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# Commercial consumers pay attention to marginal prices or average prices? Implications for energy conservation policies

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ABSTRACT

Any energy conservation policy intervention associated with energy price variation needs to consider whether consumers respond to marginal or average pricing. To the best of our knowledge, there is no such evidence for commercial electricity consumers (such as office buildings and malls), although commercial consumers are responsible for nearly 18% of electricity consumption in the United States. This study examines a four-tiered decreasing-block pricing schedule for commercial consumers. Based on individual-consumer-level data, we analyze the daily electricity consumption of 597 commercial accounts in Phoenix metropolitan, Arizona, from May 1, 2013, to December 31, 2016. We run 2SLS models with policy-induced price variation as instrumental variables to estimate the effects of marginal and average prices on commercial electricity consumption at each cutoff point. We also study the heterogenous response across industry sectors. Our analysis shows that commercial consumers respond to both marginal and average prices, but have different responses with respect to how much electricity they consume. Higher-usage consumers tend to respond more to average prices, whereas lower-usage consumers are more sensitive to marginal prices. Our findings indicate that conservation policies should be tailored differently for commercial electricity consumers. Nonlinear electricity pricing structures can reduce energy consumption, particularly for commercial consumers who have lower energy demand if the pricing structure shifts from decreasing to increasing blocks. In contrast, a flat rate with a higher price level can limit the electricity consumption of high-use consumers. As for an industry-wise policy design, nonlinear pricing can be effectively used to reduce aggregate consumption in the construction, manufacturing, real estate, and rental and leasing industries, professional, scientific, and technical services, other services (except public administration), and public administration industries.

## 1. Introduction

Any energy conservation policy intervention associated with energy price variation needs to consider whether consumers respond to marginal or average pricing. It is generally assumed that firms and consumers will optimize their consumption behavior based on marginal prices in policy discussions of taxation, nonlinear pricing, and subsidies. For example, the broad use of taxation assumes taxpayers make the best decision regarding marginal tax rates based on their income (Mirrlees, 1971; Atkinson and Stiglitz, 1976; Diamond, 1998). Similarly, scholars often take this assumption for granted when discussing residential consumers' responses to nonlinear pricing structures. Some studies find that residential consumers respond to marginal electricity prices (Reiss and White, 2005) and marginal water prices (Olmstead et al., 2007). On the contrary, other studies show that residents respond to average electricity prices rather than marginal prices (Ito, 2014; Shin, 1985; Borenstein, 2009). Carter and Milon (2005) support that residential consumers may be less directly responsive to marginal prices because of cognitive difficulty. Consumers often look to the average prices as an alternative in part because marginal prices are difficult to monitor and calculate (Liebman and Zeckhauser, 2004; De Bartolome, 1995; Ito, 2014). These studies are relevant to our study since they focus on the same topic but examine a different group of consumers, the residents. Studies on the demand response of commercial electricity consumption use qualitative methods, such as case studies and semi-structured interviews to investigate commercial energy demand. Khan et al. (2015) conduct case studies in Ontario Canada, California, Washington, Texas and New York to compare energy programs. They find a reduction in

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energy consumption with encouraging consumer satisfaction.

Almost 18% of national energy consumption in the United States is attributed to commercial buildings (Commercial Building Energy Consumption Survey (CBECS), 2015). In light of the high energy demand, commercial consumers may have different responses from residential consumers and are expected to be more price sensitive. Suppose evidence indicates that commercial consumers are more responsive to average prices. In that case, policies that rely on marginal pricing to incentivize conservation will be less effective than policies aimed at average prices. Yet, there is no empirical evidence in the literature related to commercial electricity consumption. To the best of our knowledge, we provide the first empirical evidence looking at whether commercial consumers (or firms) respond to average or marginal electricity prices. Our findings provide important implications for conservation policies that target commercial consumers.

The smart meter data enable us to construct individual-consumer-level daily panel data for 597 commercial accounts in the study area from May 1, 2013 to December 31, 2016. Our study examines a decreasing block pricing structure for commercial consumers in Phoenix metropolitan, Arizona. In this price plan, the marginal price drops when a consumer's cumulative consumption within a given month reaches 350 kWh, 530 kWh, and 685 kWh. Additionally, the marginal prices vary in summer, summer peaks, and winter. Based on a large sample of daily panel data, we analyze 684,569 observations from 597 commercial consumers across different cutoff levels. Having a larger sample size results in more reliable and generalizable results.

Our empirical analysis shows that commercial consumers respond to both marginal and average prices, but respond differently depending on how much electricity they consume. Higher-usage consumers tend to respond more to average prices, whereas lower-usage consumers are more sensitive to marginal prices. First, we examine whether electricity consumption shows discontinues at the kink points in the nonlinear price schedule. If commercial consumers perceive marginal prices, such discontinuity will be observed. The consumption distribution plots by season and by industry reveal obvious discontinuities at cutoff points. Second, we run two-stage least squares (2SLS) models with policy-induced instrumental variables to estimate the effects of marginal and average prices on commercial electricity consumption at each cutoff point. Instrumental variables are used to eliminate heterogeneity issues. The polynomial of midway daily consumption is also included to address the mean reversion problem. Our analyses suggest that both marginal and average prices appear to affect daily electricity consumption significantly. Marginal price effects are stronger at the first two cutoffs, whereas average price effects are stronger at the last. Third, the heterogeneity of industrial responses to marginal and average prices is also examined. We find that nonlinear pricing can be effectively applied to reduce aggregate consumption in the construction, manufacturing, real estate, and rental and leasing industries, professional, scientific, and technical services, other services (except public administration), and public administration industries. A robustness test is conducted within a three-day and a four-day windows. The results of both windows confirm the robustness of our main model. We also conduct a falsification test to check whether consumption changes at random cutoffs elsewhere. It shows continuous consumption at random cutoffs, confirming the responsiveness of commercial consumers to marginal prices. Finally, we conclude by offering a few suggestions for policymakers regarding energy conservation.

## 2. Material and methods

### 2.1. Data

The Salt River Project (SRP) provides electricity to the Phoenix metropolitan area in Arizona. Commercial consumers can choose from time-of-use plans, pre-pay plans, and tiered decreasing block plans at SRP. This paper uses a four-tiered price plan, which provides a decreasing block pricing for commercial consumers. Marginal prices decline when cumulative consumptions reach a certain threshold, which provides the opportunity to examine marginal price variation in relation to consumer behavior. Moreover, the price levels vary with the season.[1] Summer billing cycles include May, June, September, and October. Summer peak billing occurs from July to August. The winter billing cycle is from November through April. Table 1 displays the pricing schedule of the plan in different seasons. In the summer peak, the unit price for electricity in the first block is the most expensive. Table 2 presents the number of accounts and total observations in each industry sector (defined by the first two digits of NAICS code). There are 22 industry sectors included in our study, enabling us to conduct a heterogeneity analysis on a sector-by-sector basis so that we can verify whether the results are consistent across industries. Consider a commercial consumer who discover the marginal price will decline in the next block and whose monthly cumulative consumption is approaching one of the thresholds. Will they pay attention and respond by suddenly increasing their daily consumption until the next threshold is exceeded? If the answer is yes, then commercial consumers are responding to marginal prices.

**Table 1**
The seasonal price level of the decreasing block price plan.

| | First 350 kWh | Next 180 kWh | Next 155 kWh | All Add'l kWh |
|---|---|---|---|---|
| Summer | \$0.0973/kWh | \$0.0934/kWh | \$0.0779/kWh | \$0.0563/kWh |
| Summer peak | \$0.1189/kWh | \$0.1067/kWh | \$0.0884/kWh | \$0.0662/kWh |
| Winter | \$0.0758/kWh | \$0.0718/kWh | \$0.0652/kWh | \$0.0487/kWh |

We collected individual-level hourly electricity consumption data for 1,417 commercial accounts (32,131,637 observations) from the Salt River Project (SRP) from May 1, 2013 to December 31, 2018 in Phoenix metropolitan, Arizona. The data includes account number, date, rate plan, specific hour, NAICS (North American Industry Classification System) code, zip code, and hourly consumption for each account. We merge our data with heating degree days (HDD) and cooling degree days (CDD) by matching zip codes with temperature data. We then convert the hourly data into daily data by aggregating hourly consumption.

### 2.2. Empirical strategy

#### 2.2.1. Data preprocessing

Preprocessing data involves the following steps. First, it begins by selecting the consumers from the decreasing block plan, which gives us 1,015 commercial accounts (1,044,840 observations). Second, we delete accounts with missing zip codes because our method of obtaining temperature data involves merging daily heating degree day (HDD) and cooling degree day (CDD) based on zip codes. This step removes 232,609 daily observations. Third, we focus on commercial consumers that are still operating. Due to this, we exclude those commercial accounts with zero electricity consumption for at least 90 days.[2] This step removes 68,577 observations. Fourth, since we intend to use the first-difference equation involving on-the-same-day data from the prior year, we utilize commercial accounts with panel data for more than one year. This step removes 11,080 observations. Fifth, we exclude accounts with daily

[1] See E−36 rate plan from SRP's Standard Electric Price Plans Effective with the May 2019 Billing Cycle. March 26, 2019. Salt River Project Agricultural Improvement and Power District. https://www.srpnet.com/assets/srpnet/pdf/price-plans/electric-pricing-public-process/PP2019_FinalLG.pdf.

[2] Bankruptcy is the subject of this step. Zero electricity consumption for a period of over 90 days is considered bankruptcy, so we remove these accounts in data preprocessing.

**Table 2**
The number of accounts by industry sector.

| Industry sector[a] | First two digits of NAICS codes | No. of accounts | Observations |
|---|---|---|---|
| Agriculture, Forestry, Fishing and Hunting | 11 | 2 | 3234 |
| Utilities | 22 | 35 | 48,153 |
| Construction | 23 | 34 | 35,987 |
| Manufacturing | 31 | 4 | 4181 |
| Manufacturing | 32 | 7 | 7501 |
| Manufacturing | 33 | 10 | 12,125 |
| Wholesale Trade | 42 | 11 | 12,461 |
| Retail Trade | 44 | 33 | 34,817 |
| Retail Trade | 45 | 13 | 14,745 |
| Transportation and Warehousing | 48 | 6 | 6014 |
| Transportation and Warehousing | 49 | 6 | 6510 |
| Information | 51 | 22 | 31,597 |
| Finance and Insurance | 52 | 18 | 18,944 |
| Real Estate and Rental and Leasing | 53 | 118 | 130,721 |
| Professional, Scientific, and Technical Services | 54 | 19 | 19,203 |
| Administrative and Support and Waste Management and Remediation Services | 56 | 13 | 14,881 |
| Educational Services | 61 | 7 | 7015 |
| Health Care and Social Assistance | 62 | 45 | 51,207 |
| Arts, Entertainment, and Recreation | 71 | 22 | 26,887 |
| Accommodation and Food Services | 72 | 24 | 26,467 |
| Other Services (except Public Administration) | 81 | 107 | 134,612 |
| Public Administration | 92 | 12 | 13,738 |

[a] The sector definition are from United Stated Census Bureau (https://www.census.gov/programs-surveys/economic-census/guidance/understanding-naics.html).

**Table 3**
Summary statistics.

| Variable | Description | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Y (kWh/day) | Daily electricity consumption | 103.47 | 192.08 | 0.00 | 1708.45 |
| MP ($/kWh) | Marginal price | 0.07 | 0.02 | 0.00 | 0.12 |
| AP ($/kWh) | Average price | 0.08 | 0.02 | 0.00 | 0.12 |
| $\Delta ln$ MP (%) | Policy-induced instrument for marginal price | −0.01 | 0.29 | −0.89 | 0.89 |
| $\Delta ln$ AP (%) | Policy-induced instrument for average price | −0.01 | 0.29 | −0.87 | 0.87 |
| Midway daily consumption (kWh/day) | Daily consumption in the middle period | 100.63 | 185.61 | 0.00 | 1707.62 |
| Monthly consumption (kWh/month) | Cumulative consumption by month | 1548.06 | 3312.56 | 0.00 | 46358.64 |
| HDD (°F) | Heating degree day | 1.86 | 4.18 | 0.00 | 41.13 |
| CDD (°F) | Cooling degree day | 14.06 | 12.19 | 0.00 | 40.17 |
| Holiday | Coded 1 if it is a federal holiday, coded 0 otherwise | 0.03 | 0.16 | 0.00 | 1.00 |
| Weekend | Coded 1 if it is weekend, coded 0 otherwise | 0.14 | 0.35 | 0.00 | 1.00 |
| Firm size | Coded 1 for a small firm, 2 for a middle firm, and 3 for a large firm [a] | 1.97 | 0.72 | 1.00 | 3.00 |

[a] Small firms with monthly consumption below 25% quantile, 103.43 kWh, are coded 1, while large firms with monthly consumption above 75% quantile, 1478.84 kWh, are coded 3. The remainder is classified as middle firms and is coded 2.

consumption exceeding two standard deviations from averages of individual, industry, and billing cycle. This step removes 70,358 observations. Lastly, we calculate the cumulative bills by day based on marginal prices and cumulative consumption, then divide the cumulative bills by cumulative consumption to determine the average price.

In summary, this study examines individual-consumer-level daily electricity consumption for 597 commercial accounts in Phoenix metropolitan, Arizona, between May 1, 2013 to December 31, 2016, containing 684,569 observations. Summary statistics are provided in Table 3. The average daily consumption is 103.47 kWh/day.

### 2.2.2. *Instrumental variables*

Our goal is to quantify the causal effects of changes in marginal and average electricity prices on commercial electricity consumption. A critical problem with tiered pricing is that the marginal or average price is determined by the cumulative consumption of each month. Thus, price variables correlate with daily consumption, cumulative consumption, and error terms, causing endogeneity issues. It can be solved using instrumental variables, calculated as follows:

$$\Delta \ln MP_{id} = \ln MP_d(monthly\ consumption_{id}) - \ln MP_{d_m}\left(monthly\ consumption_{id_m}\right) \tag{1}$$

$$\Delta \ln AP_{id} = \ln AP_d(monthly\ consumption_{id}) - \ln AP_{d_m}\left(monthly\ consumption_{id_m}\right) \tag{2}$$

where $\Delta \ln MP_{id}$ and $\Delta \ln AP_{id}$ represent the instrumental variables for consumer $i$ on day $d$, measuring the policy-induced changes in marginal price and average price. As the tiered price changes according to cumulative consumption in a given month, the calculation of price instruments depends on cumulative consumption by month $monthly\ consumption_{id}$ and its corresponding marginal price $MP_d(monthly\ consumption_{id})$. Researchers commonly use $monthly\ consumption_{id_0}$ as the baseline consumption. Yet, if using $d_0$ as the baseline day, $monthly\ consumption_{id_0}$ is still correlated with the error term for causing the mean reversion problem by establishing a negative correlation in first-differenced equations for instruments. Consumption in the middle period $monthly\ consumption_{id_m}$ is recommended to address the mean reversion problem. Since we are using daily data, the middle period $d_m$ is calculated by $d_m = d - 182$ (because 182 days make up half of a year). These instruments are commonly used in previous studies (Blomquist and Selin, 2010; Saez et al., 2012; Ito, 2014).

### 2.2.3. *Two-stage least squares (2SLS) regressions*

Using daily panel data, we investigate the effects of changes in marginal and average price on the daily consumption of electricity among commercial consumers $\Delta lny_{id}$. The first differences can control confounding consumer-level factors such as building characteristics, business operations, building occupancy, and firm revenue. We conduct the following Two-Stage Least Squares (2SLS) regressions. A 2SLS model can be employed to calculate IV estimates. Equation (3) is the 2SLS model for marginal and average price effects. $\widehat{lnMP}_{id}$ is the predicted value of percentage changes in marginal price derived from equation (4). $\widehat{lnAP}_{id}$ is the predicted value of percentage changes in average price derived from equation (5).

$$\Delta \ln Y_{id} = \alpha \widehat{lnAP}_{id} + \beta \widehat{lnMP}_{id} + f\left(midway\ daily\ consumption_{id_m}\right) + \gamma X_{id} + \mu_{id} \tag{3}$$

$$\widehat{lnMP}_{id} = \rho\Delta lnMP_{id} + \delta\Delta lnAP_{id} + f(midway\,daily\,consumption_{id_m}) + \Phi X_{id} + \omega_{id} \quad (4)$$

$$\widehat{lnAP}_{id} = \sigma\Delta lnMP_{id} + \lambda\Delta lnAP_{id} + f(midway\,daily\,consumption_{id_m}) + \Omega X_{id} + \varepsilon_{id} \quad (5)$$

where $Y_{id}$ denotes consumer $i$'s daily electricity consumption on day $d$. The first-order difference term is calculated as $\Delta \ln Y_{id} = \ln Y_{id} - \ln Y_{id_0}$, where $d_0$ is the same day of the prior year. We include the logarithm terms to rescale the variables concerned into a normal distribution. Let $MP_{id}$ and $AP_{id}$ denote the marginal price and average price of consumer $i$ on day $d$, and let $\Delta \ln MP_{id}$ and $\Delta \ln AP_{id}$ denote the policy-induced marginal price and average price change. Since we use daily panel data, the cubic polynomial of midway consumption at the daily level $midway\ daily\ consumption_{id_m}$ is included to control for unobservable factors that can cause consumption changes.[3] Middle period $d_m$ is calculated by $d_m = d - 182$. $X_{id}$ is a vector of control variables including HDD, CDD, holiday indicator, weekend indicator, and firm size, plus zip-code-by-year fixed effects, billing-cycle-by-month fixed effects, day-of-month fixed effects, and day-of-week fixed effects. Specifically, HDD is heating degree day measured by 65-temperature, while CDD is cooling degree day measured by temperature-65.[4] Federal holidays and weekends are measured by dummy variables. We include firm size in our analysis because larger firms might have more workers and larger offices, resulting in higher energy consumption and different responses to price changes. However, the SRP data does not include any information about firm size. Accordingly, we classify commercial accounts based on monthly cumulative consumption into small, middle, and large firms. A company with monthly consumption below 25% quantile, 103.43 kWh, is considered a small firm, whereas a company with monthly consumption above 75% quantile, 1478.84 kWh, is considered a large firm. The rest are classified as middle firms. Zip-code-by-year fixed effects account for time-variant confounding factors at the firm level, such as management policies and environmental awareness, that might have an impact on a firm's electricity demand. Consumers with different billing cycles may experience slightly different weather impacts, so we control for effects by including billing cycle-by-month fixed effects. Let $\mu_{id}$, $\omega_{id}$, and $\varepsilon_{id}$ be the error terms for unobservable effects.

Besides aggregate consumption information, we also analyze consumer responses for specific thresholds based on consumption data near three thresholds. First, we run a 2SLS model based on aggregate price changes using all observations. Second, we run 2SLS models for the consumption levels near each threshold based on the selected data. We select an equidistance from each cutoff for the upper and lower limits, i.e., 50 kWh from each cutoff. Thus, the selected observations are cumulative consumption in the range (300 kWh, 400 kWh), (480 kWh, 580 kWh), and (635 kWh, 735 kWh) that contain the three thresholds, respectively. We did not use 100 kWh from the cutoffs as the basis for grouping to avoid overlap between different groups. We also provide the testing results of IV validity.

### 2.2.4. Heterogeneity analysis

To look at heterogeneous responses across industries, we run the same 2SLS model by industry sector to determine whether the results are consistent across industries and whether there is any difference in their response to marginal and average prices. Industry sectors with fewer than five commercial accounts are excluded in this step.

### 2.2.5. Robustness check

Daily data enable us to track each account's crossing day at each cutoff within a given month. By restricting the time sample to a small window around the crossing day, we can ensure that some other factors, such as firm revenue, business operations, and building occupancy, are unlikely to change during the short time period. We set two kinds of windows for each threshold: a window of three days before and three days after the crossing day, and a window of four days before and four days after the crossing day. We use daily consumption in the two windows when consumers cross each cutoff to run the same 2SLS model.

### 2.2.6. Falsification test

To assess the validity of the main results, a random cutoff is set for every 200 kWh of cumulative consumption. The chosen thresholds are 400 kWh, 600 kWh, and 800 kWh. As marginal and average prices are completely equal before consumption reaches 350 kWh, Stata omitted the results of average price change at a 200-kWh cutoff due to collinearity. Therefore, a cut-off of 200 kWh was not selected. We use the same method as our main model to make the falsification test comparable to our findings. Insignificant coefficients at the randomly selected cutoff points will support our conclusion that discontinuity occurs only at 350-kWh, 530-kWh, and 685-kWh, suggesting that commercial consumers' electricity consumption changes due to marginal prices.

## 3. Theory

Our theoretical framework is illustrated in Fig. 1. In the decreasing block rate, there are four tiers of marginal price $P(y)$. The marginal price is $P_1$ when consumption $y \le 350\,kWh$, $P_2$ when $350\,kWh < y \le 530\,kWh$, $P_3$ when $530\,kWh < y \le 685\,kWh$, $P_4$ when consumption $y > 685\,kWh$. Consumers will make the optimal decision to maximize their net benefits. As demonstrated in Fig. 1, from the first block to the last, marginal prices experience greater price change ($\Delta p_1$) than average prices ($\Delta p_2$), which may incentivize more electricity consumption $\Delta y_2$ under the same demand curve.

There are two conditions that consumers must meet in order to respond to marginal prices: (1) consumers need to fully comprehend how nonlinear pricing works; (2) consumers need access to real-time data and are capable of calculating real-time monthly consumption (the cumulative sum of daily consumption). As for the first condition, Liebman and Zeckhauser (2004) assert that consumers respond more to the average price rather than the marginal price since calculating the average price requires less effort (all it takes is total payment and quantity). As for the second condition, Saez (2010) and Borenstein (2009) claim that it is impractical for consumers to know their real-time

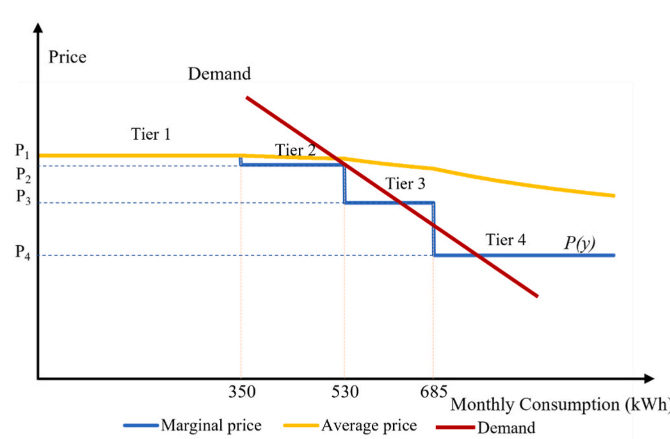


**Fig. 1.** Theoretical framework.

[3] We conduct a robustness check regarding the polynomial function of midway consumption $midway\ daily\ consumption_{id_m}$ to show that the form of $f(midway\ daily\ consumption_{id_m})$ does not change the results (see Appendix C). In the main model, we use the cubic function of midway consumption.

[4] Daily temperature data is derived from the National Oceanic and Atmospheric Administration (NOAA)'s Local Climatological Data (https://www.ncdc.noaa.gov/cdo-web/datatools/lcd).

consumption because of random fluctuations in consumption. Besides, consumers may not have access to the technology that enables them to monitor their electricity consumption (Saez, 2010; Borenstein, 2009).

For the consumers in our analysis, though, they do have online account profiles that provide real-time electricity consumption at the hourly level. Consumers can log in to their accounts and access such information, which implies that they can calculate their marginal price based on such real-time electricity consumption information.

## 4. Results

This section discusses the results of the main specifications. Appendix B also shows the robustness check results using data within three and four days of the crossing days to support our main results.

### 4.1. Descriptive evidence about the commercial response to marginal prices

We first provide visual evidence to highlight the daily electricity consumption discontinuities at the cutoff points. Based on Stata's *rdmc* command, the default MSE-optimal bandwidth selector chooses 25, 22, and 22 as the optimal bandwidth for cutoff 350-kWh, 530-kWh, and 685-kWh, respectively. Fig. 2 depicts the daily consumption plots for RDD (regression discontinuity designs) by billing cycle when cumulative consumption reaches the 350-kWh, 530-kWh, and 685-kWh cutoffs. The blue, red, and green dotted lines represent the thresholds of 350-kWh, 530-kWh, and 685-kWh, respectively. In addition to season-based plots, we also visualize the aggregate plot without season division. Fig. 2 indicates that commercial consumers might respond to marginal price, evidenced by the discontinuities in daily consumption at the cutoff points. Seasonal and aggregate plots display similar patterns. There is a gradual increase in daily consumption as the monthly cumulative consumption increases, possibly due to the decreasing-block pricing that motivates the use of electricity on a daily basis. Moreover, we can see from Fig. 2 that only the daily consumption in winter changes from 40 kWh to 60 kWh, while other seasons have larger maximum consumption of 80 kWh. It is possible that people tend to stay at home during the winter months, so commercial consumers, such as malls, consume less electricity than on warmer days.

North American Industry Classification System (NAICS) codes are used to identify business sectors, with their first two digits indicating the type of industry. Accordingly, we use the first two digits of NAICS codes to compare industry differences in response to marginal price changes. A total of 597 commercial accounts come from 22 sectors in our dataset. We present in Fig. 3 a preliminary RDD (regression discontinuity designs) plot by industry which illustrates how tiered pricing structures affect consumption behavior by causing discontinuities in daily energy consumption, indicating that commercial consumers pay attention to marginal price changes. Consumption discontinuity implies that the marginal price variations at cutoffs induce consumption changes in the commercial sector, which can be interpreted as a reaction to marginal price changes. We may observe from Fig. 3 that agriculture, forestry, fishing and hunting, utilities, professional, scientific, and technical services, administrative and support and waste management and remediation services, and other services (except public administration) have lower energy consumption than other industries due to their industry type—they are not dependent on electricity. On the other hand, manufacturing, wholesale trade, transportation and warehousing, educational services, and accommodation and food services industries have higher upper limits of daily consumption, due to their usual operating hours of all night. Following the figures obtained from visualization tools, we will present empirical evidence regarding the commercial demand response through regression analysis.

### 4.2. Overall impacts of the marginal and average price

Our primary goal is to study whether and how daily electricity consumption changes in response to marginal or average price changes. Table 4 presents the results of the 2SLS regressions as shown in equation (3), while Fig. 4 depicts the 2SLS estimates of coefficients in graphical form. In Fig. 4, hollow circles indicate the coefficient values, dark orange for $\beta$ (the coefficient of changes in marginal prices) and forest green for $\alpha$ (the coefficient of changes in average prices). Error bars represent 95% confidence intervals. If a bar intersects the zero line, it implies a nonsignificant coefficient. Both marginal and average price changes have a statistically significant negative coefficient, indicating that

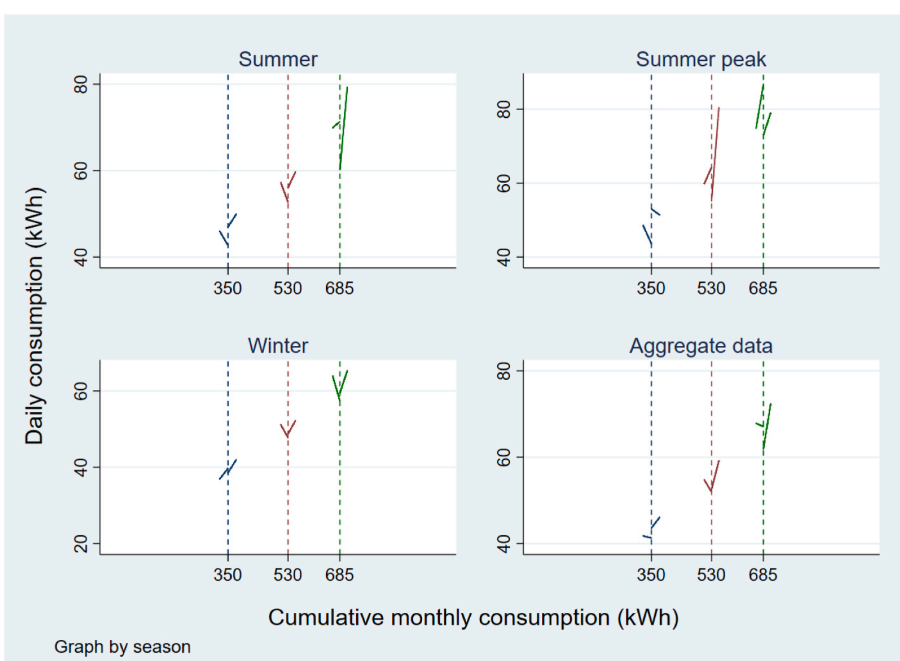


**Fig. 2.** Plots of regression discontinuity designs for electricity consumption by billing cycle. Notes: We use only observations with cumulative consumption of less than 1000 kWh for generating this figure, so we can concentrate on the consumption response when crossing the cutoffs.

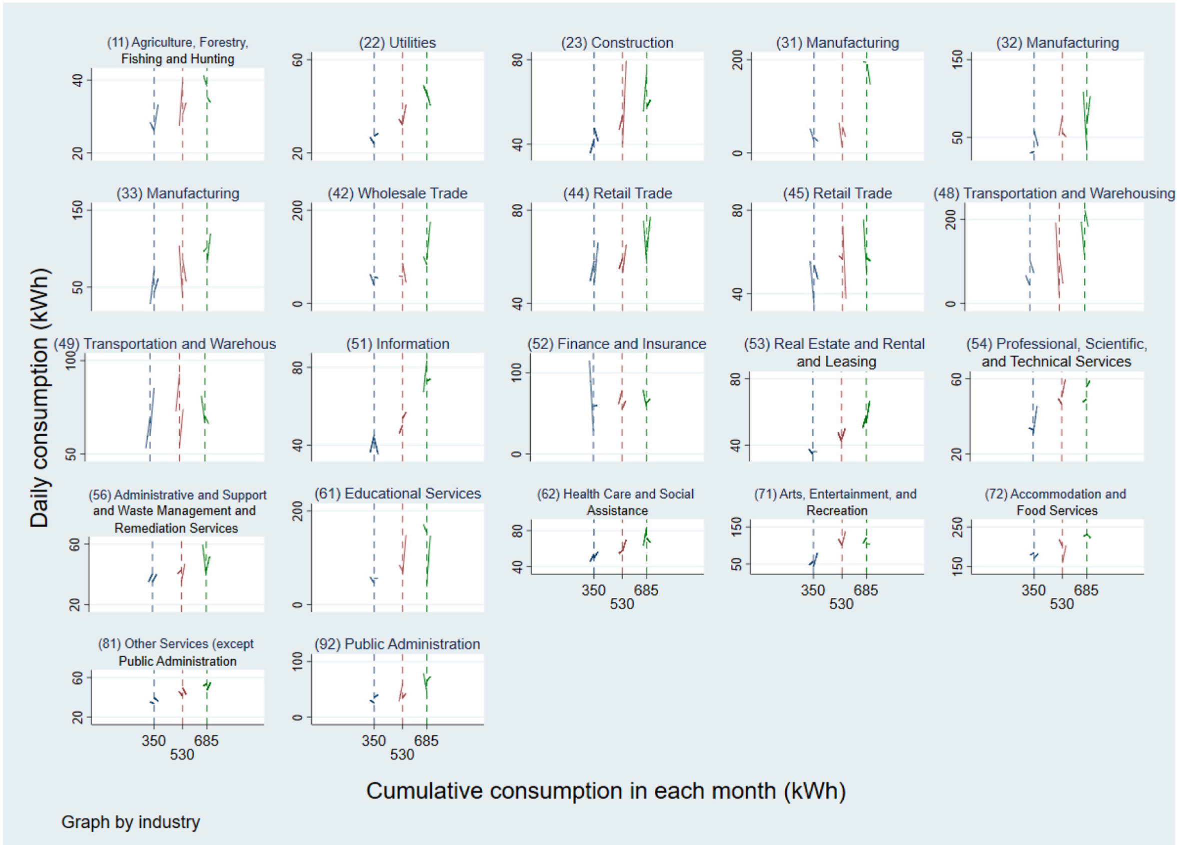


**Fig. 3.** RDD plots for electricity consumption by industry sector. Notes: the subtitle of each figure panel includes the two-digit NAICS code (in parenthesis) and industry sector. Only data less than 1000 kWh is used to concentrate on consumption changes near thresholds.

consumers' electricity consumption is negatively affected by marginal and average electricity prices. However, cutoff-based results demonstrate a different pattern of demand response. In the first two thresholds, marginal prices have a significant negative impact on consumers, but there is no such effect at the 685-kWh threshold. The average price has abnormally positive impacts on energy consumption at 350 kWh cutoff (possibly due to strong collinearity with marginal prices), has no significant impacts at 530 kWh cutoff, but shows a significant negative impact at 685 kWh cutoff. These results imply that lower-usage consumers are more sensitive to marginal prices, whereas high-use consumers who consume no less than 685 kWh per month are more sensitive to average prices. It could be because, for large electricity consumers, decreasing-block pricing becomes a relatively linear pricing schedule that charges them at tier 4—the lowest marginal price rate for a significant amount of time of a month. They are less concerned about marginal pricing as their consumption increases.

Table 4 presents the detailed results of 2SLS regressions using aggregate data and consumption data close to the three thresholds. Each model also includes the cubic equation of *midway daily consumption*$_{id_m}$. Based on aggregate results from model 1, the price elasticity with respect to marginal price is −0.370. If the marginal price declines by 10%, daily consumption will increase by 3.07%. According to aggregate results from model 1, the price elasticity with respect to average price is −0.289. If the average price decreased by 10%, daily consumption would rise by 2.89%. From an aggregate perspective, the marginal price elasticity is larger than the average price, suggesting that commercial consumers respond more to the marginal price than the average price.

Models 2–4 use cumulative consumption in the range (300 kWh, 400 kWh), (480 kWh, 580 kWh), and (635 kWh, 735 kWh), which contains three thresholds in each. Models 2 and 3 have marginal price elasticities of −2.787 and −0.510 at 350-kWh and 530-kWh cutoffs, respectively. A 10% drop in the marginal price increases consumption by about 27.87% for commercial consumers near the 350-kWh cutoff, and by about 5.10% for consumers near the 530-kWh cutoff. In contrast, at a 350-kWh cutoff, average prices have an abnormally positive effect on daily consumption. Possibly, this counterintuitive result is due to strong collinearity between marginal and average price changes (correlation coefficient of 0.89). At the 530-kWh cutoff, average prices do not affect the daily amount of energy consumption. At both 350-kWh and 530-kWh cutoff points, marginal price changes are significantly more influential than average price changes, which implies marginal pricing has a larger impact on consumers with smaller electricity use. In model 4, marginal prices no longer have a significant effect on consumption around the 685 kWh cutoff, while the average price elasticity is −0.885. A 10% decline in average prices is associated with 8.85% increases in consumption at the 685-kWh cutoff, respectively. It indicates that as block pricing gets lower, average prices begin to dominate. The results around the 685-kWh cutoff suggest that large energy consumers are less sensitive to marginal prices. The reason could be that large electricity consumers know their monthly electricity usage will exceed the third cutoff and will be charged at tier four's lowest unit price. Therefore, they respond only to average prices, leaving little thought to marginal prices.

Existing studies have estimated the price elasticities for residential and commercial consumers. In the residential sector, the short-term price elasticity is −0.2, and the long-term price elasticity is −0.7, according to Bohi and Zimmerman (1984)'s survey data in the United States. Filippini (1999) estimates the residential price elasticity in 40 Swiss cities to be −0.30. Californian households have an annual electricity price elasticity of −0.39, as determined by Reiss and White (2005). The National Institute of Economic and Industry Research (2007) finds the long-run price elasticity of electricity for residential and commercial consumers in the Australian National Electricity Market is

**Table 4**
Impact of the marginal and average price change on daily electricity consumption.

| Model | Outcome: Natural log of daily consumption change % | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| | All | 350 kWh | 530 kWh | 685 kWh |
| *ln* MP (%) | −0.370*** | −2.787*** | −0.510** | −0.088 |
| | (0.062) | (0.807) | (0.166) | (0.065) |
| *ln* AP (%) | −0.289*** | 2.197** | −0.077 | −0.885*** |
| | (0.070) | (0.803) | (0.162) | (0.131) |
| Holiday | −0.072*** | −0.024 | −0.068 | −0.089* |
| | (0.008) | (0.032) | (0.036) | (0.036) |
| Weekend | −0.078*** | −0.113*** | −0.101*** | −0.128*** |
| | (0.013) | (0.023) | (0.021) | (0.027) |
| Firm size: Middle | −0.086** | N/A | N/A | N/A |
| | (0.027) | N/A | N/A | N/A |
| Firm size: Small | −0.367*** | N/A | N/A | N/A |
| | (0.061) | N/A | N/A | N/A |
| Midway daily consumption (kWh/day) | Cubic | Cubic | Cubic | Cubic |
| HDD (°F) | Yes | Yes | Yes | Yes |
| CDD (°F) | Yes | Yes | Yes | Yes |
| Individual fixed effects | Yes | Yes | Yes | Yes |
| Zip-code-by-year fixed effects | Yes | Yes | Yes | Yes |
| Billing-cycle-by-month fixed effects | Yes | Yes | Yes | Yes |
| Day-of-month fixed effects | Yes | Yes | Yes | Yes |
| Day-of-week fixed effects | Yes | Yes | Yes | Yes |
| *KP LM* | 313.889*** | 187.38*** | 239.44*** | 230.68*** |
| *KP Wald F* | 1.7e+04 | 131.134 | 684.64 | 1471.31 |
| Observations | 435337 | 23834 | 18098 | 13800 |

*Notes*: Standard errors in parentheses: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. The KP LM statistic is used for the under-identification test, while the KP Wald F statistic is used for the weak identification test. We can observe that the KP LM statistics are all statistically significant at a 99.9% confidence interval. The KP Wald F statistics are all greater than the critical value of 10% maximal IV size provided by the Stock-Yogo weak ID test.

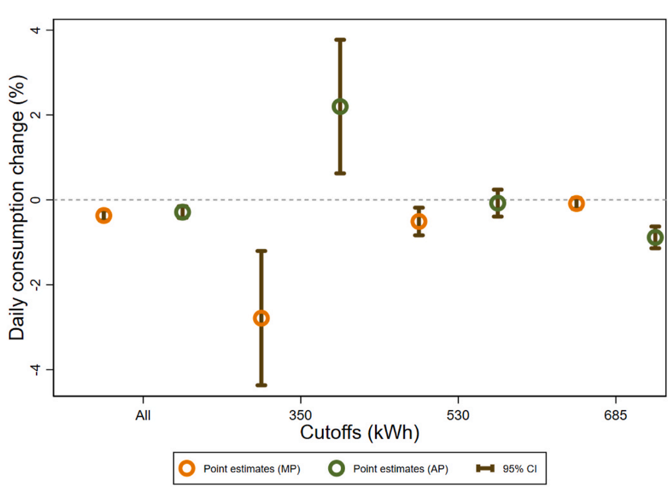


**Fig. 4.** Estimated effects of changes in marginal price and average price. Notes: The estimations are categorized by the cutoff. The term "aggregate data" refers to the use of all consumption data. "350 kWh" represents consumption in the range (300 kWh, 400 kWh), "530 kWh" indicates data in the range (480 kWh, 580 kWh), and "685 kWh" refers to the range (635 kWh, 735 kWh).

−0.25 and −0.35, respectively. As a result, the numbers that come up most often are −0.2 to −0.4 for short-run elasticity and −0.5 to −0.7 for long-run elasticity. According to our research, the marginal price elasticity on aggregate is −0.370, whereas the average price elasticity on aggregate is −0.289. Our short-run price elasticities are consistent with those in the existing literature.

Holiday coefficients are significantly negative in aggregate. During holidays, commercial consumers consume 7.2% less electricity than during non-holiday periods, possibly because all offices are closed during holidays. Weekend coefficients are similar for aggregate and cutoff-based models. Commercial consumers consume 7.8% less electricity during weekends than during weekdays. At three cutoff points, weekend consumption is 11.3%, 10.1%, and 12.8% lower than weekday consumption. The size of the firm is also taken into account in our models. The base case for our analysis is large firms. On average, midsize firms consume 8.6% less energy than large firms. A small firm consumes 36.7% less electricity than a large firm.

In our method, we include only one IV in each equation, the just-identified case. Stata's *xtivreg2* command automatically tests for both under-identification and weak identification. First, the under-identification test is designed to test if the excluded instruments are irrelevant, meaning not associated with the endogenous variables. The Kleibergen-Paap rk LM statistic is reported for the under-identification test. The null hypothesis is that the model is under-identified. In Table 4, all Kleibergen-Paap rk LM statistics are statistically significant, rejecting the null hypothesis and suggesting that the IVs for marginal and average pricing are identified. Second, weak identification occurs when the excluded variables are weakly correlated with the endogenous regressors, resulting in poor estimator performance (Stock and Yogo, 2005). We use the Kleibergen-Paap Wald rk F statistic for the weak identification test as we invoke *xtivreg2* with robust and cluster options. *Xtivreg2* also reports Stock-Yogo critical values for F statistic ranging from 10% to 25% maximal IV size. According to Staiger and Stock (1997), an IV is not weak if its F statistic is above the Stock-Yogo critical value for a 10% maximum IV size. Kleibergen-Paap Wald rk F statistics for models in Table 4 are all greater than the critical value for a 10% maximum IV size, indicating that the IVs are not weak.

### 4.3. Heterogeneity analysis

Fig. 5 illustrates the results. In the following texts, the number in parentheses represents the first two digits of the NAICS code which defines the industry sector. These industries are generally more sensitive to marginal price changes than other industries: (23) construction, (32) manufacturing, (53) real estate and rental and leasing, (54) professional, scientific, and technical services, (81) other services (except public administration), and (92) public administrations. Utility industry does not respond to marginal or average prices as a whole, but is more sensitive to marginal price change at 530-kWh cutoff. While these industries generally respond to average prices, they are more sensitive to marginal price changes at certain cutoffs: (33) manufacturing, (44) retail trade, (51) information, (61) educational services, (62) health care and social assistance. The following industries respond more to average prices: (45) retail trade, (52) finance and insurance, (71) arts, entertainment, and recreation, and (72) accommodation and food services. Neither marginal nor average prices affect the rest of the industry sectors in aggregate or at specific cutoffs.

In Fig. 5, the marginal and average price elasticities are often smaller than −1. The absolute value of our industrial price elasticities is larger than short-run price elasticity in the existing literature (−0.2 to −0.4), potentially for two reasons. First, we are examining higher-frequency consumption changes and focusing on commercial consumers. Second, in contrast to household electricity pricing, where blocking prices are increasing, block prices for commercial buildings are decreasing. Possibly, this explains why commercial findings are different from those found in household studies.

### 4.4. Robustness check

Fig. 6 shows that results using three-day and four-day windows are

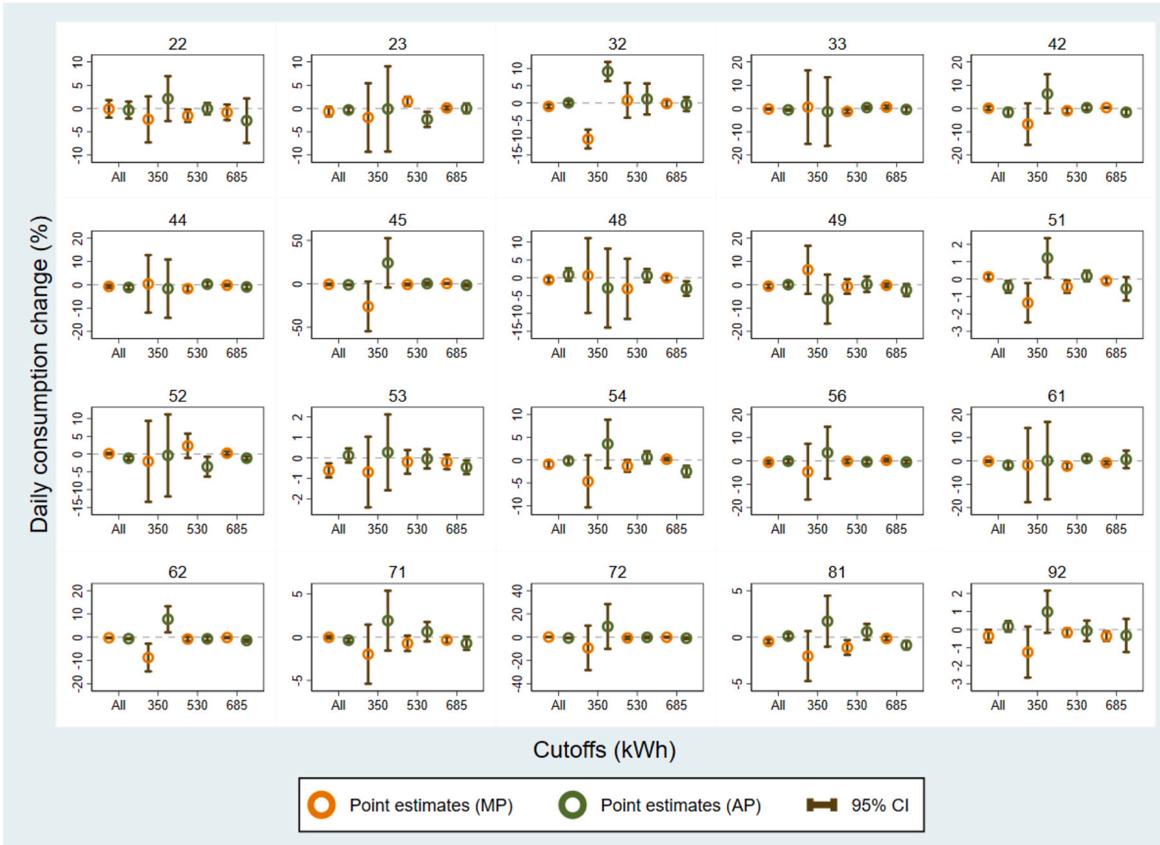


**Fig. 5.** Coefficient plots of each industry sector (See Table 1 for the definition of NAICS code, the number of accounts, and observations of each industry sector). Notes: industry sectors with no more than 5 commercial accounts are excluded. For some industries, the regression results show abnormally positive effects of average price changes due to strong collinearity between marginal and average price change (with a correlation coefficient of 0.89).

identical to our main results, confirming the robustness of our findings. In aggregate, we observe larger absolute values for marginal prices than for average prices. At the first two cutoffs, marginal prices remain significantly negative, but do not have a significant effect at the last cutoff, while average prices are only significantly negative at the 685-kWh cutoff. The marginal price variation exerts stronger effects at 350-kWh and 530-kWh cutoffs, while it exerts weaker effects at 685-kWh cutoff. As a result, the robustness check supports our main findings. In Appendix A, Table A1 presents detailed results for the three-day and four-day windows at each threshold.

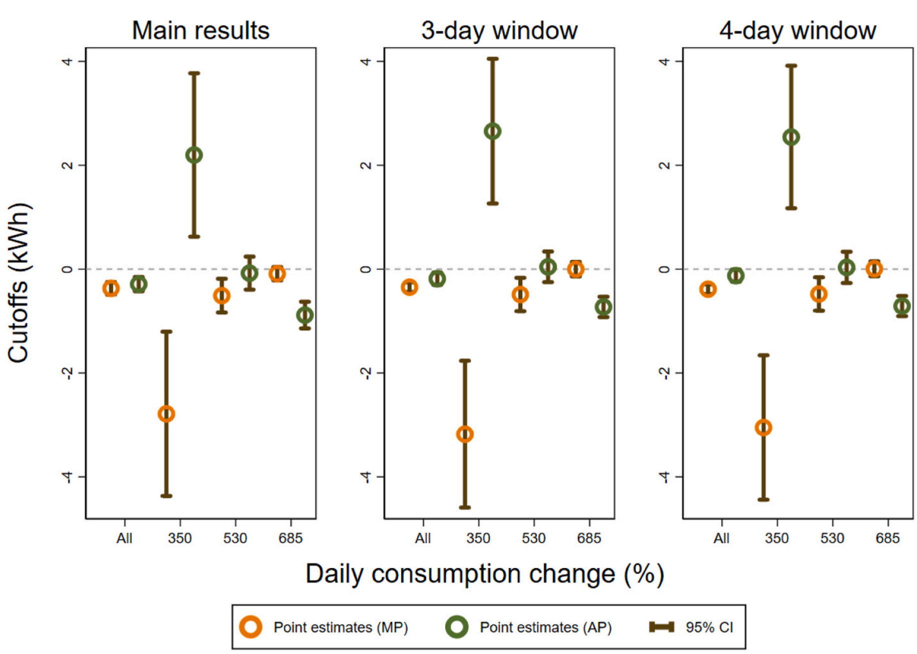


**Fig. 6.** Comparing estimated effects of price changes in main results to robustness check using three-day and four-day windows at each cutoff. Notes: The estimations are categorized by cutoff. The term “aggregate data” refers to the use of all consumption data. “350 kWh” represents consumption in the range (300 kWh, 400 kWh), “530 kWh” indicates data in the range (480 kWh, 580 kWh), and “685 kWh” refers to the range (635 kWh, 735 kWh). There are two error bars for each group, representing the 95% confidence intervals. Hollow circles on the bars indicate the coefficients’ values that represent the change in electricity consumption in response to marginal or average price changes. Dark orange circles represent marginal price changes. Forest green circles represent average price changes.

### *4.5. Falsification test*

A summary of the falsification test results is provided in Fig. 7 below (see Appendix B for detailed results in Table B1). We found no significant coefficients in any randomly selected cutoff points. This suggests that discontinuity occurs only at 350-kWh, 530-kWh, and 685-kWh, which supports our conclusion that commercial consumers' electricity consumption changes due to marginal prices.

## 5. Discussion

It is essential for policymakers to understand how consumers react to nonlinear pricing in order to evaluate the effectiveness of any policy intervention that can influence energy prices. This study adds three contributions. Firstly, our empirical findings expand on the previous discussion of commercial buildings' demand response to electricity price. We provide the first empirical evidence on whether commercial consumers respond to marginal prices or average prices. Research on electricity demand provides mixed results on whether consumers respond to marginal price changes, given the potential cause of information costs. The existing discussion focuses more on residential consumers. Ito (2014) demonstrates that consumers do not respond to marginal prices when they face substantial information costs; instead, they take average prices as a proxy for consumption behavior. However, there are no comparable studies examining commercial electricity consumers (such as office buildings and shopping malls), despite the fact that these consumers account for almost 18% of electricity consumption in the United States.

Secondly, the use of four-tiered pricing schedules allows us to investigate different responses to marginal prices based on various cutoff levels. Our empirical approach eliminates endogeneity by introducing policy-induced instrumental variables. In addition, the polynomial of midway consumption is introduced to avoid the mean reversion issue. With 2SLS regressions incorporating instrumental variables, we can consistently estimate the impact of marginal and average prices on daily electricity consumption behaviors at each cutoff in a nonlinear pricing schedule. Our large sample of individual-consumer-level daily panel data, including 684,569 observations (597 commercial consumers), also enables more convincing and representative findings. On the basis of our findings, policymakers could optimize policies by focusing more on the critical and influential factors involved in electricity consumption management in the commercial sector.

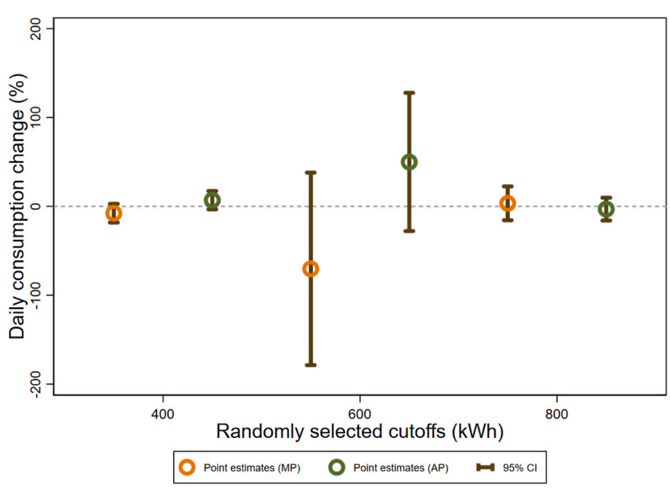


**Fig. 7.** Plots of falsification tests by season at 400-kWh, 600-kWh, and 800-kWh cutoffs.

Thirdly, policymakers should have a thorough understanding of how different industry sectors react to nonlinear electricity pricing. In this paper, we present a more comprehensive analysis of heterogeneous responses across different industry sectors. We find that nonlinear pricing would have the potential to reduce aggregate consumption effectively in construction, manufacturing, real estate and rental and leasing, professional, scientific, and technical services, other services (except public administration), and public administration industries. While these industries generally respond to average prices, they are more sensitive to marginal price changes at certain cutoffs: manufacturing, retail trade, information, educational services, health care and social assistance. The following industries respond only to average prices: retail trade, finance and insurance, arts, entertainment, and recreation, and accommodation and food services. Undertake a heterogeneous analysis of demand responses across industries is necessary for policymakers to tailor conservation policies for different industries.

Despite its strengths, this paper has some limitations. The study investigates a decreasing-block pricing schedule and concludes that marginal prices can effectively influence the electricity consumption of small-usage consumers. In contrast to household electricity pricing, where blocking prices are increasing, block prices for commercial buildings are decreasing. Possibly, this explains why commercial findings are different from those found in household studies. A study of increasing block prices might yield different results.

## 6. Conclusions

This study provides empirical evidence to show that commercial consumers' responses to electricity prices differ with respect to their amount of cumulative consumption. Lower-usage consumers are more sensitive to marginal prices, whereas higher-usage consumers, whose cumulative consumptions are no less than 685 kWh per month, respond more to average prices. It is possible because, for high-use electricity consumers, decreasing-block pricing becomes a relatively linear pricing schedule that charges them at the lowest marginal price rate (namely tier 4) for a significant amount of time in a month. Thus, the real-time marginal prices do not matter much to these firms. Lower-usage consumers, on the other hand, are more price sensitive.

Our findings concerning decreasing block pricing in Arizona have important implications for policymakers. The results of our analysis indicate that conservation policies should be tailored differently for commercial electricity consumers. Contrary to what has been found for residential electricity consumers who only respond to average price (Ito, 2014), commercial consumers are subject to marginal price responses. Thus nonlinear pricing would have the potential to reduce aggregate consumption effectively. Nonlinear electricity pricing structures can have a crucial impact on energy consumption and induce significant energy conservation, especially when applied to lower-demand commercial consumers if the pricing structure shifts from decreasing to increasing blocks. On the other hand, high-use consumers' electricity consumption can be constrained by a flat marginal rate pricing with a higher price level. When specific industry sectors are taken into account, aggregate consumption can be effectively reduced through nonlinear pricing in construction, manufacturing, real estate and rental and leasing, professional, scientific, and technical services, other services (except public administration), and public administration industries.

## Statement of data availability

The high-frequency electricity data are from the Salt River Project. As they are restricted by a non-disclosure agreement, they are available from the authors upon reasonable request and with permission from the SRP.

### CRediT authorship contribution statement

**Kaifang Luo:** Visualization, Formal analysis, Software, Validation, Writing – original draft. **Yueming (Lucy) Qiu:** Conceptualization, Methodology, Supervision, Investigation, Funding acquisition, Writing – review & editing. **Bo Xing:** Data curation.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

The data that has been used is confidential.

### Acknowledgment

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## Appendix. Robustness check: 3-day and 4-day windows

**Table A1**
Robustness check: results of 2SLS model in 3-day and 4-day windows at each cutoff.

| | 3-day window | | | | 4-day window | | | |
|---|---|---|---|---|---|---|---|---|
| | Aggregate data | 350 kWh | 530 kWh | 685 kWh | Aggregate data | 350 kWh | 530 kWh | 685 kWh |
| *ln* MP (%) | −0.347*** | −3.178*** | −0.489** | −0.001 | −0.386*** | −3.049*** | −0.479** | 0.007 |
| | (0.048) | (0.721) | (0.164) | (0.071) | (0.048) | (0.709) | (0.164) | (0.073) |
| *ln* AP (%) | −0.184** | 2.656*** | 0.044 | −0.728*** | −0.125* | 2.543*** | 0.033 | −0.711*** |
| | (0.060) | (0.711) | (0.150) | (0.100) | (0.060) | (0.700) | (0.153) | (0.099) |
| Holiday | 0.022 | 0.012 | −0.018 | −0.024 | 0.008 | 0.006 | −0.025 | −0.031 |
| | (0.013) | (0.036) | (0.030) | (0.033) | (0.012) | (0.035) | (0.030) | (0.033) |
| Weekend | −0.103*** | −0.109*** | −0.104*** | −0.123*** | −0.112*** | −0.113*** | −0.105*** | −0.118*** |
| | (0.023) | (0.025) | (0.024) | (0.031) | (0.024) | (0.025) | (0.024) | (0.030) |
| Firm size: Middle | −0.386*** | N/A | N/A | N/A | −0.329*** | N/A | N/A | N/A |
| | (0.046) | N/A | N/A | N/A | (0.038) | N/A | N/A | N/A |
| Firm size: Small | −0.688*** | N/A | N/A | N/A | −0.583*** | N/A | N/A | N/A |
| | (0.070) | N/A | N/A | N/A | (0.059) | N/A | N/A | N/A |
| Midway daily consumption (kWh/day) | Cubic | Cubic | Cubic | Cubic | Cubic | Cubic | Cubic | Cubic |
| HDD (°F) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| CDD (°F) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Zip code-by-year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Billing cycle-by-month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day-of-month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day-of-week fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 90786 | 20001 | 15547 | 11634 | 104387 | 20493 | 15666 | 11782 |

*Notes*: Standard errors in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

## *Appendix B. Falsification test*

**Table B1**
Falsification tests at 400-kWh, 600-kWh, and 800-kWh cutoffs.

| Model | Outcome: Natural log of daily consumption change (%) | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| | 400 kWh | 600 kWh | 800 kWh |
| *ln* MP (%) | −7.675 | −70.287 | 3.433 |
| | (5.370) | (55.249) | (9.718) |
| *ln* AP (%) | 6.992 | 49.948 | −3.072 |
| | (5.260) | (39.658) | (6.530) |
| Holiday | −0.005 | −0.064 | −0.120** |
| | (0.039) | (0.040) | (0.045) |
| Weekend | −0.120*** | −0.111*** | −0.114*** |
| | (0.024) | (0.028) | (0.033) |
| Midway daily consumption (kWh/day) | Cubic | Cubic | Cubic |
| HDD (°F) | Yes | Yes | Yes |
| CDD (°F) | Yes | Yes | Yes |
| Individual fixed effects | Yes | Yes | Yes |
| Zip-code-by-year fixed effects | Yes | Yes | Yes |
| Billing-cycle-by-month fixed effects | Yes | Yes | Yes |
| Day-of-month fixed effects | Yes | Yes | Yes |
| Day-of-week fixed effects | Yes | Yes | Yes |
| Observations | 22031 | 15940 | 11746 |

*Notes*: Standard errors in parentheses: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

## *Appendix C. Robustness check: the polynomial function of midway daily consumption*

**Table C1**
Robustness check using linear polynomial function of midway daily consumption.

| Model | Outcome: Natural log of daily consumption change (%) | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| | Aggregate | 350 kWh | 530 kWh | 685 kWh |
| *ln* MP (%) | −0.308*** | −1.785* | −0.276 | −0.022 |
| | (0.060) | (0.764) | (0.166) | (0.067) |
| *ln* AP (%) | −0.338*** | 1.195 | −0.266 | −0.898*** |
| | (0.068) | (0.756) | (0.160) | (0.130) |
| Holiday | −0.074*** | −0.027 | −0.066 | −0.083* |
| | (0.008) | (0.033) | (0.036) | (0.037) |
| Weekend | −0.080*** | −0.116*** | −0.103*** | −0.133*** |
| | (0.013) | (0.023) | (0.022) | (0.028) |
| Firm size: Middle | −0.072** | | | |
| | (0.027) | | | |
| Firm size: Small | −0.350*** | | | |
| | (0.061) | | | |
| Midway daily consumption (kWh/day) | Linear | Linear | Linear | Linear |
| HDD (°F) | Yes | Yes | Yes | Yes |
| CDD (°F) | Yes | Yes | Yes | Yes |
| Individual fixed effects | Yes | Yes | Yes | Yes |
| Zip code-by-year fixed effects | Yes | Yes | Yes | Yes |
| Billing cycle-by-month fixed effects | Yes | Yes | Yes | Yes |
| Day-of-month fixed effects | Yes | Yes | Yes | Yes |
| Day-of-week fixed effects | Yes | Yes | Yes | Yes |
| Observations | 435337 | 23834 | 18098 | 13800 |

*Notes*: Standard errors in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

**Table C2**
Robustness check using quadratic polynomial function of midway daily consumption.

| Model | Outcome: Natural log of daily consumption change (%) | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| | Aggregate | 350 kWh | 530 kWh | 685 kWh |
| *ln* MP (%) | −0.333*** | −2.072** | −0.396* | −0.046 |
| | (0.062) | (0.788) | (0.166) | (0.066) |
| *ln* AP (%) | −0.327*** | 1.485 | −0.170 | −0.888*** |
| | (0.070) | (0.783) | (0.160) | (0.131) |
| Holiday | −0.073*** | −0.022 | −0.064 | −0.082* |
| | (0.008) | (0.032) | (0.036) | (0.037) |
| Weekend | −0.079*** | −0.115*** | −0.101*** | −0.131*** |
| | (0.013) | (0.023) | (0.022) | (0.028) |
| Firm size: Middle | −0.077** | | | |
| | (0.027) | | | |
| Firm size: Small | −0.357*** | | | |
| | (0.061) | | | |
| Midway daily consumption (kWh/day) | Quadratic | Quadratic | Quadratic | Quadratic |
| HDD (°F) | Yes | Yes | Yes | Yes |
| CDD (°F) | Yes | Yes | Yes | Yes |
| Individual fixed effects | Yes | Yes | Yes | Yes |
| Zip code-by-year fixed effects | Yes | Yes | Yes | Yes |
| Billing cycle-by-month fixed effects | Yes | Yes | Yes | Yes |
| Day-of-month fixed effects | Yes | Yes | Yes | Yes |
| Day-of-week fixed effects | Yes | Yes | Yes | Yes |
| Observations | 435337 | 23834 | 18098 | 13800 |

*Notes*: Standard errors in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

**Table C3**
Robustness check using quartic polynomial function of midway daily consumption.

| Model | Outcome: Natural log of daily consumption change (%) | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| | Aggregate | 350 kWh | 530 kWh | 685 kWh |
| *ln* MP (%) | −0.398*** | −3.202*** | −0.575*** | −0.105 |
| | (0.061) | (0.813) | (0.167) | (0.065) |
| *ln* AP (%) | −0.266*** | 2.614** | −0.021 | −0.890*** |
| | (0.069) | (0.810) | (0.163) | (0.131) |
| Holiday | −0.072*** | −0.023 | −0.065 | −0.085* |

(*continued on next page*)

**Table C3** (*continued*)

| Model | Outcome: Natural log of daily consumption change (%) | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| | Aggregate | 350 kWh | 530 kWh | 685 kWh |
| | (0.008) | (0.032) | (0.036) | (0.036) |
| Weekend | −0.078*** | −0.111*** | −0.100*** | −0.128*** |
| | (0.013) | (0.022) | (0.021) | (0.027) |
| Firm size: Middle | −0.090*** | | | |
| | (0.027) | | | |
| Firm size: Small | −0.372*** | | | |
| | (0.061) | | | |
| Midway daily consumption (kWh/day) | Quartic | Quartic | Quartic | Quartic |
| HDD (°F) | Yes | Yes | Yes | Yes |
| CDD (°F) | Yes | Yes | Yes | Yes |
| Individual fixed effects | Yes | Yes | Yes | Yes |
| Zip code-by-year fixed effects | Yes | Yes | Yes | Yes |
| Billing cycle-by-month fixed effects | Yes | Yes | Yes | Yes |
| Day-of-month fixed effects | Yes | Yes | Yes | Yes |
| Day-of-week fixed effects | Yes | Yes | Yes | Yes |
| Observations | 435337 | 23834 | 18098 | 13800 |

*Notes*: Standard errors in parentheses. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

## References


Atkinson, A.B., Stiglitz, J.E., 1976. The design of tax structure: direct versus indirect taxation. J. Publ. Econ. 6 (1–2), 55–75.

Blomquist, Sören, Selin, Håkan, 2010. Hourly wage rate and taxable labor income responsiveness to changes in marginal tax rates. J. Publ. Econ. 94 (11–12), 878–889.

Bohi, D.R., Zimmerman, M.B., 1984. An update on econometric studies of energy demand behavior. Annu. Rev. Energy 9 (1), 105–154.

Borenstein, S., 2009. To what electricity price do consumers respond? Residential demand elasticity under increasing-block pricing. Preliminary Draft April 30, 95.

Carter, D.W., Milon, J.W., 2005. Price knowledge in household demand for utility services. Land Econ. 81 (2), 265–283.

Commercial Building Energy Consumption Survey (CBECS), 2015. U. S.Energy Information Administration (EIA).

De Bartolome, C.A., 1995. Which tax rate do people use: average or marginal? J. Publ. Econ. 56 (1), 79–96.

Diamond, P.A., 1998. Optimal income taxation: an example with a U-shaped pattern of optimal marginal tax rates. Am. Econ. Rev. 83–95.

Filippini, M., 1999. Swiss residential demand for electricity. Appl. Econ. Lett. 6 (8), 533–538.

Ito, K., 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. Am. Econ. Rev. 104 (2), 537–563.

Khan, A.A., Razzaq, S., Khan, A., Khursheed, F., 2015. HEMSs and enabled demand response in electricity market: an overview. Renew. Sustain. Energy Rev. 42, 773–785.

Liebman, J.B., Zeckhauser, R.J., 2004. Schmeduling. www.hks.harvard.edu/jeffreyliebman/schmeduling.pdf.

Mirrlees, J.A., 1971. An exploration in the theory of optimum income taxation. Rev. Econ. Stud. 38 (2), 175–208.

National Institute of Economic and Industry Research, 2007. The Own Price Elasticity of Demand for Electricity in NEM Regions. Tech. Rep. National Electricity Market Management Company.

Olmstead, S.M., Hanemann, W.M., Stavins, R.N., 2007. Water demand under alternative price structures. J. Environ. Econ. Manag. 54 (2), 181–198.

Reiss, P.C., White, M.W., 2005. Household electricity demand, revisited. Rev. Econ. Stud. 72 (3), 853–883.

Saez, E., 2010. Do taxpayers bunch at kink points? Am. Econ. J. Econ. Pol. 2 (3), 180–212.

Saez, Emmanuel, Slemrod, Joel, Giertz, Seth H., 2012. The elasticity of taxable income with respect to marginal tax rates: a critical review. J. Econ. Lit. 50 (1), 3–50.

Shin, J.S., 1985. Perception of price when price information is costly: evidence from residential electricity demand. Rev. Econ. Stat. 591–598.

Staiger, D., Stock, J., 1997. Instrumental variables regression with weak instruments. Econometrica 65 (3), 557–586.

Stock, J., Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: Andrews, D., Stock, J. (Eds.), Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge University Press, Cambridge, pp. 80–108.