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Nonlinear pricing in multidimensional context: An empirical analysis of energy consumption ☆

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A B S T R A C T

Modern business practices frequently employ a blend of pricing strategies to segment markets effectively. As a result, consumers may encounter pricing schedules that are nonlinear and multidimensional. This paper presents a structural approach for estimating multidimensional nonlinear pricing models involving multiple decision variables in an energy market. Using a unique, rich panel dataset of Chinese household electricity consumption, we structurally estimate consumer preferences under the influence of an Increasing Block Price (IBP) and a Time-of-Use (ToU) system. Our structural approach allows us to distinguish and evaluate household-level price elasticities of demand, presenting a novel explanation for consumers' feedback on marginal price changes. Through model-based simulations, we demonstrate that a 1% increase in price corresponds to a 0.7% reduction in total electricity demand. However, our analysis indicates that practical opportunities for optimization within multi-dimensional pricing systems are limited. Our findings offer distinct insights into the complex interplay between intricate pricing structures and energy consumption behavior, thereby providing valuable guidance for policymakers and regulators.

1. Introduction

The energy market balances household consumption, industrial usage, and environmental conservation. When energy demand or supply shocks occur due to unforeseen events, regulators and suppliers need to create effective pricing schedules. These schedules aim to optimize resource allocation, promote energy efficiency, and address diverse consumer needs. In December 2020, a sudden temperature drop in China's Hunan and Zhejiang provinces led to a 9% increase in energy demands from households and the hospitality industry (Ma 2020). At the same time, the global price of coal rose, putting further pressure on energy supplies. To

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cope, regulators in Hunan instituted blackout periods, a rare measure, to ensure essential facilities like schools and hospitals had adequate energy (Lee et al. 2020). As energy costs rise and climate change awareness grows, some policymakers advocate for more complex pricing systems, such as nonlinear pricing. They argue that these systems can help households plan their consumption better and improve energy efficiency under limited supply conditions (Borenstein 2012; Kök et al. 2018; Spector et al. 1995). This paper examines household decision-making under a multi-dimensional nonlinear pricing system, focusing specifically on how changes in this system affect household electricity consumption demand.

Two strands of literature have emerged that evaluate the impact of nonlinear pricing schemes on profitability, consumer surplus, and social efficiency in the energy market. The first strand treats price schedules as exogenous and employs random utility discrete choice models to estimate the distribution of consumer characteristics (e.g., Economides et al. 2008; Leslie 2004). The second strand endogenizes price and quantity schedules to assess demand and cost structure (e.g., Crawford and Shum 2007). Although some studies incorporate multidimensional consumer heterogeneity, they maintain a unidimensional decision variable for model tractability, typically the product quantity purchased by consumers. This paper proposes a novel structural approach to evaluate consumer choices and welfare implications under multidimensional pricing schedules, accounting for consumption errors that stem from households' inability to precisely control their energy consumption.

Non-linear pricing schedules are not exclusive to the energy sector but widely adopted in telecommunications and labor markets. In telecommunications, phone users must decide their monthly call duration and call timing (e.g., Luo 2023). In the labor market, self-employed workers adjust labor supply in response to nonlinear income taxation schemes, with part-time occupations chosen based on preferences for salary rates and working hours (e.g., Chetty 2012; Bastani and Selin 2014; Heckman 1983; Pestieau and Possen 1991; Parker 1999; Saez 2010). Two main challenges emerge: first, model identification becomes more difficult due to the possibility of multiple equilibria; second, developing a model that accommodates multiple decision variables while maintaining tractability is challenging. We tackle these issues by introducing a bill shock as a representation of households' inability to precisely control their energy consumption (Borenstein 2009; Grubb and Osborne 2015)., we address these issues and apply our model to rich panel data of household electricity consumption.

Our dataset boasts two significant advantages. First, it incorporates unique pricing schedules derived from two concomitantly implemented nonlinear pricing systems in the electricity market: Increasing Block Pricing (IBP) and Time-of-Use (ToU) Pricing. The IBP system, commonly employed in sectors that sometimes require consumption reduction such as the gas and water industries (Cavanagh et al. 2002; He and Lin 2017), imposes a discriminatory pricing scheme wherein marginal prices rise with increasing consumption. Conversely, the ToU system, predominantly used in sectors necessitating intensive load management like the transportation industry (Aigner et al. 1994; Kraus and Yoshida 2002), exploits households' preferences by varying day and night prices. The understanding of these pricing systems has implications beyond the energy market. Typically, electric companies adopt only one of these pricing systems. For instance, Ito (2014) examined the IBP system in California, while Train and Mehrez (1994) analyzed the ToU system using Pacific Gas and Electric Company (PG&E) data. In contrast, our dataset, derived from a 2009-2011 pricing experiment conducted by Chinese local government and industry experts, encompasses both systems. We observe consumer behavior under dual nonlinear price schedules over three years, allowing us to identify more intricate and flexible models, incorporate potential heterogeneous factors, and enhance the credibility of our counterfactual analysis. The second advantage of our dataset lies in its composition, which includes both administrative and survey data. It features an administrative dataset from the State Grid Corporation of China, detailing monthly electricity consumption, as well as peak and valley usage for each month. Additionally, it includes data from a local sample survey conducted in Hangzhou, the capital and most populous city of Zhejiang. Therefore, we benefit from both data types: administrative data facilitates more reliable and accurate measurements (Chetty 2012), whereas survey data provides comprehensive information on various household characteristics (Hausmann et al. 1979; Hajispyrou et al. 2002; Olmstead et al. 2007).

Our estimation results show that such a consumption error leads to an average final consumption that is 3%-4% higher than the planned consumption value. These results offer fresh evidence supporting Saez (2010), where consumption bunching is portrayed as a behavioral response to a nonlinear pricing system. Our counterfactual analysis measures the impact of multidimensional nonlinear pricing schedules on price elasticity, showing that a 1% increase in price leads to a 0.7% reduction in total electricity demand. We find that larger households with more appliances experience smaller welfare losses when faced with price increases. Interestingly, we also find that although multi-dimensional pricing systems theoretically provide policymakers with more flexible tools to optimize welfare and prevent energy waste (e.g., Rochet and Choné 1998), the room for optimization in practice is limited.

In sum, our paper contributes in four key aspects.

First, we build upon Ito (2014), which delivers compelling evidence that consumers are more responsive to average prices than marginal prices. This renders nonlinear pricing less effective in achieving policy goals. However, the underlying causes of this suboptimal consumer behavior remain elusive. In response, we present a structural model that elucidates consumer consumption behavior. We assume that consumers respond to marginal prices, as in Reiss and White 2005. Drawing on the concept of bill shock from Grubb and Osborne (2015) to electricity consumption, we propose that Ito (2014)'s results would be observationally equivalent to our model's case when uncertainty is sufficiently large. Shaffer (2020) investigates consumer responses to nonlinear pricing under a natural experiment and uncovers that some households respond to average price but others to marginal price. Our model provides an alternative explanation for these empirical observations. We suggest that consumers facing higher marginal prices may be more prone to considerable bill shocks, leading to larger consumption errors. This implies that some empirical results might be attributed to shifts in the relationships between model outcomes under different shock intensities.

Second, our structural model elucidates consumer preferences under intricate pricing schedules, enabling improved comprehension of future demand. We contribute methodologically by extending our analysis to encompass nonlinear pricing scenarios with multidimensional household characteristics and multiple decision variables. A primary challenge in multidimensional nonlinear pricing is the potential for agents to encounter multiple optimal choices yielding identical utility levels. Existing literature addresses this issue through theoretical models with numerical simulations (Çelik and Maglaras 2008) or by discretizing continuous decision variables and estimating nonlinear discrete model selection (e.g., Blundell et al. 1998; Hoynes 2000; Van Soest 1995). Discrete models, while avoiding multiple equilibrium problems, introduce additional estimation challenges. For example, model estimation complexity increases due to the discretization of continuous output variables, obscuring the economic implications of model parameters. Reiss and White (2005) propose a Generalized Method of Moments (GMM) approach for estimating pricing models with nonlinear budget constraints, in which consumption errors are observable and known to households. Our paper presents an alternative method for modeling tariff design that applies to kink schedules and mixed pricing issues. Specifically, in our model, households cannot precisely control their consumption and must optimize their utility under a more complex pricing system. We directly align output variables through a non-discrete model and provide corresponding estimation techniques and identification conditions.

Third, our study casts light on welfare analysis and environmental considerations in the context of electricity pricing policies (e.g., Wilson 1993). Governments have implemented various initiatives, such as Time-of-Use (ToU) and Inclining Block Pricing (IBP) schedules for household customers and smart meters, to decrease emissions and encourage renewable energy (e.g., Kök et al. 2018; Spector et al. 1995). Price schedules also substantially affect household disposable income (Borenstein 2012). Holland and Mansur (2008) assess the short-run effects of dynamic pricing on US regions, producing mixed evidence on emission reductions. Aubin et al. (1995) argue that Real-Time Pricing (RTP) generally improves welfare. In a recent empirical evaluation of Real-Time Pricing (RTP) effects, Fabra et al. (2021) underscores specific conditions necessary for the success of RTP. Contrary to previous studies, our findings suggest that complex pricing systems do not universally yield benefits, a result bearing substantial policy implications. This is especially noteworthy considering the present global context marked by heightened energy supply vulnerability and the adoption of increasingly complex pricing strategies by numerous national power companies.[1]

Fourth, our estimation method offers the advantage of computational speed, especially when incorporating observed and unobserved heterogeneous factors. In comparison to traditional discrete choice methods based on likelihood or indirect inference, our approach offers a step-by-step roadmap for avoiding computational complexity and overly complicated models (Low and Meghir 2017). Unlike conventional GMM methods, our approach exhibits greater sensitivity to consumer choices near price jumps in the data. The proposed methodology is also relatively general, applicable to similar problems in labor economics, where individuals must determine their total labor supply and part-time occupation (e.g., Parker 1999). The choice depends on an individual's preference for working hours and their pay rate in various occupations. Consequently, our study holds significance for the literature on formulating optimal tax policies in labor economics (e.g., Bastani and Selin 2014; Chetty 2012; Heckman 1983).

The remainder of the paper is organized as follows: Section 2 describes the data and sample statistics. Section 3 presents the structural model. Section 4 discusses identification and outlines the estimation framework. Section 5 reports the empirical results. Section 6 conducts a counterfactual analysis and offers policy recommendations, and Section 7 concludes.

2. Pricing system, data and sample statistics

2.1. Pricing system and data collection process

In our study, we use two primary data sources: household-level utility billing records from the State Grid Corporation of China, and a local sample survey conducted in Hangzhou. The sample period spans 36 months, from January 2009 to December 2011. Importantly, our dataset focuses exclusively on household electricity consumption, excluding electricity usage in offices and production facilities. During this period, Hangzhou functioned as a test zone for electricity pricing. The electricity bills were determined based on distinct consumption tiers and peak/valley consumption within each tier. Table 1 illustrates the electricity price structure faced by Hangzhou households. Each tier in the table consists of two prices: peak time and valley prices. The total consumption for each block is calculated by aggregating the electricity consumed during both peak and valley periods. The final column presents an example: a household consuming 250 kilowatt-hours (kWh) of electricity per month, with a peak and valley consumption ratio of 1.5 across all tiers, would incur a monthly bill of 123.50 RMB. The pricing system in our data remains in use today (as of 2023), demonstrating the feasibility and rationality of a multi-dimensional nonlinear pricing system to some extent. Since the electricity pricing structure is constant over time, we use a structural approach to simulate the effects of price changes on electricity consumption. This method aids in assessing potential price elasticities.

Moreover, it is important to note that the system does not precisely calculate household consumption during daytime and nighttime periods for each tier. When computing electricity bills, utility companies simply allocate the total daytime consumption and total nighttime consumption proportionally across each tier. For instance, consider a household that consumes a total of 100 kilowatt-hours (kWh), with the first 50 kWh used during the day and the remaining 50 kWh used at night. According to the precise calculation

[1] For instance, the Chinese government has actively promoted a combination of Time of Use (ToU) and Increasing Block Pricing (IBP) systems among provinces since 2012, encouraging responsible household electricity use. Many Chinese provinces have either implemented or are in the process of implementing this combined IBP+ToU system (Guang et al. 2019; Liu and Lin 2020). Japan has a pricing system that closely parallels our research focus, segmenting prices into three tiers based on electricity consumption levels. Additionally, Tokyo Electric Power Company employs a ToU pricing structure, offering reduced electricity rates from 11 p.m. to 7 a.m. (Nakada et al. 2016). The French electricity system introduces further complexity, setting a fixed base capacity rate premised on the IBP, subsequently followed by a ToU rate determined by both season and time of day (Ansarin et al. 2022). The power company in the Canadian province of Quebec has embraced a similar pricing approach (Pelletier and Faruqui 2022). South Korea's IBP system includes subsidies targeted at specific groups, such as large families and the elderly, thereby ensuring lower marginal costs (Kim et al. 2022).

Table 1
Structure of electricity pricing in Hangzhou.

Tier (Consumption level)	Quantity (Peak+Valley)	Peak price (8:00-22:00)	Valley price (22:00-8:00)	Example: $x = 250$ Peak $= 0.6x$ and Valley $= 0.4x$
Tier 1	$[0, 50)$	0.568	0.288	$50 \times 0.6 \times 0.568+$ $50 \times 0.4 \times 0.288 = 22.8$
Tier 2	$[50, 200)$	0.598	0.318	$150 \times 0.6 \times 0.598+$ $150 \times 0.4 \times 0.318 = 72.90$
Tier 3	≥ 200	0.668	0.388	$50 \times 0.6 \times 0.668+$ $50 \times 0.4 \times 0.388 = 27.8$
Unit	Kilowatt-Hour	RMB yuan	RMB yuan	$22.8 + 72.90 + 27.8 = 123.50$

Notes: On December 31, 2009 the Official USD to CNY Exchange Rate:1 USD = 6.8279 RMB by using the converter in https://www.exchangerates.org.uk/.

method, the first 50 kWh of consumption belongs to tier 1 daytime usage, costing $0.568 \times 50 = 28.4$. The latter 50 kWh of consumption belongs to tier 2 usage, with a cost of $0.318 \times 50 = 15.9$. Under this calculation method, the household's total electricity bill would be 44.3.

In an effort to simplify consumption planning for households, utility companies, when settling accounts, calculate based on the total electricity consumption of 100 kWh, with half of the electricity consumed during the day. In this case, the household's total electricity expenditure, according to Table 1, would be $0.568 \times 25 + 0.288 \times 25 + 0.598 \times 25 + 0.318 \times 25 = 44.3$. Because the price differences between different tiers are identical, these two calculation methods generate the same total electricity bill. Therefore, under the current pricing system, we assume that households only need to account for their total monthly electricity consumption and the daytime-to-nighttime consumption ratio. This approach is equivalent to determining specific consumption ratios for each tier separately. We will formally discuss this finding in Proposition 1.

The data recorded by the State Grid encompasses a random sample of 5,000 observations. Using systematic sampling methods, we collected data on variables such as total monthly electricity consumption, electricity bills, and total electricity consumption during peak and off-peak periods for each month. Additionally, our dataset incorporates a survey of household information. The procedure for collecting this survey data is detailed in the Online Appendix A. Based on the State Grid database, we randomly selected and contacted 500 households in Hangzhou for survey participation. We gathered information on household income, family characteristics, household electrical appliances, and other relevant data through the distribution of paper questionnaires. The survey data were then matched with the electricity consumption data from the original national grid database. Out of the 500 households contacted, 119 responded, yielding a final dataset of 4,284 observation points over three years. To incorporate comprehensive weather data, we further matched the survey data with the National Oceanic and Atmospheric Administration (NOAA) dataset.

Although our study did not survey all 5,000 households, the distribution of outcome variables in the selected sample mirrors closely the initial sample distribution. For more information, refer to the Online Appendix B. Our data provide two key advantages over existing literature, which predominantly relies on micro survey data (e.g., Hausmann et al. 1979; Hajispyrou et al. 2002; Olmstead et al. 2007). First, our measure of electricity consumption is more accurate and reliable, as we obtained electricity consumption levels directly from the national grid database rather than relying on respondents' self-reported answers (Chetty 2012). Second, excluding households that use gas or natural gas for cooking, few presently employ natural gas for heating during winter. This significantly mitigates the issue of consumers switching between different energy sources due to price fluctuations.

2.2. Sample statistics

Table 2 provides a summary of the relevant statistics. On average, the consumption ratio between peak (day) and off-peak (night) hours is 6:4. According to our data, a typical family comprises three members, most likely consisting of two adults (primarily a married couple) and either a child or an elderly relative. Such a family in our dataset generally possesses two bedrooms, with each member's living area ranging from 25 to 35 square meters. This may explain why, on average, each household owns two televisions and over two air conditioners. However, the average number of refrigerators and desktop computers per household is one, as all family members can share these items. Although Hangzhou experiences relatively mild weather, 74% of families rely on electric heating in winter, and more than half utilize electric cookers and showers. These descriptive statistics enable us to illustrate a representative household residing in a large city in Eastern China and the extent of electricity consumption for each family.

In Fig. 1, we illustrate the overall distribution of household electricity consumption under the current pricing system, examining the effects of bunching around the kink point (200 kWh). The distribution exhibits a downward trend after tier 2 and reveals slight bunching on the left-hand side of the block. Based on Fig. 1, we hypothesize that households in our dataset may be responding to marginal prices. However, these results could also be purely coincidental, arising from the distribution of electricity consumption, as the mode of the distribution does not align precisely with the 200 kWh boundary line. To further investigate, we first analyze whether consumers respond to marginal prices through regression evidence. We then apply a structural model to clarify how it would produce the observed consumption distribution.

Table 2
Summary statistics (sample size: N = 4,284).

	Variable	Mean	Standard Deviation	Min	Max
Electricity Consumption	Peak Hour (kWh)	116.91	76.57	2.24	643.09
	Valley Hour (kWh)	103.23	70.46	0.36	701.18
	Total	220.15	130.49	9.43	1259.07
Household Characteristics	Family Member	3.104	1.073	1.00	8.00
	Number of People (≥ 65)	0.74	0.86	0.00	2.00
	Number of Adults ($< 65, \geq 18$)	2.13	1.23	0.00	6.00
	Hosing Area (m^2)	70.61	24.20	29.00	190.00
	Number of Bedrooms	2.18	0.57	1.00	4.00
Electric Appliance	Computers	1.084	0.78	1.00	3.00
	Televisions	1.85	0.71	1.00	4.00
	Air Conditioners	2.24	0.86	0.00	4.00
	Refrigerators and Freezers	1.068	0.34	0.00	4.00
	Microwave Ovens (Y/N)	0.74	0.43	0	1
	Winter Heating (Y/N)	0.74	0.43	0	1
	Electricity for Cooking (Y/N)	0.69	0.46	0	1
	Electricity for Shower (Y/N)	0.75	0.43	0	1
Family Income (1000 RMB)	Income < 8	0.53	0.49	0	1
	8 ≤ Income < 15	0.37	0.48	0	1
	15 ≤ Income	0.093	0.29	0	1
Climate (Monthly)	Maximum Temperature (^0C)	29.3	8.01	7.50	39.70
	Average Temperature (^0C)	17.35	8.67	1.35	30.62
	Average Humidity (%)	69.60	8.60	35.10	81.20
	Average Rain (hours)	41.72	33.68	5.80	180.46

Notes: 1) On December 31, 2009 the Official USD to CNY Exchange Rate:1 USD = 6.8279 RMB by using the converter in https://www.exchangerates.org.uk/. 2) The weather dataset is obtained from the National Oceanic and Atmospheric Administration (NOAA).

2.3. Evidence from regression analysis

We first present regression-based evidence to elucidate the relationship between electricity consumption and pricing, drawing inspiration from the econometric models introduced by Ito (2014) and Shaffer (2020). Although the price system remains constant in our dataset, marginal and average prices vary across households over time due to the time-varying proportion of electricity consumption during peak (daytime) hours. It is important to note that the results from our regression models do not indicate causal relationships between the variables.

We propose the following regression model:

$$\ln x_{it} = \delta_{ap} \ln MP_{i,t} + \delta_{ap} \ln AP_{i,t} + \eta_{i,t}. \tag{1}$$

In the regression equation, $x_{i,t}$ represents the monthly electricity consumption for i at time t. $MP_{i,t}$ denotes the marginal price paid by household i at time t is paying at time t and $AP_{i,t} = Bill_{i,t}/x_{i,t}$ signifies the average price for the same household and time period. The marginal price, $MP_{i,t}$, is calculated as follows:

$$MP_{i,t} = \lambda_{i,t} \times p_d\left(x_{i,t}\right) + \left(1-\lambda_{i,t}\right) \times p_d\left(x_{i,t}\right), \tag{2}$$

with $\lambda_{i,t} \in [0,1]$ indicates the proportion of electricity consumption during peak (daytime) hours. Furthermore, $p_d\left(x_{i,t}\right)$ and $p_n\left(x_{i,t}\right)$ represent the corresponding peak and off-peak hour prices, respectively, as detailed in 1. $\eta_{i,t}$ is the error term.

Table 3 presents our primary regression findings, in which we account for household and time-related fixed effects across all columns and cluster error terms at the household level. In the first and second columns of Table 3, $MP_{i,t}$ and $AP_{i,t}$ are included separately, revealing a positive correlation with total consumption at a 5% statistical significance level for both variables. In the third column, when controlling for $MP_{i,t}$ and $AP_{i,t}$ concurrently, the correlation of $AP_{i,t}$ weakens, suggesting that $MP_{i,t}$ more effectively captures the relationship. These findings indicate that households in our dataset may be, at least, sensitive to both marginal and average prices.

It is crucial to emphasize that these results do not establish causality since the positive association between $MP_{i,t}$ and $x_{i,t}$ arises primarily from the pricing system; higher consumption implies higher marginal prices. Consequently, we replace $AP_{i,t}$ with $Bill_{i,t}$ in the fourth column. This modification offers the advantage of defining $Bill_{i,t}$ as $AP_{i,t} \times x_{i,t}$, which allows us to account for potential household demand for electricity. After controlling for $Bill_{i,t}$, $MP_{i,t}$ further captures the statistical relationship between marginal price fluctuations and household consumption of the next electricity unit at equal consumption levels. In the fifth column, we additionally control for the quadratic term related to $Bill_{i,t}$ to better account for the statistical association between total consumption costs and overall consumption. Results show that, after adjusting for the electricity bill, a household's marginal electricity consump-

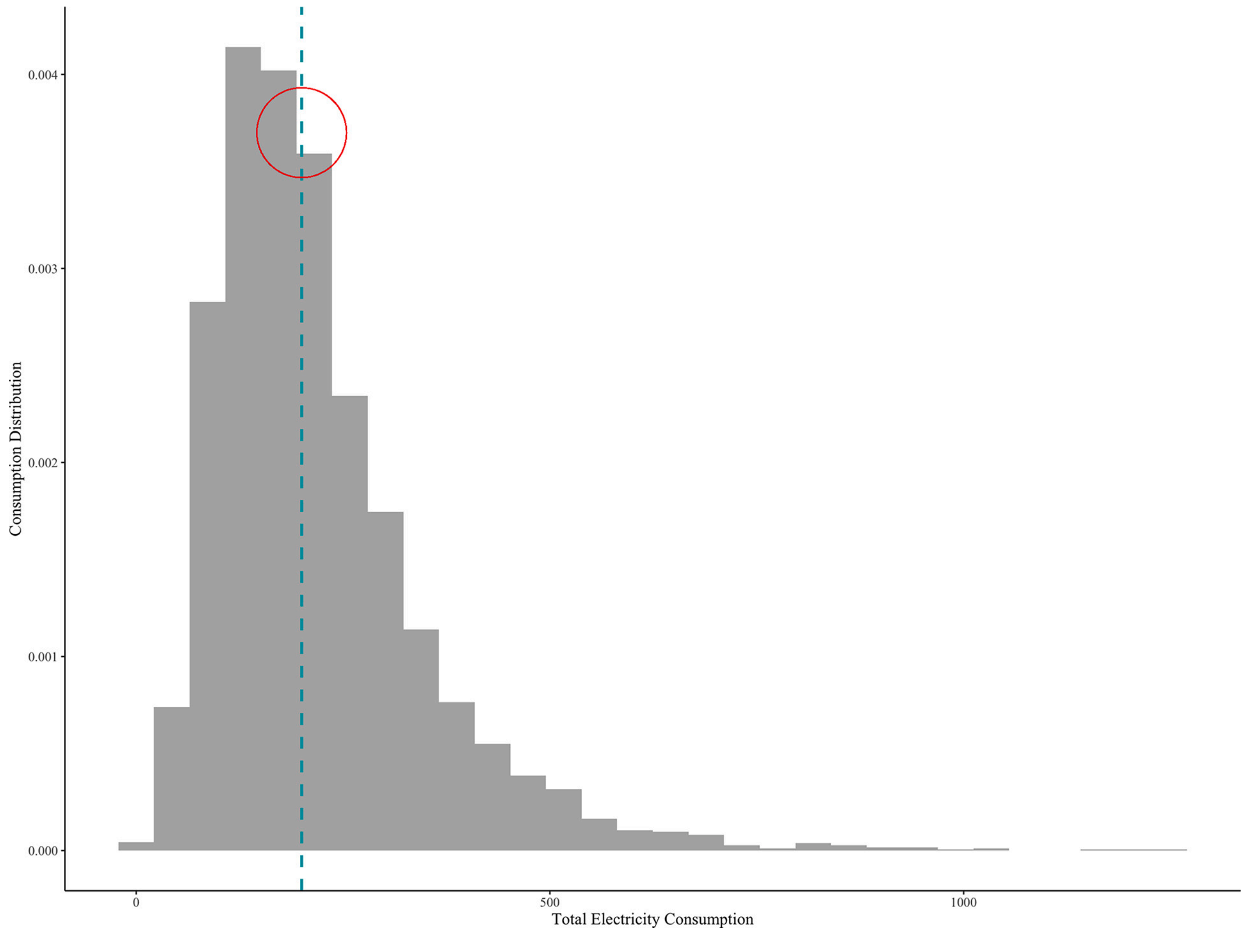

Fig. 1. Distribution of electricity consumption by household. Notes: Blue vertical dotted lines represent the interval of different tiers. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

Table 3
Regression analysis results.

	Dependent Variable: Log of Electricity Consumption $\ln x_{i,t}$				
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
$\ln MP_{i,t}$	1.428***		1.677***	-0.572***	-0.552***
	(0.103)		(0.120)	(0.014)	(0.015)
$\ln AP_{i,t}$		1.214***	-0.425		
		(0.193)	(0.252)		
$\ln Bill_{i,t}$				0.993***	1.161***
				(0.003)	(0.020)
$(\ln Bill_{i,t})^2$					-0.019***
					(0.002)
Household Fixed Effect	✓	✓	✓	✓	✓
Time Fixed Effect	✓	✓	✓	✓	✓
R^2	0.740	0.727	0.741	0.997	0.997

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Error terms are clustered at the household level.

tion remains statistically significantly correlated with marginal prices at a 5% level, exhibiting a negative correlation. This suggests that a 1% decrease in the marginal price corresponds to an approximate 0.55% increase in electricity consumption within our dataset.

To elucidate the underlying mechanisms depicted in the above tables and figures, we propose a structural model that posits consumers may experience unavoidable consumption errors. Risk aversion leads consumers to balance their spending costs by adjusting the allocation of their expenditures over time. Evaluating the extent of potential consumption inaccuracies offers an alternative explanation for the attenuated bunching effect.

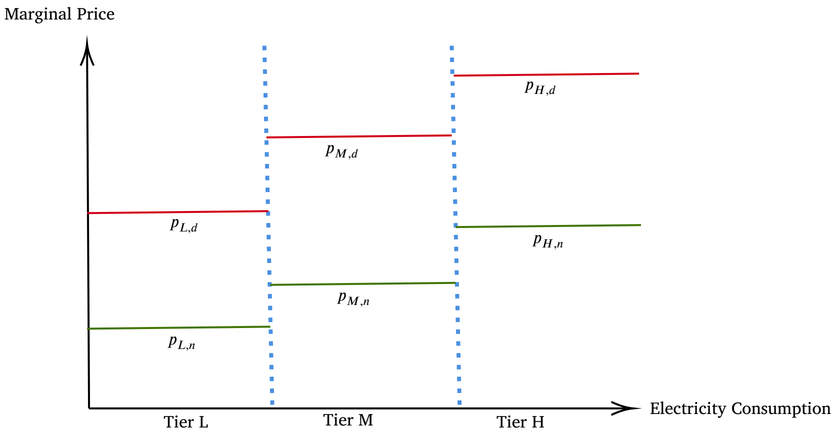

Fig. 2. Illustration of the pricing system.

3. A structural model of electricity consumption

In this section, we develop a structural model to explain household i's electricity consumption decision for $i = 1, ..., n$ at $t = 1, ..., T$. Electricity supply in China is highly centralized, with the state directly regulating electricity prices. As households are price takers, their decisions do not directly affect electricity prices. Throughout our observation period, the price system remains unchanged and, as far as we know, is still in use today. In our model, we consider the current electricity price system as given.

3.1. Pricing mechanism and decision variables

Our model aims to examine households' decisions regarding their total electricity consumption (x) and the proportion of consumption (λ) allocated to various pricing tiers. We primarily focus on the given pricing system with three tiers (basic L, ordinary M, and luxury consumption H) and two time steps (day d and night consumption n). The pricing system $\mathcal{P}$ can be represented as a 3×2 matrix, where each component denotes the marginal price of consuming one more unit of electricity in a specific tier and time periods. In this paper, the time period refers to the proportion of time within a 24-hour period, such as day-night, morning-afternoon-night, etc. More broadly, it can also signify different charges depending on the season (e.g., many countries have different electricity rates in winter and summer). We have:

$$\mathcal{P} = \begin{pmatrix} p_{L,d} & p_{L,n} \\ p_{M,d} & p_{M,n} \\ p_{H,d} & p_{H,n} \end{pmatrix}. \tag{3}$$

In a pure IBP pricing system, $\mathcal{P}$ would be a row vector of 3 elements, and in a pure ToU pricing system, $\mathcal{P}$ would be a column vector of 2 elements. Fig. 2 shows the structure of the current pricing system.

For each period $t = 1, ..., T$, household i must decide the level of electricity consumption $x_{i,t}$, and a set of $\left\{\lambda_{i,j,t}\right\}_{j\in\{L,M,H\}}$ that determines its peak hour consumption in that tier. In the context of a traditional Time of Use (ToU) system, which primarily includes peak hour and off-peak hour prices, household i simply chooses $\lambda_{i,t} \in [0, 1]$ the proportion of peak hour consumption at time t. In general, household i chooses a personalized set of decision variables:

$$\left(x_{i,t}, \left\{\lambda_{i,j,t}\right\}_{j\in\{L,M,H\}}\right) \in \mathbf{R}_+ \times [0,1]^3 . \tag{4}$$

Proposition 1. *Under the pricing system in Table 1 such that $p_{j,d} - p_{j,n} = \Delta p$, $\forall j \in \{L, M, H\}$. Determining $\left(x_{i,t}, \lambda_{i,t}\right) \in \mathbf{R}_+ \times [0, 1]$ or $\left(x_{i,t}, \left\{\lambda_{i,j,t}\right\}_{j\in\{L,M,H\}}\right) \in \mathbf{R}_+ \times [0,1]^3$ are observationally equivalent.*

Proof. Under pricing system $\mathcal{P}$, we have for all $\forall j \in \{L, M, H\}$, $p_{j,d} - p_{j,n} = \Delta p$. Therefore, the electricity bill with $\left\{\lambda_{i,j,t}\right\}_{j\in\{L,M,H\}}$ is:

$$\begin{aligned} \sum_{j\in\{L,M,H\}} \left\{x_{i,j,t}\lambda_{i,j,t}p_{j,d} + x_{i,j,t}\left(1-\lambda_{i,j,t}\right)p_{j,n}\right\} &= \sum_{j\in\{L,M,H\}} x_{i,j,t}\left\{\lambda_{i,j,t}p_{j,d} - \lambda_{i,j,t}p_{j,n} + p_{j,n}\right\} \\ &= \Delta p \sum_{j\in\{L,M,H\}} x_{i,j,t}\lambda_{i,j,t} + \sum_{j\in\{L,M,H\}} x_{i,j,t}p_{j,n}, \end{aligned}$$

where $x_{i,j,t}$ is the total level of electricity that household i consumed at time t in tier j. Now, we define $\lambda_{i,t}$ as the proportion of daytime consumption:

$$\lambda_{i,t} = \frac{\sum_{j\in\{L,M,H\}} x_{i,j,t}\lambda_{i,j,t}}{\sum_{j\in\{L,M,H\}} x_{i,j,t}},$$

and consider that in an alternative case, household i only chooses a fixed level of $\lambda_{i,t}$ for all tiers. We have:

$$\begin{aligned}\Delta p \sum_{j\in\{L,M,H\}} x_{i,j,t}\lambda_{i,j,t} &= \Delta p \lambda_{i,t} \sum_{j\in\{L,M,H\}} x_{i,j,t} \\ &= \Delta p \frac{\sum_{j\in\{L,M,H\}} x_{i,j,t}\lambda_{i,j,t}}{\sum_{j\in\{L,M,H\}} x_{i,j,t}} \sum_{j\in\{L,M,H\}} x_{i,j,t} \\ &= \Delta p \sum_{j\in\{L,M,H\}} x_{i,j,t}\lambda_{i,j,t}.\end{aligned}$$

An illustrative example is given in Section 2.1. □

Proposition 1 demonstrates that electricity consumption habits during both daytime and nighttime could be sticky under the pricing system $\mathcal{P}$, so that λ does not need to vary across tiers within a month. It is important to note that under a more general pricing structure, a highly sophisticated consumer would undoubtedly choose to consume $x_{j,d}$ and $x_{j,n}$ at each tier $j \in \{L, M, H\}$. However, Proposition 1 simplifies the model by assuming that a household's electricity consumption habits, i.e., the proportion of electricity consumption during day and night, will not change with the change of tier.[2] Proposition 1 implies that households will pay the same amount for their electricity bill under the following circumstances: (1) a household uses the washing machine during the day when marginal prices are low at the beginning of the month and uses it at night when marginal prices rise at the end of the month as it is pointless. (2) Under the same conditions, a household establishes a single level of λ across all tiers. Therefore, we do not need to consider how households make decisions specifically in our model. Each household only needs to determine $\left(x_{i,t}, \lambda_{i,t}\right)$ rather than a vector of four variables (i.e., $x_{i,t}$ and $\left\{\lambda_{i,j,t}\right\}_{j\in\{L,M,H\}}$). However, our model still allows consumers to change their consumption habits over two months. For example, electricity usage is generally higher in summer than in spring, and clothes are changed more frequently. Households can choose between doing laundry during the day in spring and at night in summer.

3.2. Bill shock and cost function

We assume that rational consumers take into account potential losses stemming from bill shocks when making decisions. In most instances, households cannot exert perfect control over their final consumption during the decision-making process. Such discrepancies become evident upon receiving bills but remain inevitable beforehand. Consequently, final consumption consistently oscillates around the anticipated consumption. For instance, 1) the actual value produced by Bitcoin mining depends on the quantity of Bitcoins (computer, time), whereas the electricity cost fluctuates with temperature; 2) the utility of a refrigerator lies in preserving food freshness, but the heat loss caused by opening and closing the refrigerator door complicates accurate estimation of electricity costs. Borenstein (2009) and Grubb and Osborne (2015) furnish typical examples of these consumption discrepancies. We further denote for household i, $\tilde{x}_{i,t} = \sum_{j,k} \tilde{x}_{i,j,k,t}$ as the planned level of electricity consumption at time t.

Assumption 1. Each household i experiences a normal consumption error $\eta_{i,t} \sim \mathcal{N}\left(0, \sigma_\eta^2\right)$. At the beginning of each month t, household i plans their electricity consumption, and the electricity consumption reported in the bill received at month's end is, in reality:

$$\ln \tilde{x}_{i,t} = \ln x_{i,t} + \ln \eta_{i,t},$$

where the value of σ_η is known by the household. The $\eta_{i,t}$ materializes solely upon paying the monthly bill.

Assumption 1 posits that users with high electricity consumption demands experience difficulty in accurately managing their consumption around kink points. When the majority of households display substantial electricity consumption levels, detecting bunching within the data becomes problematic, even if households respond to marginal prices. A consumption error of 10% indicates a deviation of 9 to 11 kWh for a household intending to consume 10 kWh per month and 90 to 110 kWh for a household consuming 100 kWh. Accounting for the consumption error helps rationalize the dataset and sheds light on the observed attenuation of bunching on both sides of the kink points. Fig. 3 illustrates the effect. In the paper, we interpret the $\eta_{i,t}$ as a "bill shock," which occurs when a household's actual total consumption is higher or lower than expected. In Table 1, we illustrate how the electricity company calculates the bill. The company allocate consumption across each tier based on total electricity consumption and charge according

[2] Additionally, as electricity bills are typically paid at the end of each month, most consumers do not check their meters daily. Consequently, they are unable to accurately allocate their consumption within each tier of the time-of-use pricing scheme. The same argument applies to Assumption 1, as it precludes the possibility that households would devise differentiated consumption strategies by sophisticatedly allocating their daytime and nighttime consumption within each tier. Instead, we interpret the consumption error in this article as the average error that households experience. That is, consumers can rationally expect the percentage of consumption error they can afford when consuming electricity, on average.

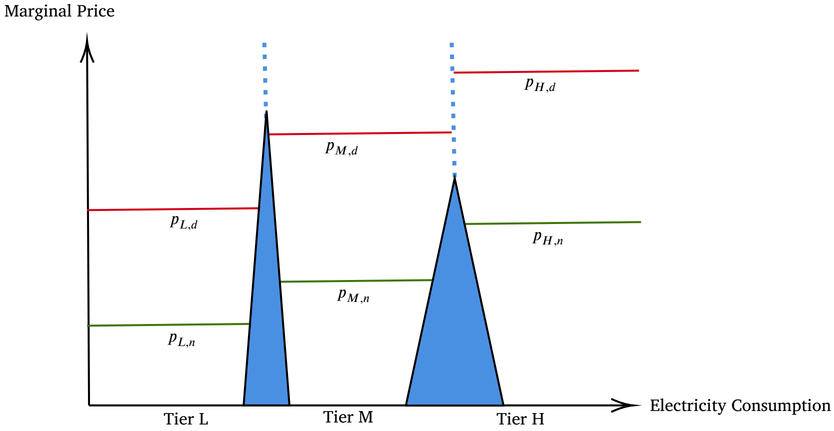

Fig. 3. Effect of adding consumption error.

to each tier's ToU prices. This calculation method supports our assumption that the shock affects daytime and nighttime electricity consumption equally and does not influence the consumption habit parameter (λ), therefore we further have $\ln \tilde{x}_{i,d,t} = \ln x_{i,d,t} + \ln \eta_{i,t}$ and $\ln \tilde{x}_{i,n,t} = \ln x_{i,n,t} + \ln \eta_{i,t}$.

We further define L_j the length of tier $j \in \{L, M\}$. The planned cost that household i pays at time t under pricing system $\mathcal{P}$ is also a step function such as:

$$C\left(x_{i,t}, \lambda_{i,t} | \mathcal{P}\right) = \begin{cases} x_{i,t}\left(\lambda_{i,t}\Delta p + p_{L,n}\right) & if\ x_{i,t} \le L_L \\ L_L\left(\lambda_{i,t}\Delta p + p_{L,n}\right) + \left(x_{i,t} - L_L\right)\left(\lambda_{i,t}\Delta p + p_{M,n}\right) & if\ L_L < x_{i,t} \le L_L + L_M \\ L_L\left(\lambda_{i,t}\Delta p + p_{L,n}\right) + L_M\left(\lambda_{i,t}\Delta p + p_{M,n}\right) + & \\ \left(x_{i,t} - L_L - L_M\right)\left(\lambda_{i,t}\Delta p + p_{H,n}\right) & if\ L_L + L_M < x_{i,t}. \end{cases} \tag{5}$$

Based on the Assumption 1, the actual cost that household i receives at time t under pricing system $\mathcal{P}$ would be $C\left(\tilde{x}_{i,t}, \lambda_{i,t} | \mathcal{P}\right)$. Given a level of $x_{i,t}$, household i needs to anticipate the final bill level to cover possible overruns. We use $EC_{i,t}\left(x_{i,t}, \lambda_{i,t}\right)$ to denote the expected electricity cost of household i at time t given $\left(x_{i,t}, \lambda_{i,t}\right)$.

Proposition 2. *Under Assumption 1, for the given $\mathcal{P}$. $EC_{i,t}$ takes the expression below:*

$$\begin{aligned} EC_{i,t} =& \pi_L e^{\sigma_\eta^2/2} x_{i,t}\left(\lambda_{i,t}\Delta p + p_{L,n}\right) + \pi_M\left\{L_L\left(\lambda_{i,t}\Delta p + p_{L,n}\right) + \left(e^{\sigma_\eta^2/2} x_{i,t} - L_1\right)\left(\lambda_{i,t}\Delta p + p_{M,n}\right)\right\} + \\ & \pi_H \times \left\{L_L\left(\lambda_{i,t}\Delta p + p_{L,n}\right) + L_M\left(\lambda_{i,t}\Delta p + p_{M,n}\right) + \left(e^{\sigma_\eta^2/2} x_{i,t} - L_L - L_M\right)\left(\lambda_{i,t}\Delta p + p_{H,n}\right)\right\}, \end{aligned} \tag{6}$$

where

$$\begin{aligned} \pi_L &= \mathbf{P}\left(\tilde{x}_{i,t} \le L_L | x_{i,t}\right) = \Phi\left(\frac{\ln L_L - \ln x_{i,t}}{\sigma_\eta}\right) \\ \pi_M &= \mathbf{P}\left(L_L + L_M \ge \tilde{x}_{i,t} \ge L_L | x_{i,t}\right) = \Phi\left(\frac{\ln\left(L_L + L_M\right) - \ln x_{i,t}}{\sigma_\eta}\right) - \Phi\left(\frac{\ln L_L - \ln x_{i,t}}{\sigma_\eta}\right) \\ \pi_H &= \mathbf{P}\left(\tilde{x}_{i,t} \ge L_L + L_M | x_{i,t}\right) = \Phi\left(\frac{\ln x_{i,t} - \ln\left(L_L + L_M\right)}{\sigma_\eta}\right). \end{aligned} \tag{7}$$

3.3. Optimal decision rule

The expected utility function of household i is defined by the following Cobb-Douglas function:

$$\mathbf{E}u\left(x_{i,t}, \lambda_{i,t} | \mathcal{P}\right) = \varrho\left(\lambda_{i,t} x_{i,t}\right)^{\gamma_d}\left(\left(1 - \lambda_{i,j,t}\right) x_{i,t}\right)^{\gamma_n} - EC_{i,t}, \tag{8}$$

where ϱ represents household i's specific preference regarding the planned total electricity consumption $x_{i,t}$, $\gamma = \left(\gamma_d, \gamma_n\right)'$ captures the substitution effect between peak and off-peak consumption. The use of a Cobb-Douglas function as the utility function is standard in many structural models, particularly when the outcome variables are continuous. In our study, both $x_{i,t}$ and $\lambda_{i,t}$ are continuous. The Cobb-Douglas function provides a natural means to incorporate and estimate the substitution and complementary effects of electricity consumption during daytime and nighttime periods. Furthermore, this function is flexible enough to capture the trade-off

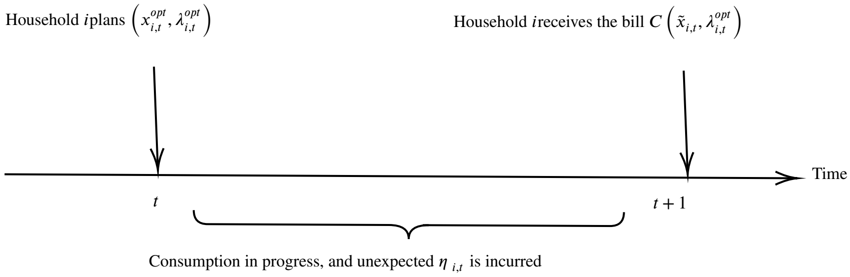

Fig. 4. Decision-making timelines.

between marginal consumption and marginal prices in household decisions, which is crucial when dealing with a nonlinear pricing system.

A household's decision-making process is now greatly simplified. We can rewrite an agent i's utility function by:

$$\mathbf{E}u\left(x_{i,t}, \lambda_{i,t}|\mathcal{P}\right) = \varrho x_{i,t}^{\gamma_d+\gamma_n}\left\{\lambda_{i,t}^{\gamma_d}\left(1-\lambda_{i,t}\right)^{\gamma_n}\right\} - EC_{i,t}. \tag{9}$$

Fig. 4 illustrate the household i's decision timeline. We thereby are able to characterize the optimal decision problem of a consumer i at time t:

$$\left(x_{i,t}^{opt}, \lambda_{i,t}^{opt}\right) \in \arg\max_{x_{i,t}\geq 0, \lambda_{i,t}\in[0,1]} \mathbf{E}u\left(x_{i,t}, \lambda_{i,t}|\mathcal{P}\right). \tag{10}$$

Assumption 2. $\gamma_n + \gamma_d = \gamma_0 \leq 1$.

Assumption 2 is a common diminishing marginal returns assumption: each household's consumption of electricity is of diminishing utility per unit as the sum of preferences parameters (i.e., $\gamma_n + \gamma_d$) is smaller than one. The assumption ensurers that $x_{i,t}$ always has an internal solution that satisfies the first order conditions. Therefore, an internal solution of $\left(x_{i,t}^{opt}, \lambda_{i,t}^{opt}\right)$ should satisfy the first order conditions is given by:

$$\varrho x_{i,t}^{\gamma_d+\gamma_n}\lambda_{i,t}^{\gamma_d}\left(1-\lambda_{i,t}\right)^{\gamma_n}\left\{\frac{\gamma_d}{\lambda_{i,t}} - \frac{\gamma_n}{1-\lambda_{i,t}}\right\} = \frac{\partial}{\partial\lambda_{i,t}}EC_{i,t}, \tag{11}$$

$$\varrho x_{i,t}^{\gamma_d+\gamma_n-1}\lambda_{i,t}^{\gamma_d}\left(1-\lambda_{i,t}\right)^{\gamma_n} = \frac{\partial}{\partial x_{i,t}}EC_{i,t}. \tag{12}$$

Lemma 1. *Under Assumption 1 and 2,* $\frac{\partial}{\partial\lambda_{i,t}}EC_{i,t}\left(x_{i,t}, \lambda_{i,t}\right) = c_\lambda$ *is a positive constant given* $x_{i,t}$.

Intuitively, since $p_{k,d} \geq p_{k,n}$ for all $k \in \{L, M, H\}$, consuming more electricity during the day increases the total cost and Δp for all $k \in \{L, M, H\}$, we have:

$$c_\lambda = x_{i,t}e^{\sigma_\eta^2/2}\Delta p. \tag{13}$$

In addition, the fact that c_λ is positive leads that the optimal $\lambda_{i,t}$ satisfies:

$$\varrho x_{i,t}^{\gamma_d+\gamma_n}\lambda_{i,t}^{\gamma_d}\left(1-\lambda_{i,t}\right)^{\gamma_n}\left\{\frac{\gamma_d}{\lambda_{i,t}} - \frac{\gamma_n}{1-\lambda_{i,t}}\right\} = c_\lambda. \tag{14}$$

Proposition 3. *If the utility function is homothetic, i.e.,* $\gamma_d + \gamma_n = 1$*,* $\lambda_{i,t}^{opt}$ *will be no longer a function of* $x_{i,t}^{opt}$.

Proposition 3 essentially gives a condition under which the optimal solution of $\lambda_{i,t}$ is independent of $x_{i,t}$. This is basically an identification condition. If we try to measure the price elasticity by using a regression model where $x_{i,t}$ is the output variable and the electricity bill is used as an explanatory variable. In this case, $\lambda_{i,t}$ is a valid instrumental variable for identifying the price-to-consumption causal relationship only if the assumption in Proposition 3 is valid. When $\gamma_0 = 1$, Equation (14) becomes:

$$\frac{1}{\lambda_{i,t}}\left(\frac{\lambda_{i,t}}{1-\lambda_{i,t}}\right)^{\gamma_d}\left(\gamma_d - \lambda_{i,t}\right) = \frac{e^{\sigma_\eta^2/2}}{\varrho}\Delta p. \tag{15}$$

The above equation well describes how the λ^{opt} varies with γ_d and ϱ. In this specific case, the optimal λ depends only on the household's preference for daytime use (γ_d) and their preference for the total electricity consumption (ϱ). On the one hand, the higher the preference for consuming electricity during the day is, the higher the lambda would be (complementary effect) as λ^{opt}

has to be smaller than γ_d. On the other hand, the higher the return on total electricity consumption is, the lower the λ would be (substitution effect), as the unit price of electricity is cheaper at night and the formula on the left-hand side of Equation (15) is a decreasing function of λ. In the case that $\gamma_0 = 1$, the $\lambda_{i,t}^{opt}$ can be approximated by a polynomial function of observed variables that proxy γ_d and ϱ, and we can expect that $\lambda_{i,t}^{opt}$ increases with the daytime electricity needs and decreases with the total electricity needs.

The above equation effectively illustrates how the optimal λ ($\lambda_{i,t}^{opt}$) varies with respect to the household's preference for daytime use (γ_d) and their preference for total electricity consumption (ϱ). In this specific case, the optimal λ depends solely on these two preferences. On one hand, as the preference for consuming electricity during the day increases, λ also increases (complementary effect), as $\lambda_{i,t}^{opt}$ must be smaller than γ_d. Conversely, as the return on total electricity consumption rises, λ decreases (substitution effect), since the unit price of electricity is lower at night, and the formula on the left-hand side of Equation (15) is a decreasing function of λ. In the case where $\gamma_d + \gamma_n = 1$, the $\lambda_{i,t}^{opt}$ can be approximated by a polynomial function of observed variables that proxy γ_d and ϱ.

It is worth noting that the situation where $\gamma_d + \gamma_n = 1$ is relatively uncommon, as this would imply that the left-hand side of Equation (12) is independent of the optimal x ($x_{i,t}^{opt}$). When $\gamma_d + \gamma_n = 1$, $\lambda_{i,t}^{opt}$ is also independent of x as it is entirely determined by the model parameters by Equation (15). The marginal effect of increasing one unit of marginal consumption x under a given λ is constant. However, the right-hand side of the equation represents the marginal increase in expected cost as x changes. It is readily observable that the partial derivative of the expected cost ($EC_{i,t}$) with respect to $x_{i,t}$ is greater than or equal to $p_{L,n}$ and less than or equal to $p_{H,d}$. Therefore, when the left-hand side value is not within this boundary range, a corner solution arises, where $x_{i,t}^{opt}$ is either infinitely large or $x_{i,t}^{opt}$ equals zero, which is unrealistic. In our data, the distribution of x approximates a Gaussian distribution, so we anticipate that the estimated sum of $\gamma_d + \gamma_n$ should be strictly less than 1.

Overall, our model investigates a nonlinear, multi-dimensional pricing system with two time tiers and three quantity tiers. Despite its specific nature, we assert that the model maintains general applicability and offers significant computational advantages. These benefits partly stem from the inclusion of the Cobb-Douglas utility function. As the pricing system's complexity increases, such as when the number of price tiers grows, the added intricacy primarily affects the cost function without substantially increasing the computational burden. In contrast, when the Time-of-Use (ToU) component becomes more complex—for instance, moving from two to three time periods—the computational load does rise due to the introduction of additional variables, such as consumer preferences across different periods. However, this does not undermine the model's adaptability, as the Cobb-Douglas framework easily accommodates the integration of new decision variables. Moreover, to the best of our knowledge, instances of more than three time periods within nonlinear pricing systems are relatively rare. Consequently, our model can be readily extended to cover the majority of real-world scenarios.

4. Model identification and estimation

4.1. Model identification

We discuss in this section the model identification problems. We observe $\left(\tilde{x}_{i,t}, \lambda_{i,t}\right)_{i=1,\ldots,n, t=1,\ldots,T}$ in the data, and the model is characterized by a set of parameter $\theta \in \Theta$, with

$$\theta = (\gamma_0, \gamma_d, \sigma_\eta, \varrho)'. \tag{16}$$

The most significant challenge is to separately identify bill shock σ_η and unobserved demand preference ϱ, which is almost impossible in the existing literature due to the uni-dimensional outcome variable. Fig. 5 illustrates this identification problem. Given that econometricians only observe a consumer's choice x_{obs} under an IBP system, x_{obs} could be an equilibrium outcome of a higher demand preference without consumption errors, or that of a simple realization of a lower demand preference with consumption errors. That is to say, infinite numbers of parameter combinations of ϱ and σ_η could potentially generate the same observed outcome x_{obs}. To tackle this problem, we use information from the changes of households' consumption habits λ. This additional observed dimension allows us to deal with the identification problem.

Another significant challenge is that the outcome variables are noised, and consumers make decisions based on their "ideal value" (the de-noised variable), which is unobserved by econometricians. There are two random error terms, η and ξ, that are not observed by econometricians in our model. The model is hard to be identified in general because we know that $\tilde{x}_{i,d,t}$ and $\tilde{x}_{i,n,t}$ are both affected by η and ξ. One would imagine that if the variances of η and ξ are large enough, then they can explain almost all of the changes in the data. Therefore, we naturally need to make an additional assumption about the structure of the error term, in addition to the assumptions made above.

Combining the two first-order conditions above, we can get a new condition:

$$\gamma_d = \gamma_0 \left(\frac{\Delta p}{c_{x_i}\left(x, \sigma_\eta\right) / e^{\sigma_\eta^2/2}} \lambda (1-\lambda) + \lambda \right), \tag{17}$$

given γ_0, γ_d is identified by the consumer's allocation of electricity consumption at different times of day and night. Once γ_d is identified as a function of $\left(\gamma_0, \sigma_\eta\right)$, ϱ can be computed as a function of x, λ γ_0, and γ_d:

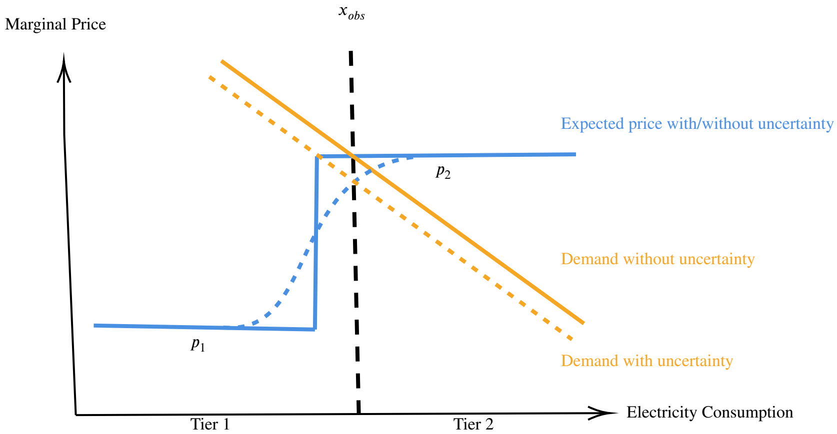

Fig. 5. Challenges in identification. Notes: A two-tiered pricing system for electricity consumption is depicted. The horizontal axis represents electricity consumption, while the vertical axis represents the marginal price. Tier 1 and Tier 2 are the two pricing tiers, with Tier 2 having a higher marginal price. The solid blue line represents the Inclining Block Pricing (IBP) system without uncertainty, showing how marginal price increases as consumption surpasses a certain threshold. The dashed blue line represents the expected price with uncertainty, illustrating how uncertainty affects household expectations. The solid orange line represents the demand curve without uncertainty. The dashed orange line represents the demand curve with uncertainty.

$$\varrho = e^{\sigma_\eta^2/2}\Delta p \times x^{1-\gamma_0} \times \left\{ \lambda^{\gamma_d} (1-\lambda)^{\gamma_0-\gamma_d} \frac{(\gamma_d - \lambda\gamma_0)}{\lambda(1-\lambda)} \right\}^{-1}. \tag{18}$$

In the data, we only observe $\tilde{x}$. Given $(\gamma_0, \gamma_d, \sigma_\eta)$, ϱ would be identified as:

$$\varrho = \mathbf{E}\left\{ \frac{1}{\gamma_0}\mathbf{E}_\eta \left[x_{i,t}^{1-\gamma_0} c_{x_i}(x_{i,t}, \sigma_\eta) \,|\tilde{x}_{i,t} \right] \lambda_{i,t}^{-\gamma_d} \left(1-\lambda_{i,t}\right)^{\gamma_d-\gamma_0} \right\}. \tag{19}$$

Finally, σ_η would be identified through the variation of bunching at the right-hand side of kink points and the dispersion of the density of $\tilde{x}_{i,t}$. Intuitively, if $\sigma_\eta = 0$, for a given γ_d, the optimal choice would be exactly at the kink point for some ϱs, which leads a bunching at the kink points and we will not be able to see any consumption in a certain area to the right of the kink point; on the contrary, if σ_η is very large, we should hardly observe any bunching effect in the data. Therefore, σ_η is de facto a measure of the bunching effect. A larger σ_η implies less bunching. Moreover, with a sufficiently large σ_η, consumers will become less sensitive to the marginal price, which refers to the situation described by Ito (2014). To understand this, imaging a consumer with a level of expected consumption “just a little bit over the kink point” if the marginal price does not change. If σ_η is very small, consumers will be responsive to the change in the marginal price by precisely stopping any further consumption before the kink point; however, if σ_η is very large, this implies that the consumer has little control over where the actual consumption point will be. The consumer will then have limited capability to respond to any change in marginal price; instead, they will plan the consumption using average price. Then based on the model's predictions, we should observe $\tilde{x}_{i,t} = x_{i,t}$ and all choices should be on the left-hand side of the kink points. The remaining gaps between $(\ln x_{i,t}, \lambda_{i,t})$ and $(\ln x_{i,t}, \lambda_{i,t})$ identify γ_0.[3]

4.2. Methodology for estimation

We describe the estimation method of the model in this section. In brief, our estimation of the model is consistent with the previous identification process. Compared with the traditional estimation-based on the likelihood or the GMM method, our method has depicted a step-by-step road-map to avoid “computational complexity” and “overcomplicated and unwieldy models” discussed in Low and Meghir (2017). Therefore, we can estimate $(\gamma_0, \gamma_d, \sigma_\eta)$ by using a nonlinear least square model:

$$\min_{(\gamma_0,\gamma_d,\sigma_\eta)} \sum_{i=1}^{n}\sum_{t=1}^{T} \left\| \begin{pmatrix} \ln \tilde{x}_{i,t} \\ \lambda_{i,t} \end{pmatrix} - \begin{pmatrix} \ln x_{i,t}^{opt} \\ \lambda_{i,t}^{opt} \end{pmatrix} \right\|_{\Omega_\theta}^2$$
$$s.t.\ \Omega_\theta = \mathbf{Cov}\left(\ln \tilde{x} - \ln x^{opt}, \lambda_{i,t} - \lambda_{i,t}^{opt}\right). \tag{20}$$

[3] We also point out that it is impossible to identify η in a dataset without ToU pricing because we can always find a ϱ_i such that $x_{i,t}(\varrho_{i,t}, \sigma_\eta = 0)$ derived from the model is equal to our observed $x_{i,t}$. With a mixture pricing system, given a level of $x_{i,t}$ also means that we have to observe the corresponding $\lambda_{i,t}(x_{i,t})$. The $\lambda_{i,t}$ we observe gives us additional constraints to help us identify σ_η. We also provide a graphic sketch illustrating our identification strategy in Appendix for Online Publication C.

where $\left(x_{i,t}^{opt}, \lambda_{i,t}^{opt}\right)$ are the model predicted optimal value of $x_{i,t}$ and $\lambda_{i,t}$, and Ω_θ is the empirical variance of $\begin{pmatrix} \ln \tilde{x}_{i,t} \\ \lambda_{i,t} \end{pmatrix} - \begin{pmatrix} \ln x_{i,t}^{opt} \\ \lambda_{i,t}^{opt} \end{pmatrix}$. Our M-estimator is basically a nonlinear least square estimator by taking Mahalanobis distance. We point out that we do not require that the empirical variance of $\ln \tilde{x}_{i,t} - \ln x_{i,t}\left(\gamma_0, \sigma_\eta\right)$ be closed to σ_η^2, although we admit this hypothesis in the model. Since the data generation process cannot be fully captured by the model, the empirical variance of $\ln \tilde{x}_{i,t} - \ln x_{i,t}\left(\gamma_0, \sigma_\eta\right)$ is usually greater than σ_η^2. Once $\left(\gamma_0, \gamma_d, \sigma_\eta\right)$ is estimated, ϱ can be estimated by using the moment condition with Equation (19).

4.2.1. Re-weighting observations around the kink point

The method above is theoretically feasible, especially as $n \times T$ goes to infinity. However, when the number of observations to the right of the kink point is considerably low relative to the overall sample size, there exists a risk of underestimating σ_η. The fact that the objective function values averaged all the observations will lead to an over-fit of observations outside of the kink. Therefore, we propose using an objective function that is more concerned with fitting the observations near the kink point (i.e., 200 kWh). We use the weighted average method to make the observations near the kink point worthy of higher importance than taking the average. We consider the objective function below:

$$\min_{\left(\gamma_0, \gamma_d, \sigma_\eta\right)} \sum_{i=1}^{n} \sum_{t=1}^{T} \omega_{it} \left\| \begin{pmatrix} \ln \tilde{x}_{i,t} \\ \lambda_{i,t} \end{pmatrix} - \begin{pmatrix} \ln x_{i,t}^{opt} \\ \lambda_{i,t}^{opt} \end{pmatrix} \right\|_{\Omega_\theta}^2 \tag{21}$$

where $\omega_{i,t}$ is the weight of an observation from household i at time t. We propose to use

$$\sum_{i=1}^{n} \sum_{t=1}^{T} \omega_{it} = 1, \; and, \; \omega_{it} = \frac{\varphi\left(\left(\log \tilde{x}_{i,t} - \log(200)\right) / \sigma_\eta\right)}{\sum_{j,t'} \varphi\left(\left(\log \tilde{x}_{j,t'} - \log(200)\right) / \sigma_\eta\right)}, \tag{22}$$

with φ the probability density function of a standard normal distribution to capture the weight of each observation. Equation (21) is an objective function for an M-estimator, so the estimator is asymptotically normal and consistent. The Equation (22) is a standard criterion function for an M-estimator. Based on Wooldridge (1994), the asymptotic distribution of $\hat{\theta}$ by:

$$\sqrt{nT}\left(\hat{\theta} - \theta\right) \sim \mathcal{N}\left(0, \mathcal{H}_\theta^{-1}\left(\mathcal{J}_\theta \mathcal{J}_\theta'\right) \mathcal{H}_\theta^{-1}\right), \tag{23}$$

where $\mathcal{H}_\theta$ would be calculated the hessian matrix of the objective function at $\hat{\theta}$ and $\mathcal{J}_\theta$ is the associated Jacobian matrix. Compared to using the first and second moments (i.e., GMM) to fit the data, our nonlinear least square estimator (NLLSE) is more sensitive to the bunching. Furthermore, since we do not make many assumptions about the probability distribution in our model, it is most appropriate to employ the NLLSE.

4.2.2. Heterogeneous preferences

In order to make our model more general, we take both the levels of electricity demand ϱ and the levels of consumption preference for day γ_d as heterogeneously given. We first assume that ϱ varies across different households and takes the following functional form:

$$\varrho_{i,t} = \exp\left\{ z_{i,t}' \beta_{z,\varrho} + \xi_{i,t} \right\}, \tag{24}$$

where $z_{i,t}$ is a vector of selected household characteristics that may potentially affect $\varrho_{i,t}$. $\xi_{i,t}$ is an error term that is known to consumers in advance, but invisible to econometricians.

Once $\left(\gamma_0, \gamma_d, \sigma_\eta\right)$ is estimated, we would be able to obtain $\varrho_{i,t}$ as a function of $\left(x_{i,t}^{opt}, \lambda_{i,t}^{opt}\right)$ by Equation (18). $\beta_{z,\varrho}$ can be estimated by the linear regression model below:

$$\ln \varrho_{i,t} = z_{i,t}' \beta_{\varrho,z} + \xi_{i,t}. \tag{25}$$

The equation above captures the unobserved heterogeneous preferences in the total electricity consumption across individuals. It is worth mentioning that we do not have to estimate β_ϱ and $\left(\gamma_0, \gamma_d, \sigma_\eta\right)$ jointly. Once we have estimates of other parameters, we can estimate β_ϱ separately outside of the objective function. In the estimation process, we find some inconveniences when γ_d remains unchanged across households. With a level of ϱ and x, if γ_d is low, the theory model always prefers a level of λ as consuming the electricity during the night time is always preferable. As a result, the observed high level of λ is hard to be captured by our model. Therefore, there is some scope to let γ_d be heterogeneous and vary across households. We give some further discussion on the identification conditions of γ_d below.

Theoretically, if the price jumps between any two tiers in the IBP scheme is infinite, for any $\varrho_{i,t}$ and any $\gamma_{i,d,t}$ we should observe a significant bunching at the kink point and no consumption occurs on the right-hand side of the kink point without the presence of consumption errors. Therefore, the observed consumption, if any, on the right-hand side of the kink point will allow us to identify σ_η. In this paper, we assume that γ_d is heterogeneous and observable such that:

$$\gamma_{i,d,t} = \frac{\gamma_0}{1 + \exp\left(-w_{i,t}' \beta_w\right)}, \tag{26}$$

Table 4
Estimation of structural parameters.

Coefficient	(1) Baseline Model	(2) Full Sample	(3) Heterogeneous Preferences
σ_η	0.204***	0.265***	0.275***
	(0.0008)	(0.0002)	(0.0009)
ϱ	5.489***	5.372***	
	(0.022)	(0.003)	
γ_0	0.729***	0.740***	0.498***
	(1.663×10^{-6})	(0.0001)	(0.0003)
γ_d			
Intercept	0.418***	0.468***	0.015***
	(3.061×10^{-7})	(0.0001)	(1.154×10^{-5})
Number of Elders			-0.066***
			(0.0007)
Number of Computers			0.006***
			(0.0001)
Number of TVs			0.045***
			(3.998×10^{-5})
High Income			0.453***
			(0.0004)
High Temp (log)			0.003
			(0.0003)
Function Value	4631.532	102692.736	4484.173

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors in parenthesis.

where $w_{i,t}$ is a individual specific vectors that is exogenously given and affects individual preferences for the consumption of electricity during the daytime. Based on Equation (17), γ_d is proportional to γ_0. Adopting a logistic curve to capture households' preference for daytime electricity consumption allows $\frac{\gamma_{i,d,t}}{\gamma_{i,d,t}+\gamma_{i,n,t}} = \frac{1}{1+\exp\left(-w'_{i,t}\beta_w\right)}$ to vary between 0 and 1. In addition, there is no constraint on the range of $w'_{i,t}\beta_w$. We have to jointly estimate β_w and $\left(\gamma_0, \sigma_\eta\right)$, and the objective function becomes:

$$\min_{(\beta'_w,\gamma_0,\sigma_\eta)} \sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{it} \left\| \begin{pmatrix} \ln \tilde{x}_{i,t} \\ \lambda_{i,t} \end{pmatrix} - \begin{pmatrix} \ln x_{i,t}^{opt} \\ \lambda_{i,t}^{opt} \end{pmatrix} \right\|_{\Omega_\theta}^2 . \tag{27}$$

We would like to emphasize that our model and estimation approach are, in fact, quite versatile. Equation (22) can be readily applied to any administrative data under a given mixture pricing system, as the model requires only a limited number of parameters to be identified. Only when we need to investigate the heterogeneous effects under price policies must we employ Equations (24) and (27). Estimating Equations (24) and (27) necessitates more refined data, as we need to capture heterogeneity through some family characteristics, which is where survey data proves useful. We will present the corresponding estimation results in the following section.

5. Estimation results

In this section, we present the results derived from the estimation of our structural model. Table 4 primarily displays the estimated parameters (σ_η, γ_0, γ_d, and ϱ) under different models and samples. The first column of Table 4 illustrates the estimated results based on the sample we utilized (i.e., the sample encompassing 500 family questionnaires). As mentioned earlier, our model and estimation method are highly versatile, with the basic model even applicable for directly estimating administrative data. Therefore, in the second column of Table 4, we further demonstrate the estimation based on administrative data from 5,000 households. The results indicate that the outcomes for the 5,000 households are strikingly similar to those for the 500 households. This further validates the representativeness of our sample and the absence of selection issues, as well as the robustness of our estimation. In the final column of Table 4, we report the estimated results of the model incorporating heterogeneous preferences. Again, the estimated results closely resemble those of the first two columns.

All parameter estimates align with expectations and are statistically significant at the 1% level. σ_η not being 0 implies the presence of consumption errors. With $\gamma_0 < 1$, Assumption 2 is satisfied. Without incorporating heterogeneous preferences for daytime electricity use, the estimation results show that, on average, γ_d is smaller than $\gamma_n = \gamma_0 - \gamma_d$. Such evidence is consistent with the data as most people prefer to use electricity at night. It is also worth noting that in all columns of Table 4, the estimated values of σ_η we obtained are remarkably similar. The values of σ_η range between 0.20 and 0.27, indicating that the overall consumption error is approximately 2% to 3%. This value does not change with variations in sample size, nor does it decrease when we incorporate additional parameters to fit the model. After introducing extra parameters in the third column, the fitted function value decreases, but the estimated value of σ_η even slightly increases compared to the first column, which suggests that our estimation of consumption errors is highly credible.

Table 5
Heterogeneous preferences in ρ.

Dependent Variable: $\ln \hat{\rho}_i$		
Coefficient	(1) Estimate	(2) Std. Error
Household Characteristics		
Number of Elders	0.020**	0.008
Number of Adults	0.056***	0.006
House Area (log)	0.058*	0.028
Number of Bedrooms	0.079***	0.013
Electric Appliance		
Number of Computers	-0.005	0.006
Number of Fridges	0.131***	0.009
Number of Air-Conditioners	0.024**	0.009
Winter Heat	0.066***	0.014
Cook Electric	0.082***	0.012
Bath Electric	0.043***	0.012
Number of TVs	0.013	0.008
Family Income		
Low Income	-0.0005	0.013
High Income	-0.027	0.025
Climate		
Average Rain (log)	-0.010	0.009
Average Temp (log)	-0.201***	0.061
Average Humidity (log)	0.145**	0.055
High Temp (log)	0.320***	0.075
Intercept	0.631*	0.291
Monthly FE	YES	
Yearly FE	YES	
Number of observations	3040	
R^2	0.247	

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The estimation results are based on the econometrics model in the last column of Table 4. In the last column, error terms are clustered at the household level.

The last column of Table 5, combined with Table 5, reveals the estimated results of the model incorporating heterogeneity. The estimates align well with our expectations, with the final column of Table 3 illustrating household preferences for daytime electricity consumption. The majority of the variables we included capture heterogeneous preferences effectively, with all variables except those related to weather being statistically significant at the 1% level. The results indicate that households with a higher number of elderly individuals prefer consuming electricity during nighttime, which aligns with expectations, as elderly people in China tend to be more frugal. The significant difference in electricity unit prices between day and night across all tiers results in elderly individuals preferring nighttime electricity consumption. Furthermore, households with higher incomes and more electrical appliances tend to prefer daytime electricity usage. This is because, as income increases and more appliances are purchased, many appliances must remain powered during the day even when not in use.

In Table 5, we further examine how our model captures the basic demand preferences for electricity consumption under different household and climate conditions. The results also conform to expectations. Table 5 demonstrates that an increase in family members, living area, and the number of appliances significantly impacts the basic demand for electricity consumption. When average temperatures are higher, the demand for electricity decreases, which we speculate may be due to elevated average temperatures reducing the need for heating devices. However, when the highest temperatures rise, demand increases, which is likely related to air conditioning usage. In addition, we find that income levels primarily influence consumption habits during the day and night, without significantly affecting basic demand preferences for electricity consumption. We conjecture that the impact of income mainly manifests in living areas and the number of appliances; once these factors are controlled for, the additional influence of income on electricity consumption becomes negligible.

6. Counterfactual policy analysis

Our model concentrates on how households maximize utility with given price schedules. In an ideal scenario where the sole objective is to maximize social welfare, aligning the marginal price with the marginal cost of electricity would suffice. Yet, energy regulation is complex, balancing competing interests such as affordability, environmental protection, and economic factors. Achieving these goals concurrently is difficult, as measures to advance one goal can impede others. For example, measures to guarantee

Table 6
Different types of price schemes: a comparison.

Dependent Variable: Average Changes			
Scenarios ($\Delta p = 1\%$)	Uniform	Daytime	Nighttime
Consumption Level			
Total Consumption (x_{it})	-0.693%	-0.644%	-0.091%
	$[-0.742\%, -0.660\%]$	$[-0.706\%, -0.589\%]$	$[-0.158\%, -0.048\%]$
Daytime Habit ($\lambda_{i,t}$)	-0.0001	-0.0009	0.0005
	$[-0.0002, 0.0000]$	$[-0.0014, -0.0006]$	$[0.0004, 0.0008]$
Utility Level			
Cost	-0.419%	-0.396%	-0.040%
	$[-0.503\%, -0.367\%]$	$[-0.491\%, -0.325\%]$	$[-0.092\%, 0.012\%]$
Utility	-0.469%	-0.445%	-0.040%
	$[-0.492\%, -0.448\%]$	$[-0.465\%, -0.423\%]$	$[-0.061\%, -0.031\%]$

low energy prices might clash with efforts aimed at mitigating carbon emissions or preserving specific economic interests (Legal Information Institute, 2022). Thus, we conduct counterfactual analysis in this section by adjusting specific aspects of the current pricing scheme (e.g., price modifications, kink point reallocation) to examine the resulting impact on household welfare.

6.1. Impact of price changes and elasticities

The pricing system in our data is highly nonlinear and multidimensional. We can observe the changes in the household's bill over time, but we cannot directly estimate the price elasticity based on such change. In order to measure the change in electricity consumption caused by the adoption of new prices in different tiers and their subsequent impact, we simulate the price elasticity through counterfactual analysis based on the parameter estimation of the model. The results of the model are used to simulate the choice of household electricity consumption under the current price system and the choice of household electricity consumption when the price changes. We construct the output variable based on the simulation results.

$$\Delta f_{i,t} = \frac{f_{i,t}^{p'} - f_{i,t}^{p}}{f_{i,t}^{p}}, \tag{28}$$

where $f_{i,t}^{p}$ represents the model output of household i at time t under the current pricing system p and $f_{i,t}^{p'}$ represents the model output of household i at time t under the counterfactual pricing system $p' = p(1+\delta)$. f can be electricity consumption, bill, utility or habit. Therefore $f_{i,t}$ captures the proportional changes in output related to the price changes from p to p'. In Table 6, we simulate three different counterfactual scenarios: uniform changes in all prices by 1%, only daytime prices in all tiers increase by 1%, and only nighttime prices in all tiers increase by 1%. In addition to changes in total electricity consumption, we also pay attention to changes in three other dimensions: (1) changes in daytime electricity consumption habits ($\lambda_{i,t}$) that capture the substitution effect caused by price variations; (2) changes in household utilities that capture the impact of price changes on consumer welfare; (3) change in costs of electricity bills that capture the impact on the revenue of an electric utility.

We predict price elasticities under different price-raising policies. We find that an overall price increase of 1% leads to an overall decrease in electricity consumption of 0.693%. Notably, in the short term, it is difficult for households to timely correct their consumption habits, which leads to inelastic price elasticities. Our estimate of elasticity is based on counterfactual analysis and structural model parameters. In our model, consumers are not limited by their consumption habits. Such results can be interpreted as long-run price elasticity. Compared with the literature, the model-based elasticities are in a reasonable range. Csereklyei (2020) shows that the long-run price elasticity of household electricity consumption is estimated between -0.53 and -0.56 in the European Union (EU) region. Compared with the EU region, Hangzhou has a low latitude. The demand for air-conditioning and heating appliances in summer and especially in winter is lower than in Europe. Average incomes are also lower than countries in the EU. These potential factors contribute to the high price elasticity estimated in our data. Krishnamurthy and Kriström (2015) find that electricity price elasticities vary across OECD countries, with an average value of -0.72, which is very close to our simulation-based results.

Table 6 shows that increasing nighttime prices have a smaller impact on overall consumption compared to rising daytime prices. We discover that households do not exhibit significant increases or decreases in daytime electricity consumption. As previously mentioned, the price difference between day and night is equal for each tier, so a general increase in prices does not trigger changes in consumption habits. We also observe that households are less flexible in using electricity at night than during the day. For example, many households rely on air conditioning in the summer and heating in the winter when they sleep. They have no choice but to continue using electricity when nighttime prices increase, as they cannot alter their biological schedule. Therefore, if the policy objective is to reduce electricity consumption by raising prices, increasing daytime prices may be a more effective option (see Table 7).

To better comprehend which households are more impacted by a uniform price increase policy, consequently reducing their utility, we conduct a regression analysis of the percentage change in utility on the variables presented in Table 5 to capture the het-

Table 7
Heterogeneous effects of price changes on household utility.

Dependent Variable: $\Delta U_{i,t}\%$ Unity changes when prices uniformly increase by 1%					
Coefficient	Model (1)		Model (2)		Model (3)
Household Characteristics		Electric Appliance		Climate	
Number of Elders	-0.0006	Number of Computers	0.0024***	Average Rain (log)	-0.0003
	(0.0006)		(0.0003)		(0.0004)
Number of Adults	0.0015***	Number of Fridges	0.0021***	Average Temp (log)	-0.0052
	(0.00032)		(0.0003)		(0.0035)
House Area (log)	0.0065***	Number of Air-Conditioners	0.0024***	Average Sunshine (log)	0.0022
	(0.0012)		(0.00055)		(0.0029)
Number of Bedrooms	0.0035***	Winter Heat	-0.0007	High Temp (log)	0.0093*
	(0.0008)		(0.0007)		(0.0046)
		Cook Electric	0.0023***		
			(0.0005)		
		Bath Electric	0.0016*		
			(0.0007)		
		Number of TVs	0.0016**		
			(0.0005)		
Intercept	-0.5142***		-0.4912***		-0.5115***
	(0.0056)		(0.0014)		(0.0125)
Monthly FE	YES		YES		YES
Yearly FE	YES		YES		YES
Number of observations	3040		3040		3040
R^2	0.117		0.109		0.075

Notes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Standard errors are clustered at the household level.

erogeneous effects of the policy. We explore the impact of price changes on households across three dimensions: family composition and room size, electrical appliances, and climate. Overall, heterogeneity is primarily derived from the family level. Krishnamurthy and Kriström (2015) demonstrate that individuals in high-income countries often exhibit high elasticity. We present consistent findings, indicating that the primary households affected by increasing prices are those with low incomes. As the number of family members grows and the living area expands, the welfare losses resulting from price increases tend to diminish. Likewise, households with sufficient affluence to possess numerous electrical appliances are less likely to be adversely affected by rising prices. In terms of climate, we discover that most factors, with the exception of the highest temperature, are not significant. This may be attributed to the inclusion of monthly and yearly fixed effects in our regression.

6.2. *Effect of uncertainty on energy consumption*

Ito (2014) presents empirical evidence suggesting that household electricity consumption may be more responsive to changes in average prices rather than marginal prices. In our study, we continue to assume that household electricity consumption is sensitive to marginal price changes while also factoring in consumption errors.

In this section, we investigate the impact of uncertainty changes on empirical research through counterfactual analysis. We simulate a clean shock to the overall marginal price and perform counterfactual analysis under varying levels of bill shocks. Our counterfactual simulation results are analyzed following the methodology employed by Ito (2014). We use the overall household consumption change before and after the marginal price changes as the dependent variable, and the changes in marginal and average prices under two pricing systems as the independent variables. Notably, our counterfactual analysis simulates a policy where prices rise by 50% across all intervals, making the impact of marginal price changes at this point serve as a treatment effect. We also control for household- and time-specific fixed effects.

Table 8 displays the regression results under counterfactual simulations. We observe these results under three levels of σ_η: the second column with $\sigma_\eta = 0.25$ is closely aligned with our estimated actual error value, while the first and third columns halve and double it, respectively. Intriguingly, despite all models assuming household responsiveness to marginal prices, we find significant differences in regression results under varying levels of σ_η differ dramatically, even when price shocks are entirely exogenous.

First, average price coefficients are statistically significant at the 5% level across all results. With $\sigma_\eta = 0.25$, we obtain results almost observationally equivalent to those of Ito (2014), revealing that household electricity consumption primarily responds to average prices, with no significant reaction to marginal prices. We hypothesize that increased σ_η leads to heightened uncertainty for households, subsequently causing a mechanical rise in errors contained in $\Delta \ln \tilde{x}_{i,t}$ and weakening the coefficients' statistical significance. This is evident in the R^2 values declining as σ_η increases across the three regressions. Furthermore, as uncertainty rises, the bunching effect is diminished, causing households to appear less sensitive to marginal prices based on observed data.

In all results, only the first column exhibits statistical significance at the 5% level for both average and marginal prices. However, extracting meaningful insights from these results is challenging due to the difficulties in interpreting the estimated variables. While we generate fully exogenous price shocks through counterfactual simulations, endogeneity issues arise when calculating average prices after price changes, as we divide the total bill by the electricity consumption value following the price change. This introduces

Table 8
Effects of marginal/average price changes on electricity consumption.

Dependent Variable: $\Delta \ln \tilde{x}_{i,t}$ Unity changes after prices uniformly increase by 50%			
Coefficient	(1)	(2)	(3)
	$\sigma_\eta = 0.10$	$\sigma_\eta = 0.25$	$\sigma_\eta = 0.5$
$\Delta \ln MP_{i,t}$	0.044**	0.047	-0.001
	(0.018)	(0.038)	(0.072)
$\Delta \ln AP_{i,t}$	0.137***	-0.164**	0.665***
	(0.038)	(0.075)	(0.171)
Monthly FE	YES	YES	YES
Yearly FE	YES	YES	YES
Number of observations	3040	3040	3040
R^2	0.089	0.056	0.047

Notes: $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$. Standard errors are clustered at the household level.

Table 9
Kink point reallocations and welfare changes.

Dependent Variable: Average Changes				
Scenarios (ΔL_2)	$\Delta L_2 = -50$	$\Delta L_2 = 50$	$\Delta L_2 = -100$	$\Delta L_2 = 100$
Consumption Level				
Total Consumption (x_{it})	2.813%	-2.515%	5.789%	-4.965%
	$[-4.633\%, 10.934\%]$	$[-11.727\%, 5.687\%]$	$[-4.858\%, 18.143\%]$	$[-21.753\%, 2.404\%]$
Daytime Habit ($\lambda_{i,t}$)	-0.0008	0.0007	-0.0018	0.0015
	$[-0.0204, 0.0000]$	$[0.0000, -0.0200]$	$[-0.0204, 0.0000]$	$[0.0000, 0.0204]$
Utility Level				
Cost	1.829%	-1.191%	-4.080%	-1.773%
	$[-4.457\%, 9.802\%]$	$[-11.110\%, 5.408\%]$	$[-5.474\%, 16.587\%]$	$[-20.081\%, 7.932\%]$
Utility	0.950%	-1.263%	1.647%	-3.038%
	$[-0.286\%, 1.866\%]$	$[-2.324\%, 0.322\%]$	$[-0.437\%, 3.326\%]$	$[-5.042\%, -0.262\%]$

$\tilde{x}_{i,t}$ into both sides of the equation. These results warrant attention as they underscore the importance of estimating σ_η using a structural model and suggest that endogeneity issues are nearly unavoidable when conducting regression analysis based solely on observed consumption data and prices.

6.3. Kink point reallocation and system improvement

Hirth and Ueckerdt (2013) discover that implementing energy policies redistributes wealth between consumers and energy producers, as well as within these groups. Moreover, redistribution mechanisms have emerged as a global concern in both developed and developing countries (Berg et al. 2018). In this section, we aim to investigate how to enhance the pricing system by reallocating the kink point of tier 2 (ΔL_2) through counterfactual analysis. To achieve this, we perform a similar counterfactual analysis as in the preceding section. We compare the total consumption changes corresponding to reallocating the current kink point (200 kWh) to both sides (from 100 kWh to 300 kWh) and analyze the respective cost and benefit alterations. Table 9 presents the results of the counterfactual analysis. In the first and second columns, we extend and reduce the length of tier 2 by 50 kWh, respectively. In the third and fourth columns, we expand and diminish the length of tier 2 by 100 kWh, respectively.

First, we find that shifting the kink point to the right improves the overall welfare of consumers by allowing more households to consume higher amounts of electricity at relatively low marginal prices. In contrast, moving to the left raises the cost of electricity consumption, leading households to consume less electricity and lose benefits. The change in the width of tier 2 does not significantly impact consumption habits because, despite the altered width, the daytime and nighttime unit electricity prices within each tier remain unchanged. Importantly, our results demonstrate that the increase in total electricity consumption and welfare with ΔL_2 is nonlinear and asymmetric. When $\Delta L_2 = 100$, the loss in household utility is more than double compared to when it is at 50, whereas when ΔL_2 moves from -50 to -100, the growth in household utility compared to the current level does not even double, only increasing from 0.95% to 1.64%. These findings imply that policymakers should cautiously consider narrowing the interval of tier 2, as the effect on household utility is entirely asymmetrical compared to expanding the interval. As most households are middle-class families with consumption within tier 2, reducing the interval would affect more households than expanding it would.

Lastly, we explore the potential for improving household welfare by optimizing electricity pricing systems through counterfactual analysis. While multidimensional nonlinear pricing theoretically allows for better welfare optimization, its practical implementation can be challenging (Rochet and Choné 1998). We simulate a scenario wherein policymakers strive to enhance household welfare by lowering electricity prices. Nonetheless, as reduced prices may result in excessive power consumption and waste, policymakers also modify the width of tier 2 (i.e., moving the kink point leftward) while raising prices. Fig. 6 illustrates the variations in total electricity usage and household utility relative to the current situation when prices decrease by 1% to 10%, and the kink point shifts from -10

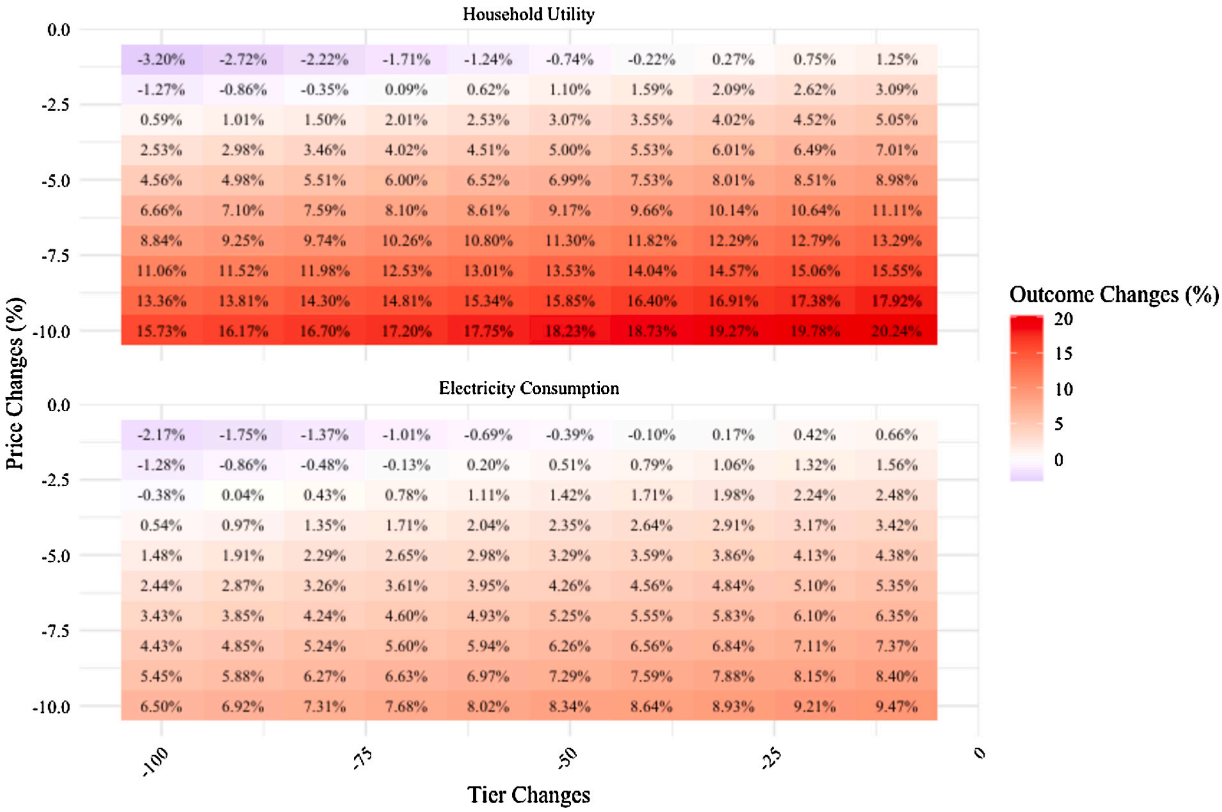

Fig. 6. Optimal policy design.

to -100. Consistent with earlier analyses, overall household welfare improves as prices decline, but this also triggers a significant increase in electricity consumption. As the kink point shifts leftward, welfare incrementally declines and electricity usage drops.

Importantly, our findings suggest that due to the counterbalancing effects of the two nonlinear pricing policies (IBP and ToU) on electricity consumption, enhancing consumer welfare through redistribution without escalating electricity usage is achievable, albeit with limited flexibility. In Fig. 6, we denote the price and tier adjustments that maintain the total electricity consumption level with white squares on the heat map. The results reveal that when the price reduction exceeds 3%, even a 100-point leftward shift of the kink point proves inadequate to counterbalance the rise in electricity consumption induced by the price decrease. To preserve electricity consumption levels while lowering prices, the available options are limited: for every one percentage point drop in price, the width of tier 2 must be shrunk by 30 points to counteract the impact of the price decrease.

In our counterfactual analysis, there are merely three sets of changes (-3%, -90), (-2%, -60), and (-1%, -30) where the amalgamation of price declines and tier adjustments resulted in no significant surge in overall electricity consumption and improved welfare. They yield 1.01%, 0.62%, and 0.27% of the household welfare impact, respectively. Consequently, policymakers must exercise utmost caution and prudence when optimizing the pricing system to elevate overall welfare through redistribution without stimulating consumption. Our structural model estimation and counterfactual analysis offer a practical approach to accomplish this goal.

7. Concluding remarks

For years, researchers have been working to reconcile the gap between theory and practice of agents' decision-making under nonlinear pricing structures. In the present study, we use a comprehensive and singular panel dataset of household electricity consumption to analyze electricity consumption patterns under a combination of two pricing systems: Increasing Block Pricing (IBP) and Time-of-Use (ToU) Pricing. The structural method we employ considers potential bunching and better reflects households' diverse preferences at different times and overall electricity usage levels. We clarify the model parameters' identification conditions and present an efficient estimation method. This method quickly delivers results without extensive computational demands.

Our structural estimates, based on observed samples, are consistent with economic intuition. We find that price elasticity varies substantially among households: a 1% increase in price results in an approximate 0.7% decrease in total power demand. The average elasticity estimate produced by our model is low because consumers can offset their electricity costs by adjusting nighttime usage under the combined IBP and ToU systems. Importantly, our counterfactual analysis reveals that modifications to mixed price schedules may have unintended consequences. The simultaneous implementation of IBP and ToU systems could create offsetting effects, ultimately rendering policies ineffective. This finding supports the theoretical predictions of multidimensional nonlinear pricing literature, where price schedules can generate counterbalancing effects and lead to inefficient outcomes.

Our study acknowledges data limitations, as no price changes are incorporated. In the future, access to more comprehensive data will allow researchers to conduct further investigations in this area. A promising direction for future research could involve combining information on production facilities' cost structures with data on industrial and office electricity consumption. This integration would enable a deeper and more robust analysis of social welfare that includes environmental considerations. It is important to note that our current data is limited to consumer welfare assessment and does not consider the effects of pricing changes on businesses reliant on electricity.

Another compelling area for future research could be exploring the integration of this study with other energy consumption sources. Substitutions between various energy sources, particularly electricity and natural gas, are possible. The prices of alternative energy sources impact household decisions and choices concerning electricity consumption. Although the impact on households may be significantly smaller than on industrial energy inputs, government pricing decisions, from a macro perspective, may rely on the concurrent consideration of all types of energy consumption. These questions merit investigation in future research endeavors.

Data availability

Data will be made available on request.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijindorg.2023.103034.

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