 561 tons yields a loss of \$21.1 million using a benefit per-ton (BPT) of \$37,692. To the extent that SO_2 emissions may have non-health impacts on ecological systems, recreation, and visibility (Burtraw et al., 1997), this estimated loss is a lower bound. Moreover, carbon emissions increase by 119 thousand tons, generating

[14]Using CEMS data from July through September, we find that the average monthly SO_2 emissions is approximately 42.2 million pounds for the NERC region. The estimates reported in Panel C of Table 3 are obtained by excluding weekends.

[15]All values are converted to 2011 dollars using the Consumer Price Index for All Urban Consumers (CPI-U), U.S. city average series for all items. Moreover, for convenience, we change the unit of emissions measurement from pounds (Table 3) to tons (Table 4). One ton equals 2,000 pounds.

[16]Specifically, the methodology calculates health damages in three steps: (1) predict the annual average ambient concentrations of SO_2 and NO_x from different sectors using source apportionment photochemical modeling. For this analysis, we apply the estimates for the electricity sector; (2) estimate the number of premature deaths for the $PM_{2.5}$ precursors, SO_2 and NO_x, and monetize using the Value of a Statistical Life (VSL). The estimates of $PM_{2.5}$ on premature mortality are from Krewski et al. (2009); (3) divide $PM_{2.5}$-related health impacts by the levels of SO_2 or NO_x to arrive at per ton benefit values. See EPA (2018) for a detailed description.

[17]The SCC varies depending on underlying assumptions about the discount rate, among other factors (Nordhaus, 2017). As there is no consensus about the appropriate discount rate to evaluate intergenerational effects, it is customary to present a range of values under different discount rates (Metcalf and Stock, 2017).

losses of \$1.4, \$4.8, and \$7.1 million under SCC values of \$12, \$40, and \$60. A higher SCC value of \$120 increases CO_2 damages to \$14.3 million.[18] Lastly, nitrate emissions decrease as a result of the observed pricing scheme by 213 tons, increasing overall benefits by \$1.2 million under a BPT of \$5,654. Overall, combined with the production cost savings of \$24.1 million, the estimated impact of the program in the regulatory region ranges from a net benefit of \$2.8 million (SCC=\$12/ton) to a net cost of \$10.1 million (SCC=\$120/ton).

Net benefits depend on BPT values and, crucially, the behavioral response to the pricing scheme. The utility clearly gains in terms of cost reductions. Whether the treatment consisting of dynamic pricing and a programmable thermostat yields positive environmental benefits, however, is ambiguous. In this experimental evaluation, SO_2 and CO_2 emissions increase, but NO_x decreases. Interestingly, net emissions vary with the VPP level. Under medium prices, all three pollutants increase, whereas we observe net decreases in both carbon and nitrates under critical prices and sulfate emissions, while still positive, see the lowest increase. This highlights the potential role for electricity pricing policy to increase net benefits through optimal rate design (e.g., by varying peak to non-peak price ratios or the number of certain peak price days).

Beyond overall net impacts, price-induced consumption increases (local) pollutants at the power source. An expansive literature documents the spatial correlation between pollution and populations of low socioeconomic status (Banzhaf et al., 2019). With power generation and its associated pollutants being no exception (Fowlie et al., 2012; Holland et al., 2019), dynamic pricing schemes may exacerbate inequitable pollution distribution. Moreover, while our results may suggest that increasing energy prices could improve net benefits (and reduce inequitable pollution at power generation sources), this, too, may place disproportionate burden on lower income consumers since the same energy price increase represents a larger budget share for low income households (Robinson, 1985; Hassett et al., 2009; Grainger and Kolstad, 2010). In this respect, careful choice of how revenues are recycled may mitigate some of the adverse distributional effects of energy price increases (Metcalf, 1999; Burtraw et al., 2009).

[18] The SCC values of \$12, \$40, and \$60 correspond to average values using discount rates of 5, 3 and 2.5 percent (IWG, 2010). The SCC value of \$120 is the 95th percentile estimate under a 3% discount rate.

5 Conclusion

Automation of household responses to dynamic pricing is becoming more prevalent. By enabling consumers to program default temperature settings and respond to price changes to control their energy consumption, pricing strategies can help utilities reduce generation costs, while potentially improving environmental quality. The latter is especially important for gaining public support given the health impacts of local pollutants, such as $PM_{2.5}$ and its precursors, and the expected climate damages from global pollutants. It is, however, unclear whether pricing policies will unambiguously yield environmental benefits if consumers respond to higher peak prices by shifting consumption to other times of the day when marginal emissions per kWh of electricity are higher.

This paper provides novel estimates of the causal impact of time-varying electricity rates on short term utility operating costs and emission using household-level electricity consumption data from a large-scale randomized control trial. We find that consumers, enabled with programmable communicating thermostats and notified of price increases a day in advance, shift demand from peak to off-peak hours in response to increased electricity rates. This load-shifting response unambiguously reduces operating costs for the Utility. The impacts on emissions are varied, where SO_2 and CO_2 emissions increase but NO_x decreases. The net effect on emissions reflects load shifting behavior from peak to off-peak hours, during which increases in electricity consumption generate higher marginal emissions in our area of study. Using back-of-the-envelope net benefit calculations, we find negative net benefits, although the overall impact is positive if one considers a low social cost of carbon value. The overall net benefits we calculate are underscored by considerable heterogeneity in the response to different price levels, where the highest VPP rate instead results in net decreases in CO_2 emissions.

To our knowledge, this is the first paper to use household-level electricity consumption data to evaluate the impacts of dynamic electricity pricing on both operating costs and emissions. In doing so, we demonstrate that dynamic electricity pricing may have unintended overall and distributional consequences. First, dynamic pricing in household electricity consumption may actually cause net increases in emissions depending on the source-generation mix of a region. For several values of the SCC, the program would lead to a net loss. Second, by shifting emissions to a different part of the day and increasing emissions on net at generation sources where low income and minorities are more likely to live, dynamic pricing schemes may create environmental justice concerns by exacerbating inequitable pollution distribution. Given the potential for such consequences, our findings caution the unconditional move toward dynamic pricing schemes from the regulator's perspective. In light of these concerns, however, the heterogeneity in the price response that we document highlights the important role of optimal policy design and provides a path forward for dynamic pricing schemes to simultaneously achieve the objectives of production cost savings and environmental quality improvements.

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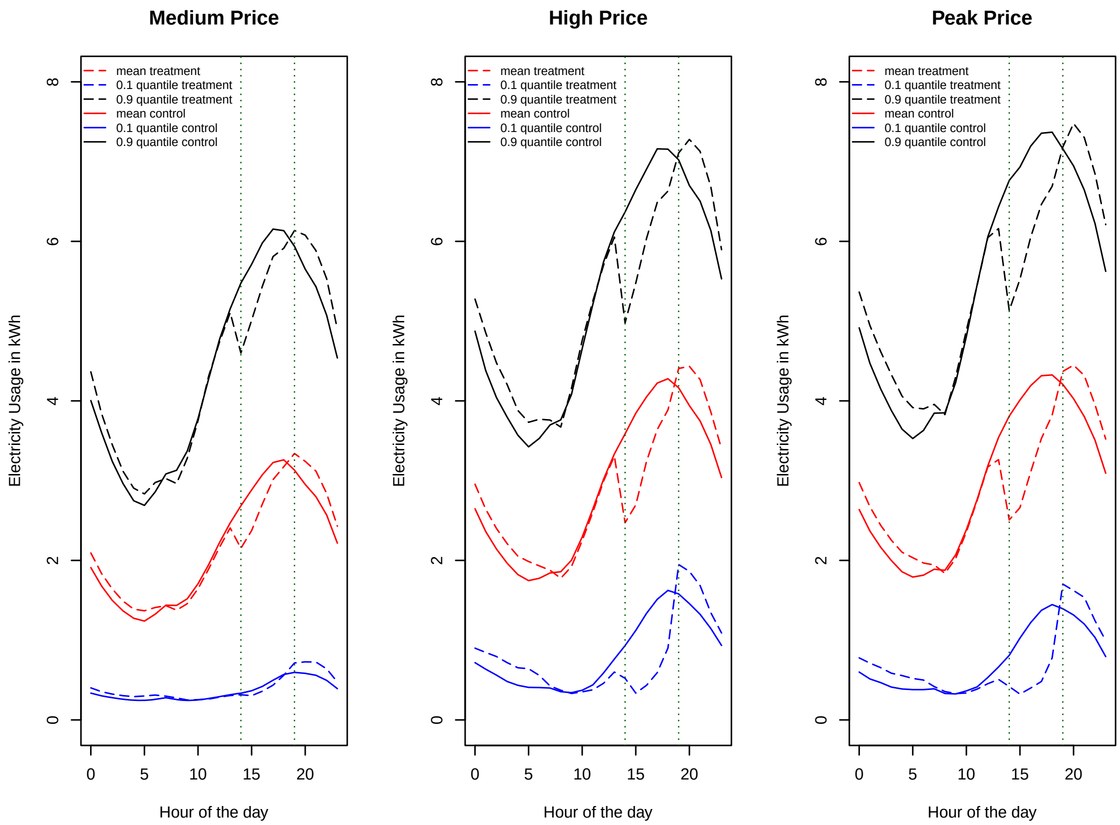
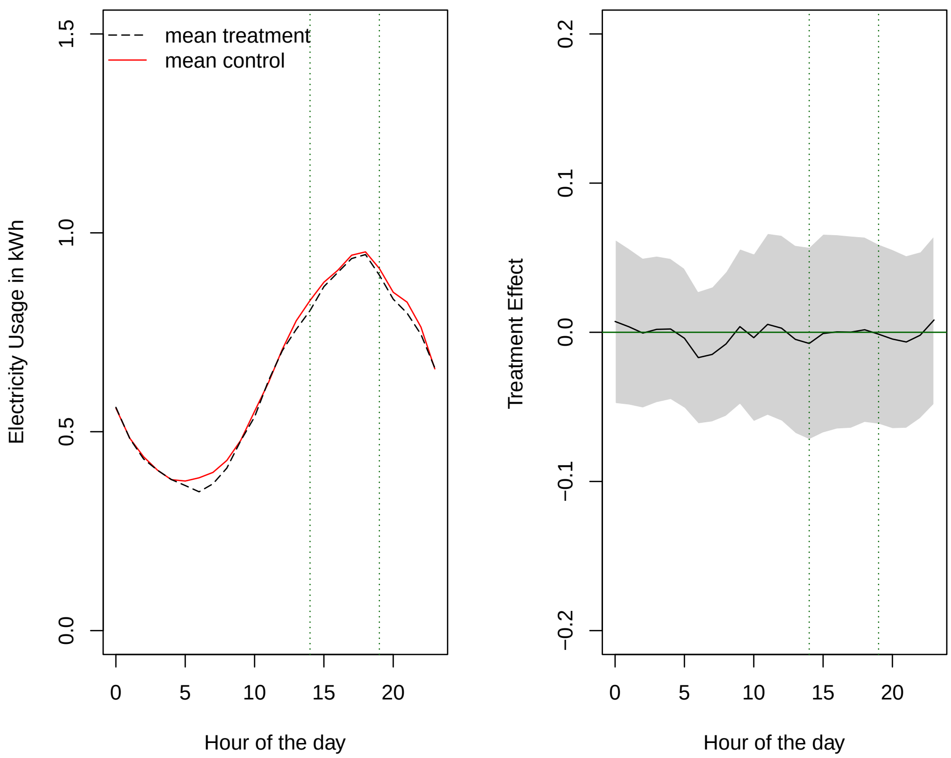
Figures

Figure 1: Average Hourly Consumption by Household Treatment Status



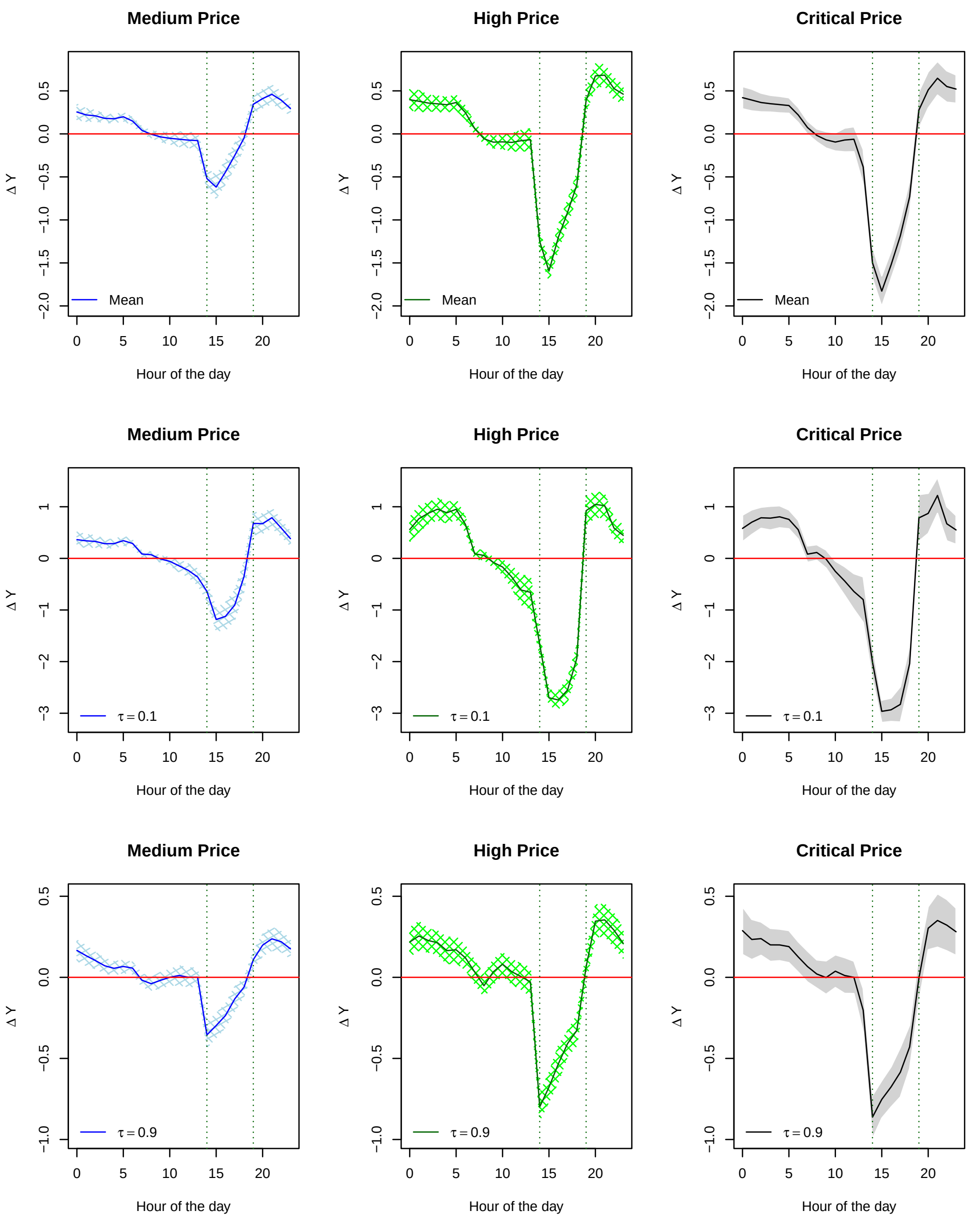
Note. The figure shows average consumption by treatment status obtained using hourly data on electricity usage in kW. The figure also shows usage at the 10th percentile and 90th percentile of the distribution of usage for treated households and households in the control group.

Figure 2: Treatment Effect of Households in 2010 (Pre-Treatment Period)



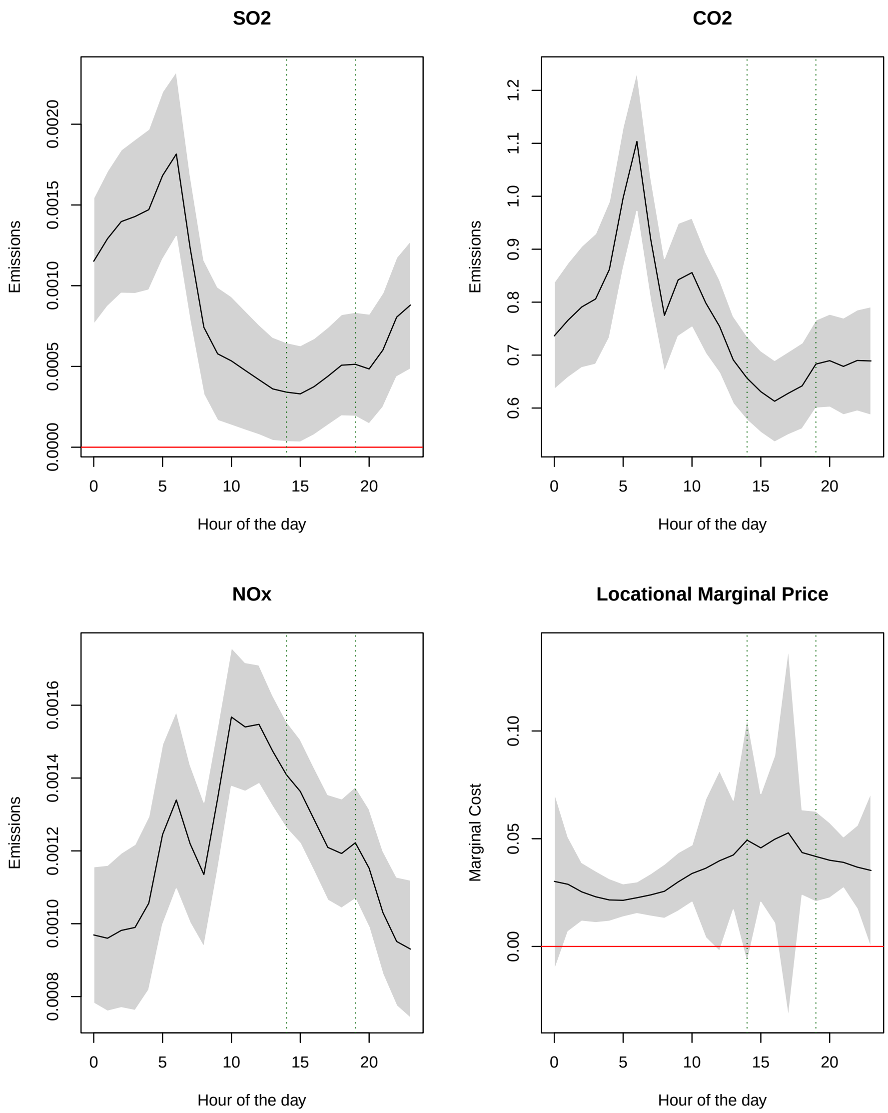
Note. The figure presents estimates of the treatment effect on electricity consumption during the summer of 2010 for households that would be treated with the VPP pricing scheme in 2011.

Figure 3: The Impact of Dynamic Pricing on Household Electricity Usage



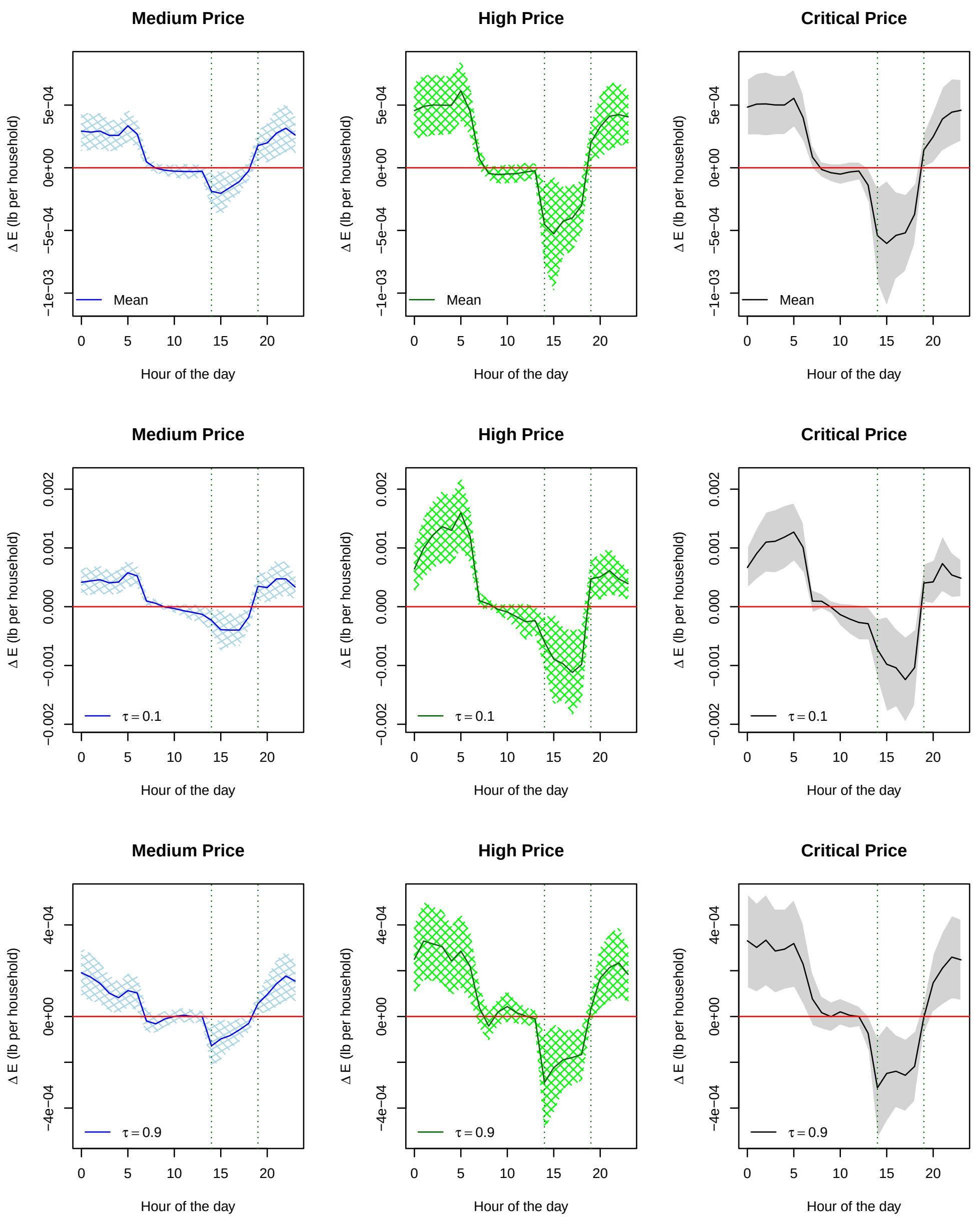
Note. Level changes in electricity consumption among treated households for each hour of the day is measured in kW. The shaded areas represent 95% point-wise confidence intervals.

Figure 4: Marginal Emissions and Marginal Locational Price of Electricity Demand



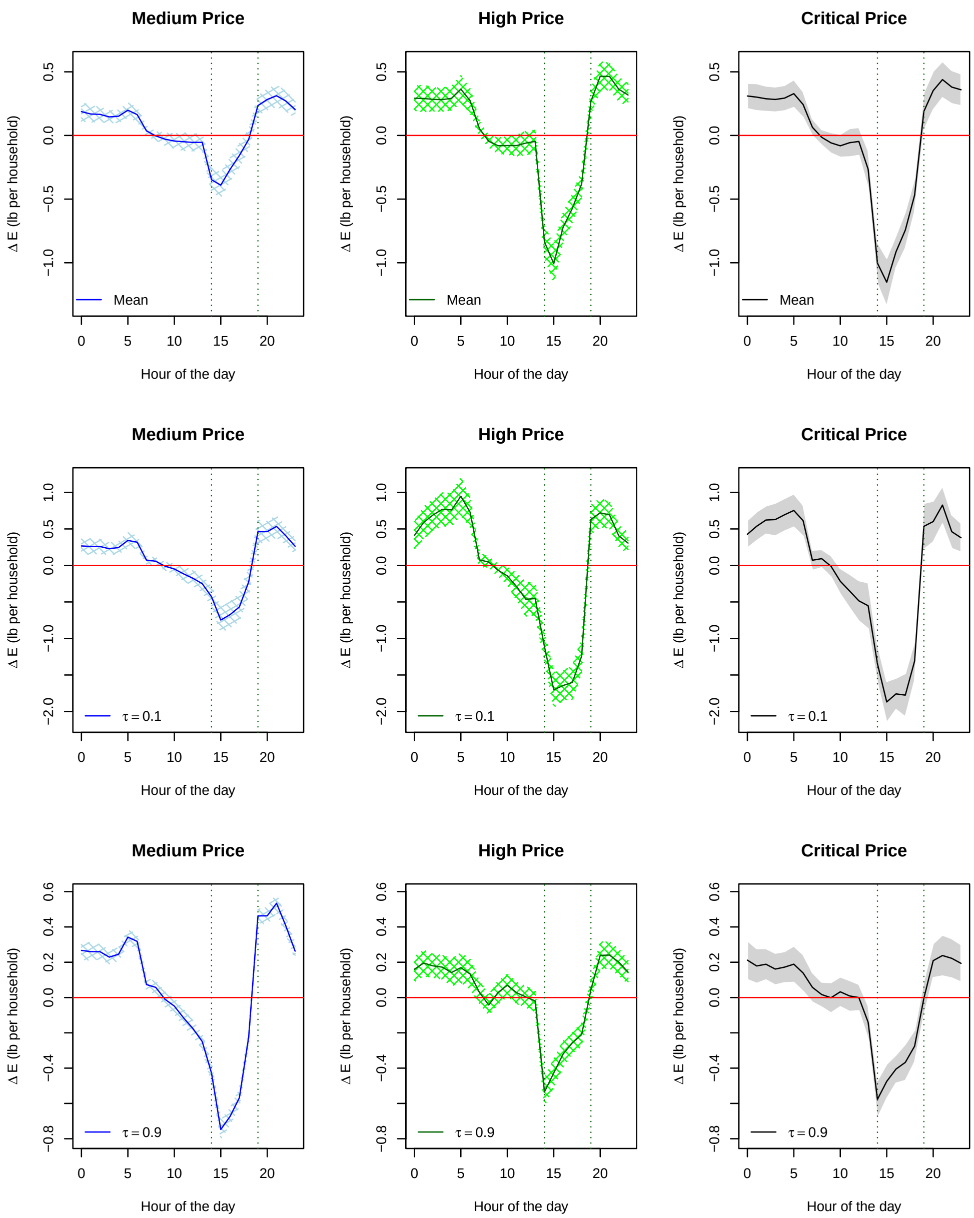
Note. The first three figures report marginal emissions for each hour obtained from estimating equation (3.4). The shaded areas represent 95% point-wise confidence intervals. The last figure shows the average locational marginal price, with confidence intervals based on the standard deviation.

Figure 5: Estimated Changes in SO_x Emissions



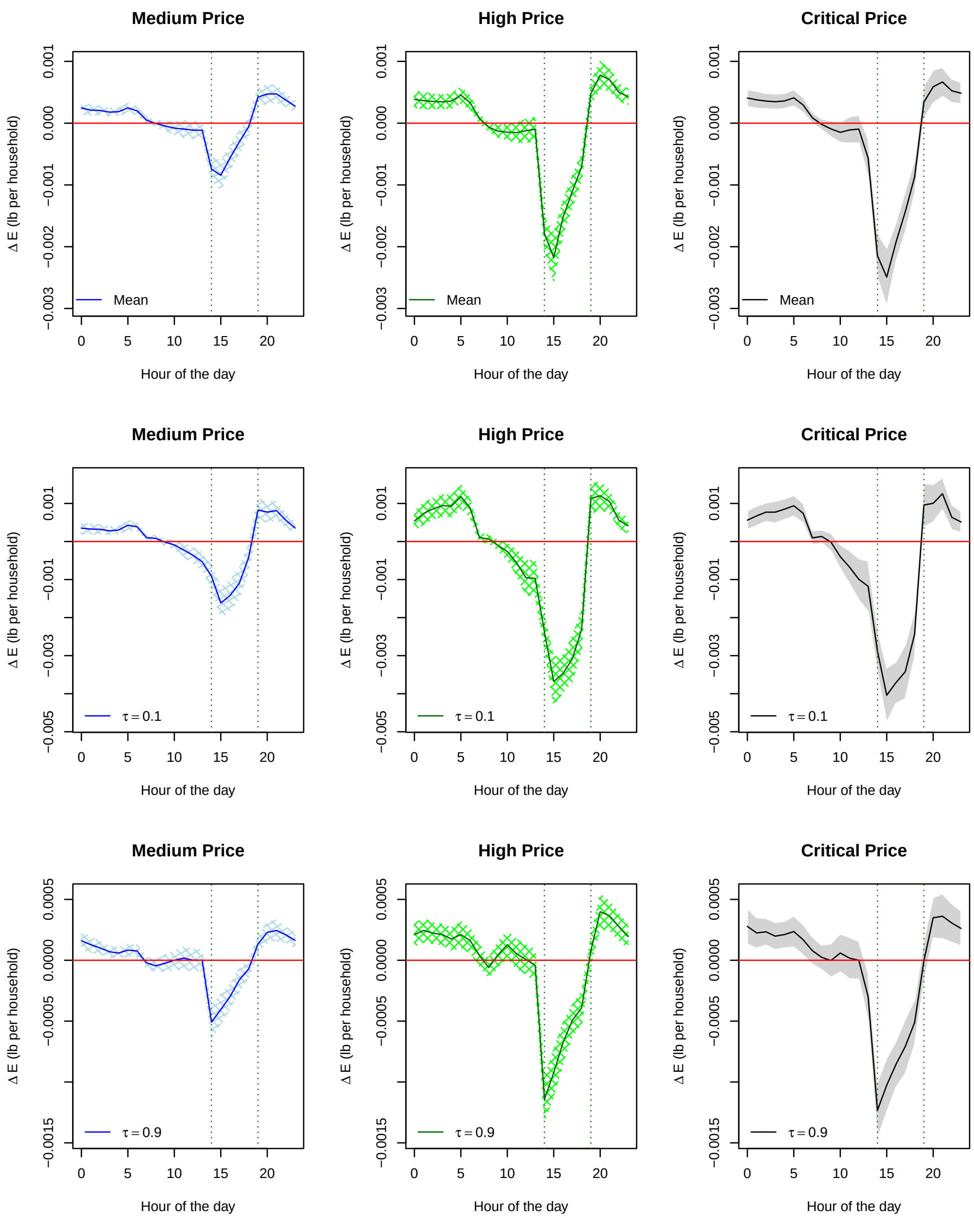
Note. The figure shows changes in SO_x emissions for each hour under treatment with dynamic pricing. The shaded areas represent 95% point-wise confidence intervals.

Figure 6: Estimated Changes in CO_2 Emissions



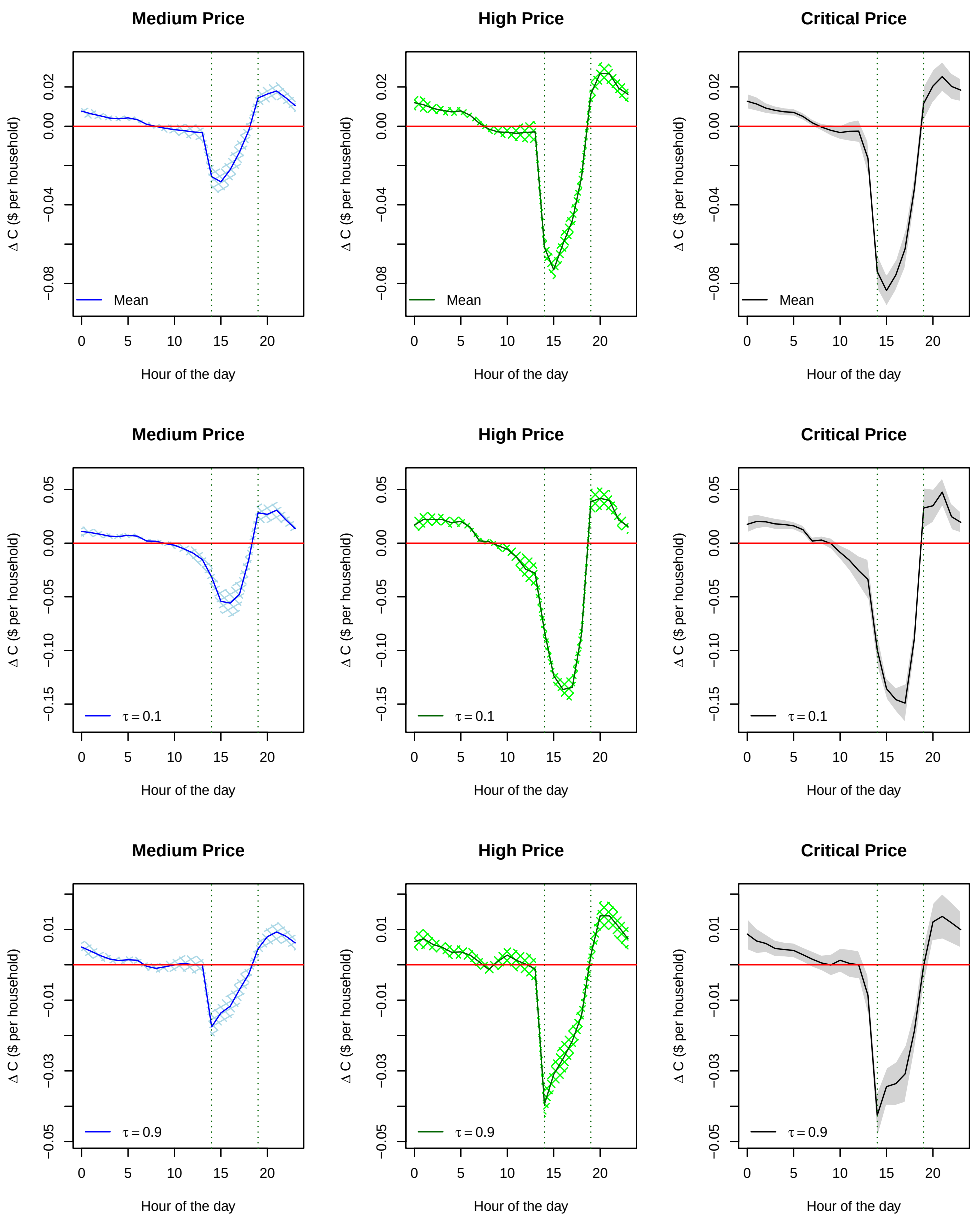
Note. The figure shows changes in CO_2 emissions for each hour under treatment with dynamic pricing. The shaded areas represent 95% point-wise confidence intervals.

Figure 7: Estimated Changes in NO_x Emissions



Note. The figure shows changes in NO_x emissions for each hour under treatment with dynamic pricing. The shaded areas represent 95% point-wise confidence intervals.

Figure 8: Estimated Changes in Marginal Generation Costs



Note. The figure shows changes in marginal generation costs under treatment with dynamic price. The shaded areas represent 95% point-wise confidence intervals.

Tables

Table 1: Number of Households by Treatment Status

A. Control Group				
	Young	Family	Mature	Total
High Income	152	156	198	506
Middle Income	66	81	59	206
Low Income	137	82	47	266
Total	355	319	304	978

B. Treatment Group				
	Young	Family	Mature	Total
High Income	60	85	69	214
Middle Income	48	53	52	153
Low Income	69	29	18	116
Total	177	167	139	483

Note. The table presents the number of households in each income and household-type bin for treatment and control groups.

Table 2: Daily Changes in Emissions and Generation Costs

	Mean Treatment			0.1 Quantile			0.9 Quantile		
	VPP1	VPP2	VPP3	VPP1	VPP2	VPP3	VPP1	VPP2	VPP3
SO_2	0.002	0.003	0.002	0.003	0.006	0.004	0.001	0.002	0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
CO_2	1.094	0.097	-0.975	0.942	-0.944	-2.430	0.445	0.367	-0.025
	(0.178)	(0.235)	(0.315)	(0.310)	(0.476)	(0.572)	(0.114)	(0.164)	(0.247)
NO_x	0.001	-0.003	-0.005	-0.001	-0.007	-0.010	0.000	-0.001	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Marginal Cost	0.007	-0.118	-0.196	-0.056	-0.336	-0.417	-0.001	-0.046	-0.080
	(0.010)	(0.011)	(0.015)	(0.018)	(0.020)	(0.027)	(0.006)	(0.008)	(0.012)

Note. The table presents the sum of point estimates during the day. Standard errors are presented in parenthesis. VPP1 means Variable Peak Pricing with medium peak price, VPP2 means Variable Peak Pricing with high peak price, and VPP3 means Variable Peak Pricing with critical price.

Table 3: Total Impacts during the Experiment (June-Sep 2011)

A. Mean Treatment Effect per Day

	SO_2 (lbs)	CO_2 (lbs)	NO_x (lbs)	Cost ($'s)
VPP1	0.002	1.094	0.001	0.007
VPP2	0.003	0.097	-0.003	-0.118
VPP3	0.002	-0.975	-0.005	-0.196

	VPP1	VPP2	VPP3
# of VPP Day	52	24	12
# of Households	5,000,000		

B. Impact for 5 Million Households

	SO_2 (lbs)	CO_2 (lbs)	NO_x (lbs)	Cost ($'s)
VPP1	624,000	284,466,000	156,000	1,768,000
VPP2	360,000	11,580,000	-300,000	-14,124,000
VPP3	138,000	-58,494,000	-282,000	-11,778,000
Total	1,122,000	237,552,000	-426,000	-24,134,000

C. Impact relative to Average Monthly Emissions

	SO_2 (lbs)	CO_2 (tons)	NO_x (lbs)
Monthly Emissions	42,182,492	11,027,703	26,930,830
% of Average Monthly Emissions	0.66%	0.27%	-0.40%

Note. The table presents estimated aggregate changes in emissions. During the summer of the experiment, there were 52 medium peak price days, 24 high peak price days, and 12 critical peak price days. In Panel A, we reproduce the mean treatment effects on emissions and production cost for a single day from Table 2. In Panel B, we calculate the change in each pollutant and production costs for the months of June through September assuming 5 million households were treated with the VPP scheme. Specifically, we multiply the treatment effect in lbs/household/day by 5 million households and by the number of days with medium, high, or critical prices. Panel C presents the percent average change in emissions in each month relative to the average monthly emissions for the NERC region (1 ton = 2,000 lbs). We remove weekends in the calculation of average monthly emissions for the NERC region to be consistent with the estimation sample.

Table 4: Net Benefits under Regional Adoption

A. Total Change in Benefits and Costs

	SO_2 (tons)	CO_2 (tons)	NO_x (tons)	Cost ($'s)
Treatment Impacts	561	118,776	-213	-24,134,000
SO_2 Benefits	VPP1	VPP2	VPP3	Total
$37,692/ton	-11,759,951	-6,784,587	-2,600,758	-21,145,296
CO_2 Benefits	VPP1	VPP2	VPP3	Total
$12/ton	-1,706,796	-69,480	350,964	-1,425,312
$40/ton	-5,689,320	-231,600	1,169,880	-4,751,040
$60/ton	-8,533,980	-347,400	1,754,820	-7,126,560
$120/ton	-17,067,960	-694,800	3,509,640	-14,253,120
NO_x Benefits	VPP1	VPP2	VPP3	Total
$5,654/ton	-440,998	848,073	797,189	1,204,264

B. Net Benefits under various SCC values

	$12	$40	$60	$120
Net Benefits	2,767,656	-558,072	-2,933,592	-10,060,152

Note. The table presents the change in emissions (in tons) for 5 million households at the observed number of each VPP price days from June through September. It then evaluates the monetary impact using values of SO_2, CO_2, and NO_x, where a range values for the Social Cost of Carbon (SCC) are used. Monetary values are in 2011 dollars.

Online Supplement: Environmental and Social Benefits of a Randomized Dynamic Pricing Experiment

Matthew Harding*, Kyle Kettler†, Carlos Lamarche‡, and Lala Ma§

July 14, 2021

In this Supplement, we present additional empirical results and robustness checks.

S.1 ARRA Smart Grid Investments

The implementation of time-varying pricing is achieved through significant public and private investments in system-wide infrastructure. The benefits of these investments are traditionally evaluated from a purely financial perspective. More recently, significant interest has been dedicated under the heading of "sustainable finance" to understanding the positive impact of various investments on the environment. No clear metric has emerged however for best practices to quantify the benefits of such investments and typical studies focus on firm valuations (Krueger, 2015). In the U.S., a major source of public investment in the energy sector were grants awarded under the American Recovery and Reinvestment Act of 2009 (ARRA). By increasing investment in renewable power, the ARRA aimed to generate environmental benefits while spurring economic activity. It led to significant public investments in modernizing U.S. energy infrastructure. It provided $4.5 billion investments in the electric power grid. The energy industry provided additional funds for cost-shared smart grid projects involving almost 100 electric utilities and totalled $8 billion. Numerous infrastructure needs were addressed including the deployment of new technology, increasing cybersecurity and resilience, collection of data, and the provision of smart in-home devices

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to customers. Funds from this grant program were also used to design and implement a series of RCTs involving time-varying pricing and enabling technologies. The pilot described and evaluated in the paper is one such program.

While data confidentiality agreements prevent us from disclosing identifying details, we also collected stock price data for 17 ARRA recipients that are also listed as electric or power generation companies on the NYSE. We compare the stock price of these companies with that of 14 other electric or power generation companies that did not receive ARRA funding in Figure S.1. ARRA grant fund recipients had higher stock price valuations and a higher stock price growth rate in the years after receiving public funds. The majority of projects were implemented during 2010 and 2011 and finalized by 2015.

The causal estimated in the paper highlight an indirect channel through which energy policies (in this case, the ARRA) can affect behavior and outcomes. These estimates serve as inputs into calculating the marginal value of public funds (MVPF). Comparison of the MVPF for different policies can help to better allocate public dollars toward uses with higher social welfare impacts (Hendren and Sprung-Keyser, 2020; Finkelstein and Hendren, 2020).

The core messages of this paper is however that the financial and environmental impact of public investments is subtle and multi-dimensional and not adequately captured by evaluating stock prices alone.

S.2 Dynamic Impacts of Prices

This section presents results for the mean treatment effect, β_h^k, and quantile treatment effect, $\beta_h^k(\tau)$. The point estimates are used to estimate changes in electricity consumption induced by dynamic pricing as shown in Figure 3.

Table S.1 presents mean treatment effects by hour of the day and price level. In columns, we denote medium price level by VPP1, high price level by VPP2, and critical price level by VPP3. For instance, the second column in the table shows $\hat{\beta}_h$ for medium price level. The table also offers 95 percent confidence intervals for each point estimate. Moreover, Tables S.2 and S.3 show quantile treatment effect estimates, $\hat{\beta}_h^k(\tau)$, and their 95 percent confidence intervals. Table S.2 presents results for the quantile function estimated at the 0.1 quantile of the conditional distribution of electricity consumption, and Table S.3 presents results for the quantile model estimated at the 0.9 quantile.

S.3 Heterogeneous Dynamic Impacts

As discussed in the manuscript, increasing energy prices could improve net benefits while they may place a disproportionate burden on low-income households since the same energy price increase represents a larger budget share for low income households. Our study, however, abstracts away from heterogeneity of treatment effects with respect to income. This section extends the analysis in the manuscript and estimates daily net impacts on emissions and generation costs by price level and income of the household.

Specifically, we estimate the net impacts considering households in the low-income group and high-income group. The changes in consumption are presented in Figures S.2 and S.3. Then, using Table S.4, we report the net impact on emissions and generation costs by summing the average and quantile treatment impacts over the course of the day. Panel A presents results for low-income households and Panel B presents results for high-income households.

The results are mixed. If we concentrate on CO_2 emissions, the results suggest that low-income households are associated, in general, with larger daily reductions in emissions than high-income households. This is explained by the load shifting behavior of low-income households, who do not seem to significantly reallocate energy use to off-peak hours.

S.4 Measuring Total Impacts: Quantile Regression Results

A difficulty of measuring the impact in the same region using quantile regression estimates relates to estimating the number of households whose price elasticities are similar to the elasticity obtained in the low quantile of the conditional distribution of electricity consumption. It is not possible to overcome this important challenge, but at the same time, it is informative to uncover the heterogeneity of impacts to obtain a broader understanding of the benefits and costs of emissions.

In our experimental sample, approximately 25 percent of households are low-income households, with yearly earnings less than \$30,000. The analysis presented in Tables S.5 and S.6 assume that the proportion of low-income households in the region is similar to the proportion of low-income households in our experimental sample. While scaling the quantile treatment effects by 1.25 million households is likely to not be accurate, our estimates are not expected to change the sign of the impacts.

Table S.5 presents results for the total impact by estimating consumption changes, ΔY_h^k, at the 0.1 quantile of the distribution. Then, Table S.6 presents the monetized value of these impacts. Lastly, Tables S.7 and S.8 show results based on estimating consumption changes at the 0.9 quantile, assuming that 2.5 million households reside in the region (50 percent of high-income households in the experimental sample).

Figure S.1: Stock Prices for Recipients of ARRA Grants compared to Non-Recipients

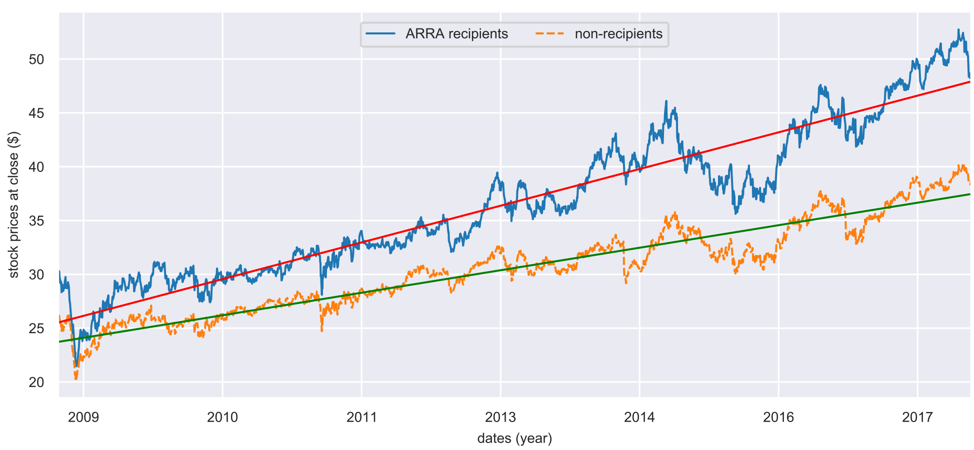
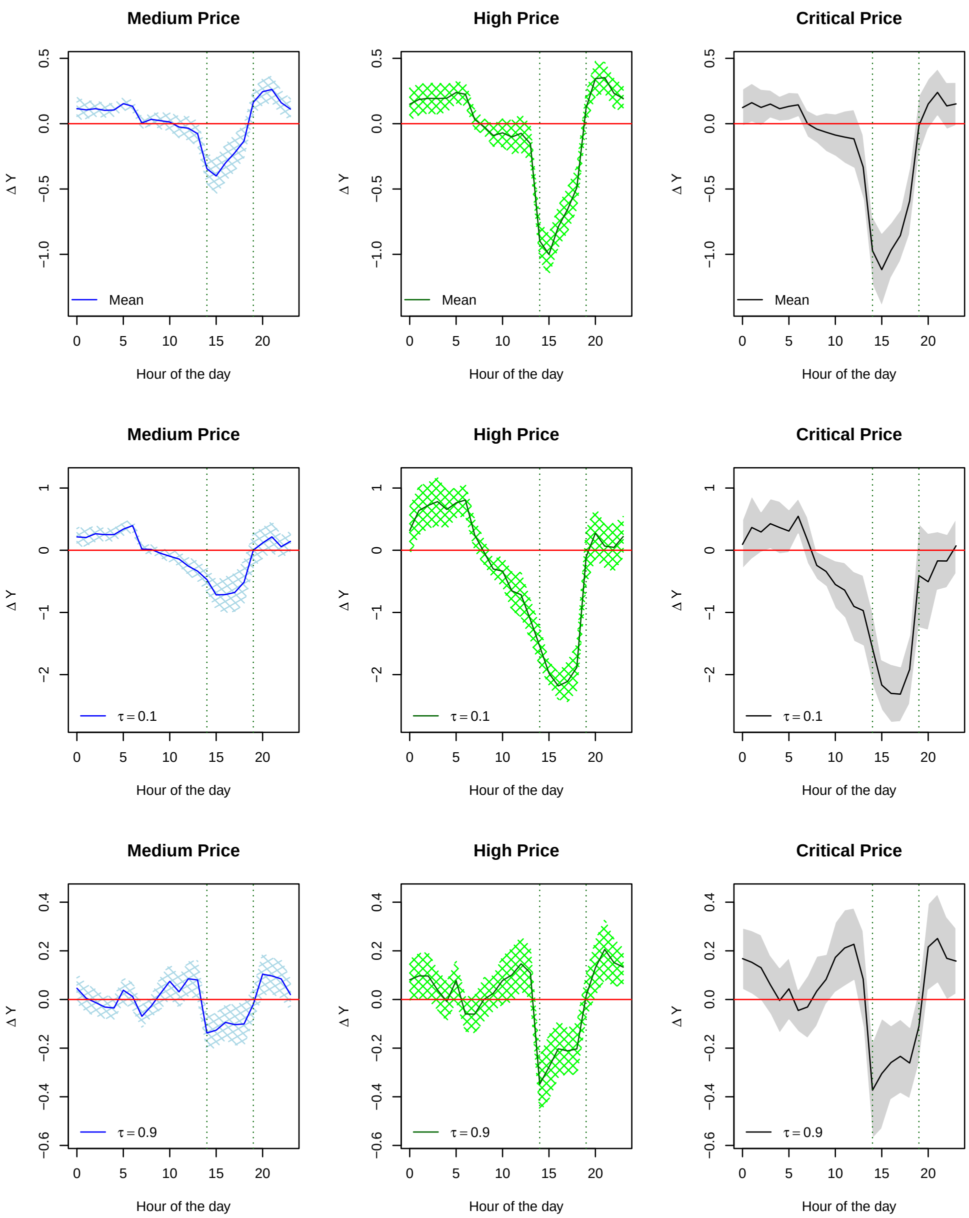
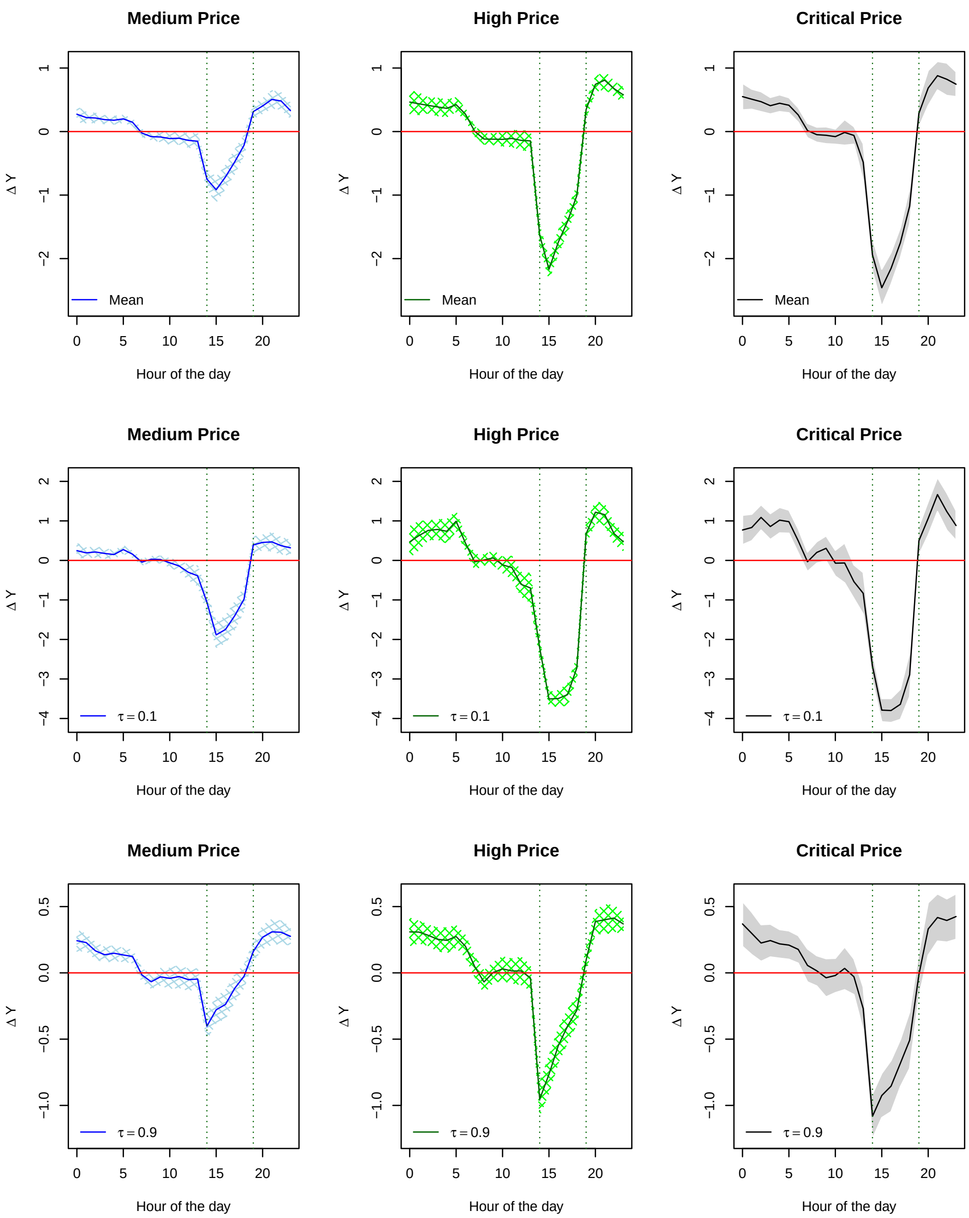


Figure S.2: Changes in Electricity Usage among Low Income Households



Note. The figure shows level changes in electricity consumption among treated, low income households for each hour of the day is measured in kW. The shaded areas represent 95% point-wise confidence intervals.

Figure S.3: Changes in Electricity Usage among High Income Households



Note. The figure shows level changes in electricity consumption among treated, high income households for each hour of the day is measured in kW. The shaded areas represent 95% point-wise confidence intervals.

Table S.1: Mean Treatment Effect (kW), Point Estimates

Hour	VPP1	95% C.I.		VPP2	95% C.I.		VPP3	95% C.I.	
0	0.125	0.081	0.169	0.140	0.100	0.180	0.148	0.104	0.192
1	0.123	0.083	0.164	0.149	0.101	0.197	0.154	0.107	0.200
2	0.131	0.093	0.169	0.155	0.116	0.193	0.156	0.112	0.199
3	0.124	0.093	0.156	0.164	0.122	0.206	0.162	0.120	0.204
4	0.129	0.095	0.163	0.171	0.128	0.213	0.168	0.124	0.212
5	0.149	0.114	0.184	0.190	0.146	0.233	0.169	0.126	0.211
6	0.106	0.076	0.137	0.130	0.091	0.169	0.115	0.071	0.158
7	0.028	-0.002	0.058	0.033	-0.001	0.067	0.038	-0.001	0.078
8	-0.003	-0.031	0.026	-0.031	-0.062	0.000	-0.009	-0.050	0.031
9	-0.023	-0.062	0.015	-0.049	-0.085	-0.013	-0.034	-0.082	0.013
10	-0.030	-0.071	0.010	-0.041	-0.078	-0.005	-0.041	-0.086	0.004
11	-0.032	-0.077	0.013	-0.038	-0.078	0.001	-0.026	-0.078	0.025
12	-0.033	-0.073	0.007	-0.027	-0.068	0.015	-0.020	-0.066	0.026
13	-0.032	-0.071	0.007	-0.020	-0.060	0.019	-0.115	-0.178	-0.052
14	-0.215	-0.262	-0.168	-0.428	-0.472	-0.385	-0.500	-0.563	-0.437
15	-0.242	-0.292	-0.191	-0.536	-0.579	-0.493	-0.608	-0.671	-0.546
16	-0.156	-0.204	-0.108	-0.353	-0.400	-0.306	-0.452	-0.504	-0.400
17	-0.081	-0.127	-0.034	-0.243	-0.284	-0.202	-0.321	-0.376	-0.266
18	-0.015	-0.052	0.022	-0.149	-0.186	-0.112	-0.185	-0.235	-0.135
19	0.104	0.074	0.134	0.090	0.060	0.120	0.064	0.015	0.113
20	0.130	0.098	0.162	0.158	0.126	0.190	0.119	0.072	0.167
21	0.152	0.118	0.186	0.167	0.138	0.197	0.157	0.112	0.202
22	0.142	0.108	0.176	0.142	0.109	0.175	0.146	0.100	0.191
23	0.125	0.089	0.162	0.141	0.109	0.173	0.156	0.109	0.203

Note. The table presents average treatment effects and 95 percent point-wise confidence intervals. C.I. denotes confidence interval. VPP1 means Variable Peak Pricing with medium price, VPP2 Variable Peak Pricing with high price, and VPP3 Variable Peak Pricing with critical price.

Table S.2: Quantile Treatment Effect ($\tau = 0.1$), Point Estimates

Hour	VPP1	95% C.I.		VPP2	95% C.I.		VPP3	95% C.I.	
0	0.174	0.108	0.240	0.191	0.117	0.266	0.199	0.118	0.279
1	0.184	0.123	0.245	0.282	0.196	0.368	0.259	0.181	0.337
2	0.198	0.137	0.260	0.342	0.270	0.413	0.310	0.242	0.377
3	0.189	0.140	0.238	0.396	0.319	0.472	0.329	0.247	0.411
4	0.202	0.151	0.253	0.395	0.318	0.472	0.360	0.282	0.438
5	0.245	0.188	0.301	0.434	0.359	0.510	0.352	0.283	0.420
6	0.197	0.157	0.237	0.316	0.254	0.378	0.267	0.191	0.343
7	0.057	0.018	0.097	0.047	-0.009	0.103	0.042	-0.038	0.123
8	0.048	0.009	0.086	0.030	-0.014	0.075	0.059	-0.017	0.135
9	-0.008	-0.050	0.035	-0.040	-0.091	0.011	-0.006	-0.092	0.079
10	-0.034	-0.080	0.012	-0.076	-0.141	-0.010	-0.112	-0.205	-0.019
11	-0.077	-0.141	-0.014	-0.147	-0.243	-0.052	-0.173	-0.291	-0.055
12	-0.111	-0.171	-0.050	-0.227	-0.344	-0.110	-0.225	-0.357	-0.093
13	-0.158	-0.226	-0.089	-0.219	-0.338	-0.101	-0.256	-0.408	-0.103
14	-0.272	-0.349	-0.195	-0.623	-0.724	-0.521	-0.751	-0.908	-0.594
15	-0.529	-0.631	-0.427	-1.211	-1.308	-1.114	-1.342	-1.486	-1.199
16	-0.455	-0.571	-0.339	-1.131	-1.247	-1.015	-1.204	-1.345	-1.063
17	-0.329	-0.444	-0.214	-0.926	-1.051	-0.802	-1.065	-1.265	-0.866
18	-0.114	-0.211	-0.017	-0.602	-0.709	-0.495	-0.638	-0.776	-0.499
19	0.196	0.136	0.255	0.200	0.145	0.256	0.171	0.078	0.264
20	0.205	0.153	0.257	0.235	0.183	0.287	0.196	0.115	0.277
21	0.248	0.194	0.301	0.241	0.191	0.291	0.278	0.208	0.347
22	0.206	0.155	0.257	0.157	0.106	0.208	0.175	0.095	0.254
23	0.159	0.102	0.216	0.137	0.079	0.194	0.164	0.086	0.242

Note. The table presents point estimates and 95 percent point-wise confidence intervals estimated at the 0.1 quantile. C.I. denotes confidence interval. VPP1 means Variable Peak Pricing with medium price, VPP2 means Variable Peak Pricing with high price, and VPP3 means Variable Peak Pricing with critical price.

Table S.3: Quantile Treatment Effect ($\tau = 0.9$), Point Estimates

Hour	VPP1	95% C.I.		VPP2	95% C.I.		VPP3	95% C.I.	
0	0.084	0.052	0.115	0.079	0.047	0.111	0.104	0.052	0.155
1	0.076	0.042	0.111	0.103	0.067	0.138	0.094	0.046	0.142
2	0.067	0.034	0.099	0.101	0.069	0.132	0.104	0.061	0.148
3	0.051	0.018	0.083	0.103	0.068	0.138	0.095	0.049	0.142
4	0.043	0.011	0.075	0.086	0.044	0.129	0.102	0.054	0.150
5	0.053	0.023	0.083	0.093	0.050	0.136	0.101	0.050	0.151
6	0.042	0.015	0.069	0.066	0.026	0.106	0.067	0.018	0.116
7	-0.012	-0.040	0.016	0.018	-0.021	0.056	0.035	-0.015	0.084
8	-0.028	-0.056	0.001	-0.028	-0.066	0.010	0.011	-0.035	0.057
9	-0.012	-0.045	0.020	0.017	-0.022	0.055	-0.001	-0.050	0.049
10	0.000	-0.029	0.029	0.035	0.005	0.065	0.016	-0.026	0.058
11	0.006	-0.025	0.037	0.013	-0.016	0.042	0.004	-0.036	0.044
12	0.000	-0.026	0.027	0.002	-0.025	0.028	0.000	-0.031	0.031
13	0.000	-0.023	0.024	-0.009	-0.035	0.018	-0.059	-0.098	-0.020
14	-0.142	-0.171	-0.113	-0.252	-0.280	-0.224	-0.257	-0.297	-0.216
15	-0.109	-0.136	-0.082	-0.194	-0.221	-0.167	-0.208	-0.240	-0.176
16	-0.080	-0.103	-0.056	-0.142	-0.173	-0.111	-0.176	-0.210	-0.142
17	-0.042	-0.066	-0.018	-0.102	-0.121	-0.082	-0.146	-0.186	-0.106
18	-0.019	-0.036	-0.002	-0.080	-0.103	-0.056	-0.104	-0.138	-0.071
19	0.034	0.018	0.051	0.015	-0.006	0.037	-0.001	-0.036	0.033
20	0.065	0.044	0.086	0.084	0.060	0.108	0.073	0.041	0.104
21	0.082	0.057	0.106	0.090	0.066	0.115	0.088	0.048	0.128
22	0.082	0.059	0.105	0.081	0.053	0.109	0.088	0.046	0.130
23	0.076	0.051	0.102	0.066	0.038	0.095	0.087	0.043	0.131

Note. The table presents point estimates and 95 percent point-wise confidence intervals estimated at the 0.9 quantile. C.I. denotes confidence interval. VPP1 means Variable Peak Pricing with medium price, VPP2 means Variable Peak Pricing with high price, and VPP3 means Variable Peak Pricing with critical price.

Table S.4: Daily Changes in Emissions and Generation Costs by Income

A. Low Income

	Mean Treatment			0.1 Quantile			0.9 Quantile		
	VPP1	VPP2	VPP3	VPP1	VPP2	VPP3	VPP1	VPP2	VPP3
SO_2	0.001	0.001	0.000	0.002	0.002	-0.003	0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
CO_2	0.448	-0.734	-2.139	-0.503	-3.822	-7.832	0.010	0.192	0.557
	(0.261)	(0.269)	(0.308)	(0.492)	(0.674)	(0.871)	(0.173)	(0.201)	(0.258)
NO_x	0.000	-0.003	-0.005	-0.003	-0.011	-0.017	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Marginal	-0.014	-0.122	-0.198	-0.117	-0.452	-0.619	-0.006	-0.011	-0.001
Cost	(0.016)	(0.013)	(0.017)	(0.031)	(0.031)	(0.047)	(0.009)	(0.010)	(0.013)

B. High Income

	Mean Treatment			0.1 Quantile			0.9 Quantile		
	VPP1	VPP2	VPP3	VPP1	VPP2	VPP3	VPP1	VPP2	VPP3
SO_2	0.002	0.003	0.003	0.000	0.003	0.005	0.002	0.003	0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)
CO_2	0.107	-1.115	-1.600	-2.516	-3.770	-2.478	1.001	0.868	-0.208
	(0.292)	(0.330)	(0.409)	(0.486)	(0.629)	(0.817)	(0.184)	(0.210)	(0.299)
NO_x	-0.001	-0.005	-0.007	-0.007	-0.012	-0.011	0.001	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)
Marginal	-0.060	-0.221	-0.280	-0.264	-0.523	-0.506	0.020	-0.033	-0.105
Cost	(0.017)	(0.013)	(0.020)	(0.030)	(0.024)	(0.036)	(0.010)	(0.010)	(0.014)

Note. The table presents the sum of point estimates during the day separately for low income (Panel A) and high income (Panel B) households. Standard errors are presented using parenthesis. VPP1 means Variable Peak Pricing with medium price, VPP2 means Variable Peak Pricing with high price, and VPP3 means Variable Peak Pricing with critical price.

Table S.5: Total Impacts for 0.1 Quantile Treatment

A. 0.1 Quantile Treatment Effect per Day

	SO_2 (lbs)	CO_2 (lbs)	NO_x (lbs)	Cost ($'s)
VPP1	0.003	0.942	-0.001	-0.056
VPP2	0.006	-0.944	-0.007	-0.336
VPP3	0.004	-2.430	-0.010	-0.417

	VPP1	VPP2	VPP3
# of VPP Day	52	24	12
# of Households	1,250,000		

B. Impact for 1.25 Million Households (June-Sep)

	SO_2 (lbs)	CO_2 (lbs)	NO_x (lbs)	Cost ($'s)
VPP1	221,000	61,197,500	-52,000	-3,653,000
VPP2	168,000	-28,323,000	-216,000	-10,068,000
VPP3	61,500	-36,447,000	-147,000	-6,256,500
Total	450,500	-3,572,500	-415,000	-19,977,500

C. Impact relative to Average Monthly Emissions

	SO_2 (lbs)	CO_2 (tons)	NO_x (lbs)
Monthly Emissions	42,182,492	11,027,703	26,930,830
% of Average Monthly Emissions	0.27%	-0.004%	-0.39%

Note. During the summer of the experiment, there were 52 medium peak price days, 24 high peak price days, and 12 critical peak price days. In Panel A, we reproduce the 0.1 quantile treatment effects on emissions and production cost for a single day from Table 2. In Panel B, we calculate the change in each pollutant and production costs for the months of June through September assuming 1.25 million households were treated with the VPP scheme. Specifically, we multiply the treatment effect in lbs/household/day by 1.25 million households and by the number of days with medium, high, or critical prices. Panel C presents the percent average change in emissions in each month relative to the average monthly emissions for the NERC region (1 ton = 2,000 lbs). We remove weekends in the calculation of average monthly emissions for the NERC region to be consistent with the estimation sample.

Table S.6: Net Benefits for 0.1 Quantile Treatment

A. Total Change in Benefits and Costs

	SO_2 (tons)	CO_2 (tons)	NO_x (tons)	Cost ($'s)
Treatment Impacts	225	-1,786	-208	-19,977,500
SO_2 Benefits	VPP1	VPP2	VPP3	Total
$37,692/ton	-4,164,983	-3,166,141	-1,159,034	-8,490,157
CO_2 Benefits	VPP1	VPP2	VPP3	Total
$12/ton	-367,185	169,938	218,682	21,435
$40/ton	-1,223,950	566,460	728,940	71,450
$60/ton	-1,835,925	849,690	1,093,410	107,175
$120/ton	-3,671,850	1,699,380	2,186,820	214,350
NO_x Benefits	VPP1	VPP2	VPP3	Total
$5,654/ton	146,999	610,613	415,556	1,173,168

B. Net Benefits under various SCC values

	$12	$40	$60	$120
Net Benefits	12,681,946	12,731,961	12,767,686	12,874,861

Note. The table presents the change in emissions (in tons) for 1.25 million households at the observed number of each VPP price days from June through September. It then evaluates the monetary impact using values of SO_2, CO_2, and NO_x, where a range values for the Social Cost of Carbon (SCC) are used. Monetary values are in 2011 dollars.

Table S.7: Total Impacts for 0.9 Quantile Treatment

A. 0.9 Quantile Treatment Effect per Day

	SO_2 (lbs)	CO_2 (lbs)	NO_x (lbs)	Cost ($'s)
VPP1	0.001	0.445	0.000	-0.001
VPP2	0.002	0.367	-0.001	-0.046
VPP3	0.002	-0.025	-0.002	-0.080

	VPP1	VPP2	VPP3
# of VPP Day	52	24	12
# of Households	2,500,000		

B. Impact for 2.5 Million Households (June-Sep)

	SO_2 (lbs)	CO_2 (lbs)	NO_x (lbs)	Cost ($'s)
VPP1	143,000	57,876,000	13,000	-117,000
VPP2	108,000	21,990,000	-42,000	-2,778,000
VPP3	51,000	-741,000	-48,000	-2,409,000
Total	302,000	79,125,000	-77,000	-5,304,000

C. Impact relative to Average Monthly Emissions

	SO_2 (lbs)	CO_2 (tons)	NO_x (lbs)
Monthly Emissions	42,182,492	11,027,703	26,930,830
% of Average Monthly Emissions	0.18%	0.090%	-0.07%

Note. During the summer of the experiment, there were 52 medium peak price days, 24 high peak price days, and 12 critical peak price days. In Panel A, we reproduce the 0.9 quantile treatment effects on emissions and production cost for a single day from Table 2. In Panel B, we calculate the change in each pollutant and production costs for the months of June through September assuming 2.5 million households were treated with the VPP scheme. Specifically, we multiply the treatment effect in lbs/household/day by 2.5 million households and by the number of days with medium, high, or critical prices. Panel C presents the percent average change in emissions in each month relative to the average monthly emissions for the NERC region (1 ton = 2,000 lbs). We remove weekends in the calculation of average monthly emissions for the NERC region to be consistent with the estimation sample.

Table S.8: Net Benefits for 0.9 Quantile Treatment

A. Total Change in Benefits and Costs

	SO_2 (tons)	CO_2 (tons)	NO_x (tons)	Cost ($'s)
Treatment Impacts	151	39,563	-39	-5,304,000
SO_2 Benefits	VPP1	VPP2	VPP3	Total
$37,692/ton	-2,694,989	-2,035,376	-961,150	-5,691,515
CO_2 Benefits	VPP1	VPP2	VPP3	Total
$12/ton	-347,256	-131,940	4,446	-474,750
$40/ton	-1,157,520	-439,800	14,820	-1,582,500
$60/ton	-1,736,280	-659,700	22,230	-2,373,750
$120/ton	-3,472,560	-1,319,400	44,460	-4,747,500
NO_x Benefits	VPP1	VPP2	VPP3	Total
$5,654/ton	-36,750	118,730	135,692	217,672

B. Net Benefits under various SCC values

	$12	$40	$60	$120
Net Benefits	-644,593	-1,752,343	-2,543,593	-4,917,343

Note. Table presents the change in emissions (in tons) for 2.5 million households at the observed number of each VPP price days from June through September. It then evaluates the monetary impact using values of SO_2, CO_2, and NO_x, where a range values for the Social Cost of Carbon (SCC) are used. Monetary values are in 2011 dollars.