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Time is Money: The Social Benefits of Time-of-Use Tariffs

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Abstract
In this study, we first estimate the impact of a mandatory time-of-use (TOU) pricing policy on the aggregate electricity load and find evidence for statistically significant load-shifting effects. Next, we develop a data-driven method to examine the impact of the TOU pricing policy on social benefits in the electricity industry, including reductions in fuel costs, greenhouse gas emissions, capital investment in generation capacity, transmission congestion, and ancillary services. Our estimates reveal that the TOU tariffs yielded social benefits equivalent to 4.5 percent of wholesale electricity generation costs. With tariff redesign, this percentage could increase to 7.6 percent. Our analysis suggests that, when formulating TOU tariffs, policymakers should prioritize their impact on capital investment, from which the majority of social benefits (98%) stem.

JEL Classification: D40, Market Structure, Pricing, and Design: General; L94, Electric Utilities; D61, Allocative Efficiency; Cost-Benefit Analysis; C15, Statistical Simulation Methods: General

Keywords
pricing, demand response, social benefits, machine learning

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1. Introduction

When the marginal cost of a good varies over time, ensuring that prices adjust instantly in response to cost fluctuations would lead to real-time economic efficiency. A prime example is electricity markets in which the cost of electricity generation fluctuates with demand and renewable energy supply (Allcott 2011; Joskow and Wolfram 2012). However, economists have raised two main concerns about implementing dynamic tariffs for end users. First, the effectiveness of such tariffs may diminish if prices change too frequently, and second, consumers find it mentally costly to comprehend and respond to regular price variations (Sallee 2014; Wolak 2011). Therefore, decision makers often prefer simpler tariff schemes such as time-of-use (TOU) pricing, which charges a fixed higher rate during periods of high demand

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and a fixed cheaper rate at other times. Although existing literature has been skeptical about the efficiency gain from TOU tariffs relative to real-time pricing tariffs, recent studies have shown that the former can reasonably replicate the load shifting incentives provided under latter (Schittekatte et al. 2024).

In this study, we aim to answer three important research questions related to the effectiveness of TOU pricing policies. First, what is the impact of mandatory TOU tariffs on the total electricity load (i.e., demand). To answer this question, we employ both traditional econometric methods and advanced machine learning (ML) counterfactual prediction techniques to estimate the inter-period substitution and overall energy conservation effects of TOU tariffs on the total electricity load of Guangdong, the most affluent and populous province in China. Notably, both methodologies yield similar results, demonstrating the consistency of our estimates across diverse specifications and approaches. Our findings indicate the significantly negative inter-period substitution effects of TOU tariffs, whereas the overall energy conservation effects do not significantly deviate from zero. This finding concurs with conventional wisdom that the energy conservation effects of TOU tariffs are limited (Faruqui et al. 2015; Qiu et al. 2018).

Second, how much do TOU tariffs benefit society? In addition to enhancing market efficiency and thereby reducing the overall fuel costs of electricity generation, TOU pricing benefits the electricity industry in other ways, including reduced requirements for peaking plants, lower greenhouse gas emissions, and reduced costs of transmission congestion and ancillary services. In this study, we define the sum of these benefits as the "social benefits." We develop a data-driven approach to estimate these social benefits. Taking Guangdong as a case study, our analysis reveals that the social benefits of existing TOU tariffs can reach approximately 4.5 percent of wholesale electricity generation costs, with nearly 98 percent of these benefits arising from savings in capacity investment. This finding is consistent with related empirical studies (Fowlie et al. 2021; Guo 2023).

Third, how to design the optimal TOU tariffs for society? To answer this question, we evaluate the social benefits of TOU tariffs across all feasible combinations of peak/shoulder/off-peak price ratios and identify the one that maximizes social benefits. Our results demonstrate that in Guangdong, widening the price gap between the peak and off-peak periods can substantially enhance the social benefits. Under the optimal TOU tariffs, the social benefits will increase by approximately 70 percent (relative to the existing TOU tariffs), resulting in a potential rise in the social benefits of TOU tariffs to 7.6 percent of wholesale electricity generation costs.

An expanding literature shows that the effectiveness of TOU tariffs depends critically on institutional design, market structure, and enabling technologies (Bollinger and Hartmann 2020; Di Cosmo et al. 2014; Guo and Weeks 2022; Jessoe and Rapson 2014). Evidence from advanced economies emphasizes the roles of smart meter penetration, consumer heterogeneity, regulatory frameworks, and equity considerations in shaping demand response and welfare outcomes (Gheouany et al. 2025). Studies from emerging markets further highlight that institutional readiness, public trust, and transparent communication are key to public acceptance of tariff reform (Gupta et al. 2025; Normasari et al. 2025). Experiences from Latin America are particularly instructive: TOU policies are implemented within highly regulated retail electricity sectors, where political feasibility, affordability, and distributional concerns strongly constrain tariff design (Fischer et al. 2000; Humeres 2022). In Brazil and Chile, TOU pricing has generated potential efficiency gains but has been limited by high metering costs, concerns over residential bill impacts, and regulators' preference for simple and predictable tariff structures (Ferreira et al. 2013; García-Santander et al. 2022).

Related literature also emphasizes that observed load shifting under TOU and other time-varying tariffs may involve non-negligible private adaptation costs. I&C users often rely on complementary investments such as on-site generation, storage, automation, or production rescheduling, to respond effectively to price signals, implying that participation is typically concentrated among firms with pre-existing flexibility or the ability to incur upfront adjustment costs (Pallonetto et al. 2016). Consequently, part of the welfare gains attributed to time-varying pricing may reflect privately borne investment and organizational costs that are not directly observed in consumption data (Nezamoddini and Wang 2017; Wang and Li 2015). Notably, our welfare analysis focuses on system-level gross benefits and does not explicitly account for heterogeneous private adaptation costs. The reported welfare effects should therefore be interpreted as upper-bound estimates of net social gains.

In terms of optimal tariff design, previous engineering studies construct classic or mathematical optimization algorithms to derive dynamic tariffs meeting a variety of objectives such as lowering bills, maximizing comfort, minimizing generation costs, minimizing the peak-to-average ratio of demand, and maximizing retailers' profits (Jordehi 2019). By contrast, our study focuses on the objective of maximizing social benefits. Nevertheless, we do not overlook the significance of the engineering aspects in the electricity industry, where efficient transmission and real-time balancing of the electricity system play crucial roles in determining the total cost of electricity for end users.

Our study makes three contributions to the literature. First, we combine conventional econometric methods with machine learning (ML)-based counterfactual prediction to identify the causal impact of mandatory TOU tariffs in the absence of a valid control group. While most existing studies rely on econometric approaches such as difference-in-differences, which require credible control groups, such conditions are often unavailable in mandatory policy settings. By predicting counterfactual electricity load using ML and estimating treatment effects based on the divergence between actual and counterfactual outcomes, we provide a complementary identification strategy. The consistency between the econometric and ML-based estimates strengthens the credibility of our results.

Second, we propose a data-driven framework to quantify the social benefits of TOU tariffs in a system-wide manner. Prior studies typically focus on one or two dimensions of benefits, such as fuel cost savings or emissions reductions (e.g., Borenstein and Bushnell 2022; Fell et al. 2021; Holland and Mansur 2008; Sexton et al. 2021), while overlooking impacts on system balancing, congestion, and ancillary services. Our approach integrates all major components of the electricity supply chain, enabling a comprehensive assessment of social benefits. More broadly, the framework is applicable to evaluating the system-level impacts of various external shocks, including renewable integration, energy storage deployment, and climate-induced demand changes.

Third, we contribute to the literature on welfare-maximizing tariff design in demand response programs (Jordehi 2019; O'Connell et al. 2014). Using an exhaustive search over feasible TOU price combinations, we show that approximately 98 percent of the social benefits arise from reduced investment in peaking capacity. As a result, tariff structures that minimize capital investment costs coincide with those that maximize overall social benefits. This finding implies that policymakers can substantially simplify tariff design by focusing on investment effects rather than relying on complex multi-dimensional optimization.

The remainder of this study is organized as follows. Section 2 describes the institutional background. Section 3 outlines the data used in our empirical analysis. Section 4 estimates the impact of TOU tariffs on electricity load patterns. Section 5 estimates the social benefits of TOU tariffs. Section 6 explores the optimal TOU tariff that maximizes social benefits. Finally, Section 7 concludes.

2. Institutional Background

This study adds a fresh data point to the understudied topic of dynamic electricity pricing in developing countries. In particular, we focus on the mandatory TOU pricing policy implemented among I&C users in Guangdong province, which is the largest consumer of electricity among China's provinces. By 2022, Guangdong's gross domestic product (GDP) had reached $1.92 trillion, accounting for approximately 11 percent of China's GDP. In the same period, electricity consumption in Guangdong totaled 787 TWh, constituting 9.1 percent of China's electricity usage. Electricity consumption by the primary, secondary, and tertiary industries was 14.9, 463.6, and 173.2 TWh, respectively, while residential consumption totaled 135.3 TWh, accounting for 1.9%, 58.9%, 22.0%, and 17.2% of the total, respectively (GPEC 2023).[1] Given these statistics, Guangdong stands to benefit the most from the TOU pricing policy, among all provinces in China.

In Guangdong, the TOU tariff was introduced as a mandatory, top-down policy applied exclusively to I&C users, reflecting the province's gradual transition from a regulated monopoly to a more market-oriented electricity system. The TOU framework has a long policy lineage: initial discussions and pilot programs date back to the early 2000s, when Guangdong first experimented with differentiated pricing for large industrial consumers under China's broader electricity-pricing reform. Throughout the 2010s, the province progressively refined this structure by expanding pilot programs, defining standard peak, shoulder, and off-peak periods, and incorporating these schedules into electricity contracts for major I&C users. By the mid-2010s, TOU pricing had become a defining feature of Guangdong's demand-side management strategy, laying the institutional foundation for subsequent large-scale reforms.

The latest significant reform (October 2021) redesigned pricing periods to align with Guangdong's aggregate load pattern. Additionally, it expanded the peak/shoulder/off-peak (PSO) price ratio from 1.65:1:0.5 to 1.7:1:0.38 to further incentivize load shifting. Figure 1a shows the TOU pricing periods and rates applicable to I&C users in Guangdong prior to and post the reform. While the off-peak hours remained 24:00 to 08:00, the peak and shoulder hours changed. The October 2021 reform also incorporated a critical-peak pricing mechanism to be implemented in July, August, and September (the summer months) of each year as well as on other days whenever the maximum temperature exceeds 35°C. This critical-peak rate, set at 25 percent above peak prices, was applicable for three hours of the day, from 11:00 to 12:00 and from 15:00 to 17:00. Our study focuses on the three-year sample period from October 2019 to September 2022, wherein the major reform took place in the third sample year.

Figure 1b compares the standardized daily average load patterns in October 2019, 2020, and 2021.[2] The figure shows that the electricity load in Guangdong peaks between 11:00 and 12:00 as well as between 15:00 and 17:00. Consequently, the readjusted pricing periods align more closely with Guangdong's load profiles. Due to the reform, the standardized electricity load during peak periods in October 2021 was much lower than that in October 2019 and October 2020. Meanwhile, the standardized load in the off-peak periods of October 2021 was substantially higher than that in the other two months. This suggests that the reform may result in a distinct shift of load from peak and shoulder to off-peak periods.

In addition to the October 2021 reform, from December of the same year, TOU tariff rates were adjusted monthly in accordance with the prevailing wholesale electricity prices in the month-ahead forward market, costs of ancillary services, and cross-subsidization between

[1]By comparison, Germany consumed 484 TWh in 2022, while generating a GDP of $4.07 trillion. Industrial users accounted for 47% (228 TWh) of the nation's electricity demand. Source: World Bank Open Data and the International Energy Agency.

[2]The standardized load in the figure is defined as the actual load divided by the monthly average load.

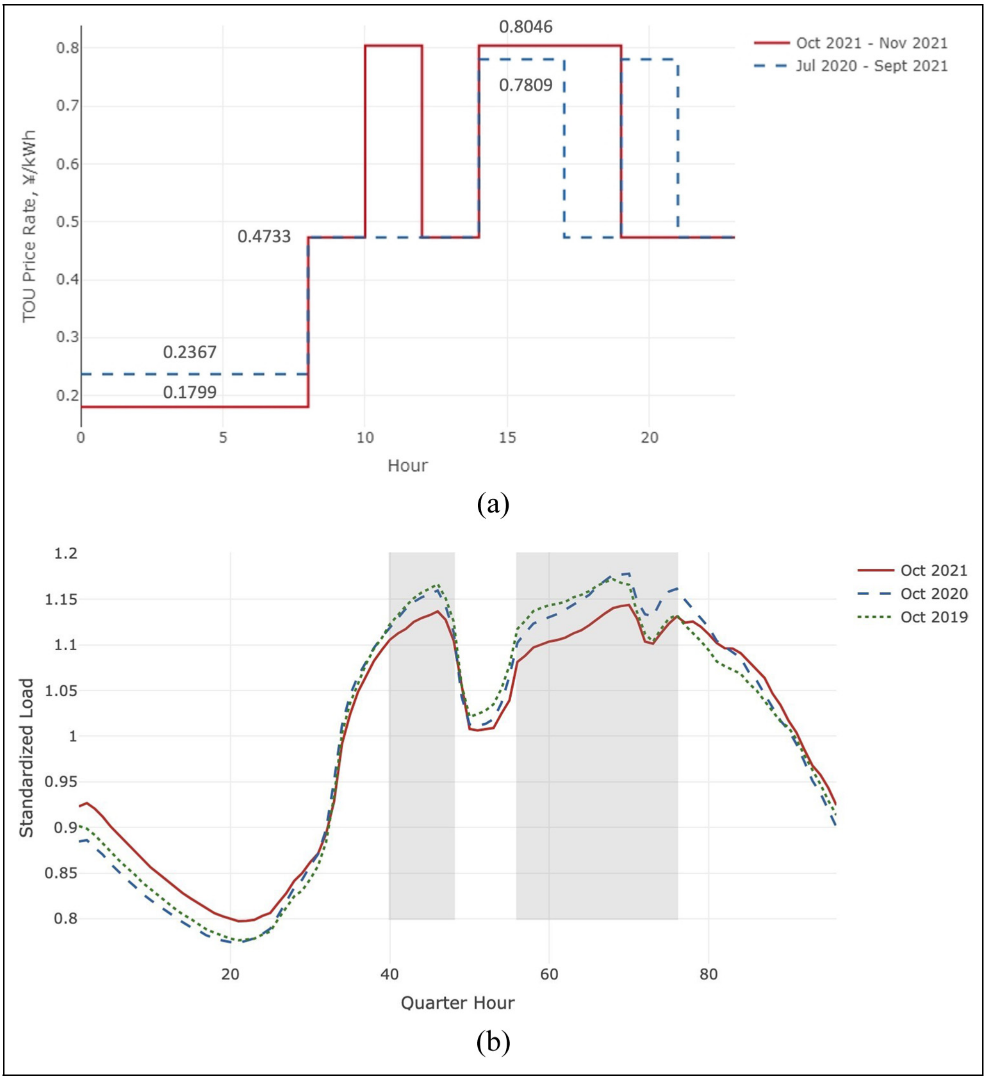

Figure 1. TOU tariffs and load before and after the reform: (a) TOU tariff periods and rates in Guangzhou and (b) electricity load patterns in Guangdong.
Note. The shaded area refers to peak hours after the reform in October 2021.

I&C entities and residential/agricultural consumers.[3,4] Meanwhile, the PSO price ratio was fixed. The scatterplot in Supplemental Appendix Figure E.11 depicts the relationship between the shoulder rates in each month and average prices in the month-ahead forward wholesale market from December 2021 to September 2022. Although the data points are not aligned along a single line, the best-fitting line suggests that the two prices are highly correlated.

[3]See http://drc.gd.gov.cn/gkmlpt/content/3/3693/mmpost_3693270.html\#877 (in Chinese).
[4]In China, I&C users are charged higher electricity tariffs so that tariffs can be reduced for residential and agricultural consumers. The aim of this split is to ensure electricity is affordable for all in China. The electricity tariff for end-users comprises three components: the energy charge, transmission & distribution (T&D) fees, and government surcharges. The latter two are fixed rates pre-approved by regulatory authorities. Here, we focus on the impact of temporal variations in the energy charge on consumer behaviors.

Table 1. TOU Prices in Guangdong, October 2019 to September 2022.

Period	Unit	Obs.	Mean	S.D.	Min.	Max.
Off-peak	¥/MWh	1,096	222.8	20.7	179.9	236.7
Shoulder	¥/MWh	1,096	484.9	24.5	473.3	569.5
Peak	¥/MWh	1,096	815.8	55.8	780.9	968.2
Critical-peak	¥/MWh	98	1,036.2	87.2	883.5	1,142.6

Supplemental Appendix Figure E.10 presents the timeline of events that are related to TOU tariff in Guangdong during the sample period.

Finally, it is noteworthy that Guangdong did not trial any dynamic tariff nor implement a smart metering program among residential users during the sample period. All residential users thus faced fixed standard residential tariffs throughout the sample period. Consequently, households had no direct incentive to change their electricity consumption.

3. Data

This study assembles a comprehensive dataset linking high-frequency electricity generation, tariff schedules, power system operations, and market prices to examine the impact of mandatory TOU tariffs on aggregate electricity demand, the associated social benefits, and optimal tariff design. The sample period spans October 2019 to September 2022. Table 1 reports summary statistics for TOU price rates faced by I&C users in Guangdong. During the sample period, the PSO price ratio changed only once, whereas since December 2021, TOU price levels have been adjusted on a monthly basis (see Supplemental Appendix Figure E.10).

To analyze the impact of mandatory TOU tariffs on aggregate electricity demand, we use fifteen-minute provincial-level electricity load data obtained from the Guangdong Power Exchange Center. Weather controls, including temperature and wind speed, are sourced from Weather Underground.[5] To account for potential disruptions to economic activity during the COVID-19 pandemic, we also incorporate daily counts of newly confirmed COVID-19 cases.[6] Data on COVID-19 cases are collected from the Health Commission of Guangdong Province.[7]

To examine energy conservation effects, particularly the relationship between daily average electricity prices and aggregate load, we employ daily maintenance capacity planning (MCP) and coal prices as instrumental variables. MCP data are obtained from the Guangdong Power Exchange Center, while coal prices are sourced from the Wind Economic Database.[8] Summary statistics for electricity load and related variables are reported in Table 2.

To quantify the social benefits associated with TOU tariffs and to inform optimal tariff design, we further assemble high-frequency data covering electricity generation, emissions, capacity investment, transmission congestion, and ancillary services in Guangdong. These data enable a system-wide assessment of how changes in the temporal distribution of electricity load affect multiple stages of the electricity supply chain.

[5]See https://www.wunderground.com/.

[6]During the sample period, China consistently implemented a strict zero-COVID policy. Any COVID cases would result in a community-wide lockdown. The policy started in January 2020 and was lifted in December 2022.

[7]See http://wsjkw.gd.gov.cn/.

[8]The steaming coal price (Q5500) at Guangzhou (i.e., the capital of Guangdong) port is obtained from wind.com.cn.

Table 2. Summary Statistics of Electricity Load and the Other Variables.

Variable	Unit	Obs.	Mean	S.D.	Min.	Max.
Load	MW	105,216	82,934.0	21,895.5	22,616.3	143,298.8
Maintenance	MW	1,096	11,274.2	6,002.0	0.0	27,991.3
Large coal	MW	105,216	12,181.9	4,866.2	702.7	23,640.1
Medium coal	MW	105,216	11,410.4	4,032.4	2,880.3	21,513.6
Small coal	MW	105,216	10,722.9	2,545.9	4,182.0	17,160.2
Double-shaft gas	MW	105,216	6,087.9	2,282.5	1,838.3	14,728.8
Single-shaft gas	MW	105,216	2,496.9	1,510.5	0.0	7,058.0
Temperature	°F	52,608	75.2	11.9	37	104
Wind speed	mile/hour	52,608	6.5	4.0	0.0	38.0
New Covid case	case	1,096	4.4	12.7	0.0	127.0
Coal price	¥/ton	1,096	1,005.9	389.8	575.0	2,600.0
LNG	¥/ton	1,096	5,065.2	1,029.1	2,800.0	9,650.0
Guangdong ETS	¥/tCO_2	654	30.5	4.7	24.5	44.4
National ETS	¥/tCO_2	442	53.7	6.5	46.5	61.4
Nodal price	¥/MWh	3,258,720	560.6	203.7	0.0	1,500.0
Nodal supply	MW	3,258,720	418.3	506.4	0.0	3,866.0
Day-ahead price	¥/MWh	35,040	562.6	190.6	0.0	1,274.4
Real-time price	¥/MWh	35,040	581.8	244.1	0.0	1,500.0
Day-ahead load	MW	35,040	82,350.7	24,906.7	27,710.0	145,000.0
Real-time load	MW	35,040	81,273.2	24,364.3	26,153.9	143,330.0

Electricity generation data consist of fifteen-minute, plant-level observations aggregated by fuel type, including small, medium-sized, and large coal plants, as well as single- and double-shaft gas turbines.[9] These data are obtained from the Guangdong Power Grid Corporation. Daily spot prices for steaming coal and liquefied natural gas (LNG), which characterize fuel cost conditions, are sourced from the Wind Economic Database.

To assess environmental impacts, we combine generation data with information on fuel-specific thermal efficiency to construct hourly measures of marginal emissions. Carbon prices faced by electricity generators are drawn from Guangdong's local emissions trading system (ETS) prior to July 16, 2021, and from the national ETS thereafter. Prices for the former are obtained from the Guangzhou Emissions Exchange, while those for the latter are sourced from the Wind Economic Database.[10]

Data on peak capacity requirements are used to evaluate potential savings in generation investment. Capital cost estimates for representative coal- and gas-fired plants are taken from the *Projected Costs of Generating Electricity, 2020 Edition* published by the International Energy Agency and the OECD Nuclear Energy Agency.

Transmission congestion is analyzed using detailed nodal price and nodal supply data from the Guangdong electricity spot market. Because Guangdong adopts nodal (locational) pricing, differences in nodal prices provide information on congestion costs along transmission links, conditional on electricity supply at each node (see Supplemental Appendix C.6 for details).[11] As the spot market was not operational prior to November 2021, congestion-

[9]Small coal plants have a capacity below 350 MW compared with between 600 and 700 MW for medium-sized coal plants and above 1,000 MW for large coal plants. Single-shaft gas turbines are usually more efficient than double-shaft gas turbines, but less flexible.

[10]See https://www.cnemission.com/.

[11]As each power plant is connected with a node, the nodal generation is actually the electricity generation from the corresponding power plant.

related variables are observed only after this date. Electricity load data from earlier periods are therefore used to infer congestion outcomes outside the spot-market window.

Finally, data from the day-ahead and real-time markets are used to characterize the costs of ancillary services. As there is no intraday market in Guangdong,[12] the difference between day-ahead and real-time prices, interacted with realized load, provides information on system balancing costs. Owing to data availability, these variables are directly observed only after the spot market began operation. All ancillary-service-related data are obtained from the Guangdong Power Exchange Center.

4. Impact of TOU Tariffs on Electricity Load

In this section, we estimate the impact of TOU tariffs on electricity load. First, we focus on the load-shifting effects of TOU tariffs and estimate the inter-period substitution effects. Next, we estimate the overall energy conservation effects of TOU tariffs, specifically the impact of daily average prices and PSO price ratios on daily average load. We first employ conventional econometric methods to complete these tasks. To enhance the credibility of our estimation results, we also employ the ML counterfactual prediction approach to re-estimate the impact.

4.1. Inter-period Substitution Effects

To estimate the inter-period substitution effects, we analyze how a change in the price ratio between two periods influences the associated load ratio. We treat off-peak periods as the benchmark and compare shoulder and peak periods with them. This approach can also be viewed as a standardization technique: for each day, both TOU prices and electricity load in the shoulder and peak periods are standardized by dividing their original values by the benchmark values. Specifically, we estimate the following reduced-form regression:

$$\frac{q_{d,i,m}}{\bar{q}_{d,\text{bm}}} = \beta_{0,i} + \beta_{1,i}\frac{p_{d,i,m}}{\bar{p}_{d,\text{bm}}} + \sum_{k=2}^{K} \beta_{k,i} X_{k,d,i,m} + \epsilon_{d,i,m}, \forall i. \tag{1}$$

Here, the subscript d represents days, $i = \{1, \cdots, 16\}$ represents the sixteen-hour time intervals for shoulder and peak periods (between 08:00 and 24:00), and $m = \{1, 2, 3, 4\}$ denotes the four 15-minute time blocks within each hourly interval. We define the sixteen-hour periods as the *targeted period*. The subscript "bm" denotes the *benchmark period* spanning the time window from 24:00 to 08:00 and $k = \{2, \cdots, K\}$ represents the numbering of control variables in the regression. $\bar{q}_{d,\text{bm}}$ is the average electricity load during the benchmark period on day d. Consequently, the dependent variable is the ratio of the load in period i block m to the average load during the benchmark period.

The explanatory variable of interest is $p_{d,i,m}/\bar{p}_{d,\text{bm}}$, which represents the TOU price ratio between period i block m and the benchmark period. The slope coefficients $\beta_{1,i}$ estimate the effect of a change in the price ratio on the load ratio between period i and the benchmark period. Essentially, these coefficients provide insights into the inter-period substitution effects between the two periods. The control variables $X_{k,d,i,m}$ include temperature, wind speed, new Covid-19 cases, day-of-the-week and fifteen-minute fixed effects, and the interaction between the yearly and monthly fixed effects.

[12]There are no agents doing trading to reduce the spread in prices between day-ahead and real-time in the electricity market running for Guangdong, neither financial traders or virtual bids.

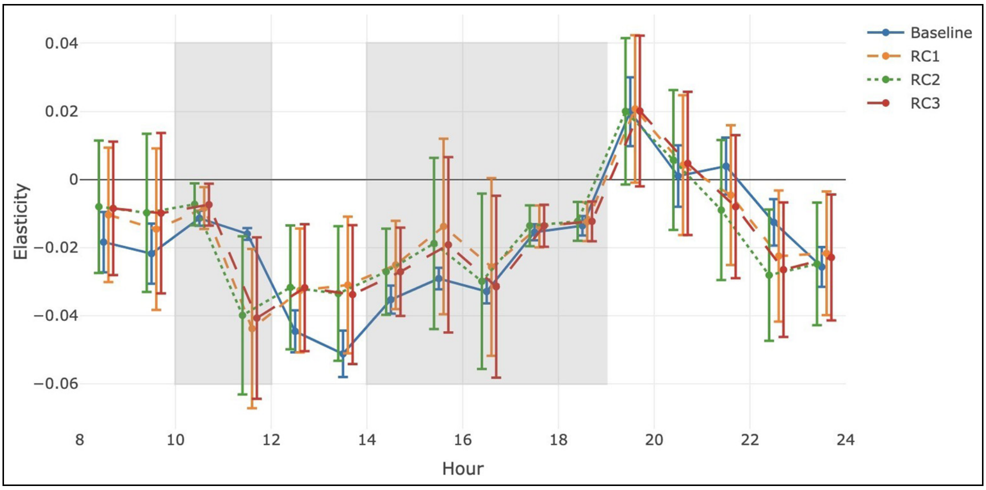

Figure 2. Estimated inter-period substitution effects.
Note. The shaded area corresponds to the peak hours following the reform in October 2021. The error bars include the 90% confidence intervals of the estimates. In the baseline results, the regression solely includes the load ratios regressed on the price ratios. Robustness Check 1 (RC1) and Robustness Check 2 (RC2) introduce additional control variables. In the case of Robustness Check 3 (RC3), along with incorporating these additional control variables, the sample period is shortened.

Specification (1) is applied to each of the sixteen-hour targeted periods, which include the entire shoulder and peak (and critical-peak) periods.[13] $p_{d,i,m}/\bar{p}_{d,\text{bm}}$ is considered to be exogenous because the changes in the PSO price ratio were solely due to the policy reform.

In the baseline regression, we omit all the control variables ($X_{k,d,i}$). Robustness Check 1 (RC1) incorporates all the time fixed effects, while excluding the weather and COVID-19 variables. RC2 includes all the control variables, resulting in the same specification as equation (1). In RC3, we include all the control variables but narrow the sample period from three to two years, specifically, the period from October 2020 to September 2022. This adjustment addresses concerns that the length of the sample period could impact the estimation results due to macroeconomic fluctuations. Figure 2 illustrates the estimated inter-period substitution effects for the baseline and robustness checks.[14] The horizontal axis represents the sixteen-hour targeted periods of the day and the vertical axis represents the estimated impacts. The 90% confidence interval for each estimate is also reported.

Most of the estimated inter-period substitution effects are negative and statistically significant, implying that an increase in the price ratio within these periods reduces the corresponding load ratio. In essence, the load during shoulder and peak periods is shifted to off-peak periods owing to the increased price ratio. However, there are certain exceptions. During evening hours (19:00–21:00), the estimated inter-period substitution effects are positive, indicating that an increase in the price ratio raises the corresponding load ratio. Possible explanations include electricity consumption during these periods being complementary or

[13]The error terms among these regressions may be correlated. Hence, because the regressions treat each day as a single observation and electricity load within a day can be highly correlated, we also estimate the inter-period substitution effects within the seemingly unrelated regression framework. The results obtained using this method are remarkably close. Therefore, for the sake of simplicity, we conduct separate ordinary least squares (OLS) regressions.
[14]Supplemental Appendix Tables D.4 and D.5 present the detailed regression results of the robustness checks. Due to space limits, we only report the estimates on the effect of a change in the price ratio on the load ratio ($\beta_{1,i}$), estimates on coefficients for other control variables are available upon request.

consumers responding to average instead of marginal prices (Ito 2014). Additionally, Guo (2023) found evidence for the existence of a spillover effect of peak pricing and highlighted that electricity consumers might overreact to peak prices by decreasing their post-peak electricity consumption. Overall, the total electricity load appears to be more responsive to TOU prices around midday (11:00–13:00), in the afternoon (13:00–17:00), and late night (22:00–24:00).

Recall that the validity of our estimation relies on the assumption of exogeneity in the price ratio. If this assumption holds, excluding all control variables in $X_{k,d,i}$ should still give us a valid estimation of $\beta_{1,i}$, while including these variables would improve estimation efficiency. As the baseline regression excludes all the control variables while RC1 and RC2 include them, we can test the hypothesis of exogeneity by comparing the results of these regressions. Figure 2 confirms that the results of RC1 and RC2 align with the baseline findings, validating the hypothesis.

Another potential concern may arise regarding why our estimation of substitution effects compares two TOU regimes rather than a TOU and a flat tariff. The main reason lies in our research focus on examining not only the performance of TOU pricing relative to non-TOU schemes but also the efficiency differences among alternative TOU designs, with the ultimate goal of identifying the optimal structure of TOU rates. Accordingly, our empirical specification captures how incremental adjustments in the PSO price ratio or the timing of pricing periods affect system-level outcomes. Although the assumption of a linear relationship between price and load ratios permits reasonable extrapolation to a flat tariff scenario (as discussed in Section 5), this scenario primarily serves as a benchmark reference.

4.2. Energy Conservation Effects

The TOU tariff reform in October 2021 may have an impact on the total energy demand through two channels, indirect and direct. The indirect impact is to change the average prices of end-use electricity, which eventually influences overall electricity consumption. However, whether the reform increased or decreased the average price is controversial because it raised the peak rate while reducing the off-peak rate. The direct impact is to widen the PSO price ratio to achieve a more substantial load shift. However, supposing that the reform did not change the average prices of end-use electricity, it is still possible that not all of the reduced demand shifted to off-peak periods. Instead, consumers may have responded to the reform simply by reducing their overall electricity consumption.

It is impossible to identify both channels of the energy conservation effects by directly investigating the impact of the reform on total electricity consumption. The reason is that the impacts of the two channels may have different signs, making the estimation results unreliable. Therefore, we assess them separately by examining a different timeframe of the sample period. Specifically, we first examine the impact of average prices on the total electricity consumption, choosing the sample period when the PSO ratio was fixed but the average prices varied (i.e., from October 2021 to September 2022; recall Supplemental Appendix Figure E.10). In this manner, we will show that the average prices have no statistically significant impact on the total electricity consumption. If this finding is robust, when we estimate the impact of the reform on total electricity consumption, we can identify the pure effect of PSO price ratios on total electricity consumption.

4.2.1. Impact of Average Prices on Electricity Demand. To estimate the impact of average prices on electricity load, we employ the following regression specification:

$$\ln Q_d = \theta_0 + \theta_1 \ln \bar{p}_d + \sum_{j=2}^{J} \theta_j X_{j,d} + e_d. \quad (2)$$

Here, $X_{j,d}$, with $j = \{2, \cdots, J\}$, denotes the numbering of control variables and d signifies days. The dependent variable $\ln Q_d$ corresponds to the natural logarithm of daily average electricity load. The explanatory variable of interest, $\ln \bar{p}_d \equiv \ln 1/96 \cdot \sum_{h,m} p_{d,h,m}$, with $h = \{1, \cdots, 24\}$ representing the twenty-four hours of the day,[15] captures the natural logarithm of the daily average TOU prices on day d.[16] Similar to Specification (1), the set of control variables $X_{j,d}$ includes daily average temperature, wind speed, new COVID-19 cases, day-of-the-week fixed effects[17] and a binary variable indicating the days with critical-peak periods.

As Specification (2) is meant to estimate the demand curve of electricity consumption, it naturally becomes a component of the classic empirical model that includes supply and demand dynamics. Consequently, the variable of interest $\ln \bar{p}_d$ could be endogenous. Addressing the endogeneity of prices when estimating demand often involves the introduction of supply-side instruments. In our case, we employ maintenance capacity planning (MCP) as our instrumental variable (IV). MCP can be linked to electricity prices through two channels. On the one hand, high MCP might raise wholesale electricity prices owing to the reduction in available capacity for electricity generation. This situation could amplify market power and price markups over marginal costs, increasing end-use prices. In this scenario, MCP exhibits a positive correlation with prices. On the other hand, electricity generators might strategically time their maintenance schedules to maximize profits. For example, they might schedule preventive maintenance during periods in which they anticipate low wholesale electricity prices, thus minimizing the opportunity cost of maintenance. In these instances, MCP would demonstrate a negative relationship with prices. Importantly, it is widely recognized that unless blackouts occur (an extremely rare event in China), MCP should remain uncorrelated with electricity demand.

Other supply-side instruments, including fuel prices, could also be valid. While fuel prices might influence electricity consumption in the long term owing to the potential complementarity between electricity and fossil fuels, coal prices serve as a viable secondary instrument in our context because we are estimating the short-run demand curve. The secondary IV allows us to conduct an overidentification test to assess instrumental exogeneity.

To identify the impact of average prices on total electricity demand, we use the sample period from October 2021 to September 2022. This is because during this period, the PSO price ratio is fixed while the average prices fluctuate. Moreover, our regression analysis takes the critical-peak pricing mechanism into consideration by incorporating two strategies: first, we introduce a binary variable representing days with critical-peak prices into the regression; second, we divide the sample period into two subsamples—one containing only days without critical-peak prices, while the other comprises only days with critical-peak prices.

Table 3 presents the results from the first strategy. Column (i) presents the OLS estimates, and columns (ii) to (iv) present the IV estimates. In columns (ii) and (iii), MCP and coal prices are employed as the instruments, respectively, whereas both MCP and coal prices serve as the instruments in column (iv). Although the OLS results suggest a negative impact of the

[15]To clarify, i represents the sixteen-hour shoulder and peak periods (or targeted periods) within a day.

[16]The subscripts $h = \{1, \cdots, 24\}$ and $m = \{1, 2, 3, 4\}$ denote hours and fifteen-minute time blocks, respectively.

[17]As TOU prices vary monthly, introducing monthly fixed effects would result in substantial multicollinearity between the prices and monthly fixed effects. Hence, we exclude the monthly fixed effects from the regressions. Furthermore, given that the sample period used to analyze the energy conservation effects spans just one year (the rationale is detailed in the subsequent paragraphs), the yearly fixed effects are also omitted.

Table 3. The Impact of Average Prices on Total Electricity Demand.

Variable	(i) ols	(ii) iv	(iii) iv	(iv) iv
$\ln\bar{p}_d$	−0.276*	0.293	0.129	0.145
	(0.111)	(0.434)	(0.287)	(0.285)
Temperature	0.011***	0.011***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Wind speed	0.005*	0.007**	0.006**	0.006**
	(0.002)	(0.003)	(0.002)	(0.002)
New Covid cases	−0.000	−0.001	−0.001	−0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Critical-peak$_d$	0.120***	0.111***	0.114***	0.113***
	(0.018)	(0.020)	(0.019)	(0.019)
Constant	10.278***	10.667***	10.554***	10.566***
	(0.095)	(0.302)	(0.204)	(0.203)
Day-of-week FE	Yes	Yes	Yes	Yes
Instruments		MCP	Coal	MCP+Coal
Num. obs.	365	365	365	365
R-squared	.690	.666	.678	.677
Weak instruments		0.000	0.000	0.000
Wu-Hausman		0.093	0.033	0.026
Over-identification				0.636

Note. All diagnostic tests report p values. ***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

average price on electricity demand, the results from the IV estimates indicate that the impact of average prices on electricity demand is statistically insignificant.

The bottom rows of Table 3 present the results of diagnostic tests, which further validate the effectiveness of the IV estimates. In all three regressions, the weak instrument hypothesis is rejected, signifying that the instrument relevance conditions are met.[18] Notably, all the IV regression results from the Wu–Hausman test allow us to reject the hypothesis of the exogeneity of average prices at the 10% significance level. This finding substantiates the need to employ IV approaches to address the potential endogeneity. The results of the overidentification tests in column (iv) further reinforce the instrument exogeneity assumption. These tests indicate that our IVs have no partial impact on electricity consumption (upon accounting for average prices and any omitted variables) and that the IVs are not correlated with the omitted variables.

Finally, we explore the impact of average prices on electricity demand using the second strategy, reported in Supplemental Appendix Table D.7. Specifically, columns (a.i) and (a.v) present the OLS results, while the remaining columns show the IV estimates. Again, all the IV estimates support the earlier findings that the effect of average prices is negligible. These findings align with empirical evidence from other relevant studies (Faruqui et al. 2015; Qiu et al. 2018). Notably, the estimation results indicate that the effect is not only statistically but also economically insignificant given that the estimated coefficients are small in absolute terms.

4.2.2. Impact of PSO Price Ratios on Electricity Demand. In the previous subsection, we found that the impact of average prices on total electricity demand is not statistically significant. This indicates that if we estimate the impact of the October 2021 reform on daily average

[18]Supplemental Appendix Table D.6 reports the first-stage regression results.

Table 4. The Impact of PSO Ratio on Total Electricity Demand.

Variable	(v)	(vi)	(vii)
D(REFORM)	−0.032	−0.031	0.009
	(0.030)	(0.030)	(0.022)
Temperature			0.015***
			(0.001)
Wind speed			0.014***
			(0.002)
New Covid cases			0.007
			(0.004)
Constant	11.345***	11.359***	10.144***
	(0.011)	(0.028)	(0.070)
Day-of-week FE	No	Yes	Yes
Num. obs.	426	426	426
R^2	.003	.018	.480

***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

electricity demand, we will be directly estimating the impact of PSO price ratios on electricity demand. To do this, we implement the following regression specification:

$$\ln Q_d = \gamma_0 + \gamma_1 D(\text{REFORM}) + \sum_{j=2}^{J} \gamma_j X_{j,d} + v_d. \tag{3}$$

Recall that ln Q_d refers to the natural logarithm of daily average electricity load, and $X_{j,d}$ is a vector of control variables containing daily average temperature, wind speed, new COVID-19 cases, and day-of-the-week fixed effects. The variable of interest in Regression (3) is D(REFORM), a dummy variable equal to one for periods post the implementation of the reform (October 2021). As we have substantiated in Section 4.1, we employ OLS estimation because the reform enters the regression exogenously.

To minimize the impact of macroeconomic fluctuations on electricity demand, we restrict our sample period to between October 2020 and November 2021. In that period, COVID-19 had been successfully brought under control due to the strict zero-COVID policy. Moreover, the average price had been stable—the TOU price rates had not been adjusted regularly until December 2021.

Table 4 reports the regression results. The logic of the robustness checks is similar to that in Section 4.1: specification (v) only includes D(REFORM) as explanatory variables; specification (vi) controls for day-of-week fixed effects in addition; and specification (vii) further controls for weather and COVID-19 variables. The results suggest that we should not reject the null hypothesis that the reform has a statistically insignificant impact on the total electricity demand. Because we found no evidence supporting the hypothesis that the average price has a significant impact on total electricity demand in the previous subsection, we also failed to support the hypothesis that the PSO ratio has a significant impact on total electricity demand.

4.3. ML Counterfactual Prediction Estimation

Despite conducting several robustness checks for our estimates of the impact of TOU tariffs, the absence of control groups might still raise a concern about the validity of the causal inference. To address this concern, we adopt ML counterfactual prediction techniques. First, we use data from the first two years of the sample period to train the ML model. Then, we apply this trained model to predict the load for the third year, which gives the counterfactual load in the absence of the October 2021 reform. This exercise provides a pseudo-control group. Considering the actual load as the treatment group, we then employ conventional econometric methods to investigate the causal inference between TOU tariffs and electricity load.

Supplemental Appendix A provides details about the ML technique employed, namely the eXtreme Gradient Boosting (XGBoost) algorithm. Supplemental Appendix B gives details about the estimation process and the associated results. In summary, the results from the ML counterfactual prediction estimation are consistent with the conventional econometric methods.

5. Social Benefits of TOU Tariffs

In this section, we examine whether the TOU pricing policy in Guangdong can benefit society and explain the source and extent of any benefits. First, we construct the counterfactual load grounded in the estimated impact of TOU tariffs on electricity demand, as discussed in Section 4. Next, we deploy data-driven methodologies to quantify the social benefits (with details reported in Supplemental Appendix C). The calculation of these benefits is contingent upon the disparity between the actual and counterfactual load. There are three of these counterfactual scenarios: one in which the TOU tariff was not introduced, implying that all users in Guangdong adopted a flat tariff; a second in which the TOU tariff reform in October 2021 was not executed; and a third in which the reform was implemented earlier.[19]

Because the TOU tariff in Guangdong was implemented as a mandatory, top-down policy for I&C users, this study adopts a system-level cost perspective when evaluating its benefits. Under this perspective, the analysis focuses on reductions in system operating and investment costs, rather than changes in individual consumer welfare that would arise under voluntary participation or market-based adoption. Consistent with this scope, the estimated benefits do not incorporate private adaptation costs borne by users, such as investments in self-generation, energy storage, or demand-response technologies undertaken in response to TOU pricing. The reported estimates should therefore be interpreted as gross system benefits, rather than net social welfare gains after accounting for user-side adjustment and investment costs.

Table 5 presents the estimated social benefits of the TOU pricing policy in Guangdong, compared with flat tariffs. One can also make comparisons between the two TOU tariff schemes. It is equivalent to the sum of cost savings in electricity generation (Supplemental Appendix C.3), the social benefits of reduced greenhouse gas emissions (Supplemental Appendix C.4), the value stemming from reduced installed capacity needs (Supplemental Appendix C.5), and the decreased costs of transmission congestion and ancillary services (Supplemental Appendices C.6–C.7). Supplemental Appendix Figure E.14 provides a waterfall decomposition of these components over the three-year sample period.

The results demonstrate that the mandatory TOU tariffs yielded significant economic benefits. Notably, during the first two years of the sample period, Guangdong implemented less aggressive TOU tariffs. By contrast, in the final year of the sample period, the reform led to a wider PSO price ratio and readjusted pricing periods, resulting in more aggressive TOU tariffs. Over the three-year sample period, the TOU pricing policy generated social benefits of ¥24.9 billion, equivalent to 4.5 percent of the wholesale electricity generation costs during the same period.[20] Furthermore, our estimates suggest that the TOU tariff reform in October

[19]The referenced counterfactuals in this section differ from those in Section 4.3, where they only relate to the predicted counterfactual load between October 2021 and September 2022 obtained using the ML method.

[20]Wholesale electricity generation costs are estimated as the sum of the product between short-run marginal costs and dispatch volume from the different fuel types.

Table 5. Social Benefits of the TOU Pricing Policy in Guangdong, Billion ¥.

	10/2019–09/2020		10/2020–09/2021		10/2021–09/2022	
Saved costs	PRE	POST	PRE	POST	PRE	POST
Generation	0.043	0.091	0.080	0.169	0.108	0.229
	(0.009)	(0.013)	(0.017)	(0.023)	(0.022)	(0.031)
Emission	−0.002	−0.004	−0.004	−0.009	−0.005	−0.010
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Investment	6.813	9.269	7.334	9.386	7.060	10.123
	(0.629)	(0.728)	(0.687)	(0.743)	(0.711)	(0.861)
Congestion	0.050	0.069	0.047	0.123	0.016	0.072
	(0.003)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)
Ancillary services	0.030	0.043	0.030	0.032	0.010	0.003
	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)
Total	6.934	9.468	7.487	9.701	7.189	10.417
	(0.631)	(0.731)	(0.688)	(0.747)	(0.710)	(0.862)

Note. Standard deviations from the Monte Carlo analysis are reported in parentheses. “PRE” refers to the scenario in which I&C users pay TOU tariffs equal to those before the major reform in October 2021. “POST” refers to the scenario in which I&C users pay TOU tariffs equal to those after the major reform in October 2021.

2021 increased these benefits substantially. Specifically, in the subsequent twelve-month period, the reform increased the social benefits by 45.4 percent compared with the scenario without the reform. Similarly, implementing the reform earlier would have led to greater social benefits. Most of these benefits stem from reduced investment in new power plants, contributing to approximately 98 percent of the total benefits. This finding is consistent with the results of previous studies such as Fowlie et al. (2021) and Guo (2023), which also highlighted that the primary social benefit resulting from implementing TOU tariffs is the reduction in necessary investment for load capacity.

6. Optimal TOU Tariffs

In Section 5, we found a substantial increase in social benefits owing to the TOU tariff reform in Guangdong. In this section, we investigate whether the current TOU tariffs are optimal and if not, the direction which further reforms should take. The redesign of TOU tariffs involves two main steps. In the first step, we determine which hourly periods within the day should be designated as peak, shoulder, or off-peak. In the second step, given the pricing periods defined in the first step, we look for the optimal PSO price ratio that maximizes the social benefits.

Determining the optimal peak, shoulder, and off-peak hours is relatively straightforward. In an electricity system with limited renewable energy supply, we expect the TOU pricing policy to maximize the social benefits by designating high-demand hours as the peak period and low-demand hours as the off-peak period.[21] The reason is that usually the marginal costs of electricity generation during high-demand hours are higher, and reducing electricity load in these hours results in a significant reduction in the investment in peaking plants.

[21]For electricity systems with a high share of renewable energy supply, such as the Californian electricity system, the cost of electricity generation may be greater during night hours due to increased residual demand as renewable generation, especially solar power, decreases. In such scenarios, considering the residual load curve could help categorize peak and off-peak hours.

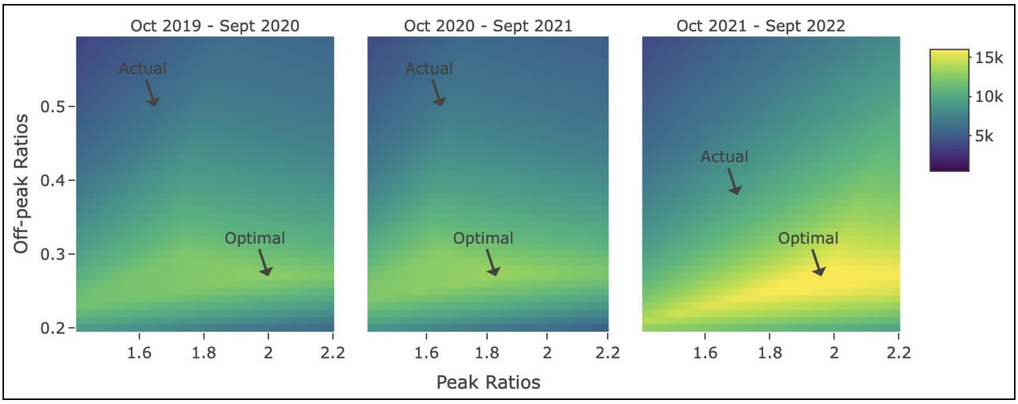

Figure 3. Heatmaps for the social benefits under different PSO price ratios.

Supplemental Appendix Figure E.12 demonstrates the standardized daily average electricity load over the three-year sample period, assuming that the flat tariff (instead of TOU tariffs) is implemented.[22] The shaded region represents the redefined peak periods following the reform in October 2021. The hours with the highest demand fall within this shaded region, indicating that the correct choice regarding peak periods has been made by the reform. Similarly, the hours with the lowest demand are already categorized as the off-peak period. This observation underscores the fact that the reform has made the optimal choice of peak, shoulder, and off-peak periods; hence, the pricing periods of the mandatory TOU tariffs in Guangdong do not need to be readjusted further.[23]

Determining the optimal PSO price ratio that maximizes the social benefits involves two main steps. First, we replicate the procedure outlined in Supplemental Appendix C.1 to construct the counterfactual load under any proposed PSO price ratio. Second, using this estimated counterfactual load, we adopt the methodology described in Supplemental Appendix C.3 to C.7 to estimate the associated social benefits. Specifically, we denote the PSO price ratio by $\bar{u} : 1 : u$. The values of $\bar{u}$ and u are selected based on their real-world variations during the three-year sample period. This selection is driven by the requirement that the load impact estimates in Section 4 remain mostly valid within the observed value ranges of $\bar{u}$ and u in the sample. These ranges are 1.65 to 2.125 for $\bar{u}$ and 0.38 to 0.5 for u. When searching for the optimal PSO price ratio, we extend these value ranges slightly to $(1.4, 2.2]$ and $[0.2, 0.6)$.

We set the granularity of the $\bar{u}$ and u values to 0.01, resulting in 3,200 ($= 80 \times 40$) possible PSO price-ratio combinations. The recorded social benefits of TOU pricing policies (relative to the flat tariff) for each combination are used to construct heatmaps illustrating the relationship between $\bar{u}$, u, and the social benefits, as shown in Figure 3. Our heatmap analysis indicates that to increase the social benefits, u should be below the actual value, whereas $\bar{u}$ should be above it. Interestingly, our findings suggest that the optimal value for u is 0.27 throughout the entire sample period. However, the optimal range for $\bar{u}$ varies between 1.83 and 2, as reported in Table 6. This underscores the potential advantages of frequently adjusting PSO price ratios to ensure the dynamic optimization of TOU tariffs.

Table 6 also summarizes the social benefits under the optimal TOU tariffs for each year compared with the actual social benefits under actual TOU tariffs. These results suggest that

[22]These load curves are derived from our earlier estimates of the counterfactual load in Supplemental Appendix C.1.
[23]Alternatively, a similar conclusion can be drawn by examining the residual load curve under the flat tariff, as presented in Supplemental Appendix Figure E.13.

Table 6. Social Benefits Under the Optimal PSO Price Ratios.

Figure	First Year	Second Year	Third Year	Three-year Ave.
Optimal PSO ratios	2:1:0.27	1.83:1:0.27	1.96:1:0.27	1.96:1:0.27
Optimal social benefits (b.¥)	12.772	13.210	16.650	14.062
Actual social benefits (b.¥)	6.934	7.484	10.438	8.285
Potential improvements	84.2%	76.5%	59.5%	69.7%

Note. In reality, in the first and second years, Guangdong adopted less aggressive TOU tariffs than it did in the third year. "Potential improvements" measures the percentage improvements in the social benefits when switching from the existing TOU tariffs to the optimal ones.

there are potentially social benefits to be gained if policymakers choose to widen the PSO price ratios. Under the optimal TOU tariffs, the estimated average social benefits over the three-year sample period approach ¥14.1 billion, accounting for approximately 7.6 percent of wholesale electricity generation costs during that period.

Finally, further investigation reveals that the PSO price ratios that maximize savings in capital investment costs are identical to those that maximize the social benefits.[24] This congruence arises primarily because the majority of the social benefits stem from the reduced need to invest in new power plants. This significant insight implies that when designing TOU tariffs, policymakers can concentrate solely on the impact of TOU tariffs on capital investment, streamlining the decision-making process.

7. Conclusions and Policy Implications

In this study, we focus on the mandatory TOU pricing policy in China's Guangdong province. Our research comprises three key stages. First, we examine the impact of TOU prices on electricity load, revealing statistically significant load-shifting effects, although the energy conservation effects appear to be negligible. Next, we develop a data-driven methodology to examine the influence of TOU tariffs on the social benefits of the electricity industry. We find that between October 2019 and September 2022, the social benefits induced by the TOU pricing policy accounted for approximately 4.5 percent of wholesale electricity generation costs. Notably, the predominant proportion (98%) of these benefits is due to the reduction in capital investment. This indicates that when designing TOU tariffs, policymakers can focus solely on capital investment rather than on all the other social benefits, simplifying the decision-making process. The final stage involves designing the optimal TOU tariff that maximizes the social benefits. Our analysis underscores that a modest expansion of the PSO price ratio could substantially raise the social benefits by 70 percent.

This study has several important policy implications. Although TOU tariffs generate statistically significant load-shifting effects, the magnitude of the response suggests that economic incentives alone may be insufficient to fully unlock demand flexibility. Policymakers could therefore complement tariff reforms with enabling measures such as information disclosure, automation technologies, and mandatory reporting or benchmarking mechanisms to enhance demand responsiveness and amplify social benefits. The effectiveness of TOU design is highly context-dependent, as optimal tariff structures hinge on regional characteristics including load profiles, fuel mixes, market structures, and the technical attributes of marginal generation units, underscoring the need for region-specific tariff schemes. Finally, given the sizable and largely untapped potential on the residential side and China's extensive

[24]The detailed results are available upon request.

experience with TOU pricing for I&C users, a natural next step is to pilot dynamic pricing for residential consumers.

It should be noted that the system-level benefits estimated in this study do not incorporate private adaptation costs incurred by users when adjusting their consumption in response to TOU tariffs. These include both user-side investment and behavioral adjustment costs, implying that the reported welfare gains should be interpreted as upper-bound estimates. More broadly, the implementation of TOU tariffs may entail additional social costs related to infrastructure and metering deployment, tariff design and administration, regulatory complexity, and legal considerations. Although such costs are likely to be modest relative to the aggregate social benefits identified in this study, they warrant explicit consideration in future research. In particular, heterogeneous consumer responses may generate uneven welfare effects: while some users face constraints or higher costs when shifting peak consumption to off-peak periods, others may increase off-peak usage in ways that complicate welfare assessment. Future work could therefore integrate both system-level benefits and user-side costs into a unified cost-benefit framework to provide a more comprehensive evaluation of TOU tariff policies.

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Supplemental Material

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