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Pricing policies for efficient demand side management in liberalized electricity markets[☆]

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ABSTRACT

International experience has shown that electricity consumers react to pricing policies by switching retailers or shifting part of their consumption from peak to off-peak hours. This behavior has a direct effect on the competition between retailers. In the light of this evidence (and considering the increasing penetration of smart meters) this study presents a theoretical framework in which retailers compete on time-of-use (ToU) pricing. In this case, the model is calibrated with Spanish data. Our objective is to determine whether the ToU pricing that emerges from the retail competition makes for greater efficiency than a fixed tariff, and if so, then to what extent. We also examine how efficiency gains are distributed between retailers and consumers. According to the results, the price signal to consumers under ToU pricing may be effective for modifying their consumption patterns and obtaining social welfare gains. As for the intermediate values of consumers' elasticities, ToU pricing is a win–win for both retailers and consumers. This has substantial implications in terms of cost-efficiency.

1. Introduction

Dynamic pricing, also known as revenue management, refers to pricing strategies aimed at increasing profits. These strategies are most useful when consumption is met at a certain point in time (travel and leisure, telecommunications, online retailing, etc.) and capacity can only be increased at a relatively high marginal cost. These characteristics also create the potential for price discrimination. In particular, liberalized electricity markets comply with the requirements for potential dynamic price discrimination.

Indeed, in electricity systems with large-scale penetration of intermittent renewable generation, the supply of reserve capacity has proven to be insufficient for maintaining balance in the system, due to its high maintenance costs (Strbac, 2008). Additionally, large-scale storage technologies are not mature enough to guarantee sufficient capacity (Fraunholz et al., 2021). For this reason, previous studies (Freeman, 2005; Conchado and Linares, 2012; Finn and Fitzpatrick, 2014; Wolak, 2019) have suggested that pricing policies directed at demand-side management (DSM) might foster the penetration of renewable sources and contribute to the efficiency of electricity systems.[1] Part of the consumption would then be shifted to hours in which generation, transport and distribution can be handled more efficiently (in terms of less resources and/or lower prices), thus reducing electricity costs.[2] Hence, DSM policies have a two-fold effect of reducing electricity consumption during peak hours and permitting flexibility in grid management to establish a better match between supply and demand, including variations in renewable sources (Pina et al., 2012). DSM policies that include economic incentives for electricity users can also induce persistent welfare improvements, particularly when long-term effects, such as habit formation and habituation, are taken into account (Ito et al., 2018).

Meanwhile, price mechanisms provide signals for efficient allocation of resources. In fact, previous research has indicated that the apparent inelasticity of electricity demand is mainly caused by the

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[1] The intermittence of many renewable technologies (e.g., wind or solar) can affect the technical efficiency of electricity grids. This problem can be reduced by energy storage systems (currently unavailable or extremely expensive) or by the use of DSM strategies.

[2] In this study we use two different concepts related to efficiency: technical efficiency (related to the optimization of the resources for electricity generation) and economic efficiency (related to the potential welfare gains derived from lower prices).

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absence of a price signal to final consumers (Ilic et al., 2002; Lijesen, 2007). The wholesale market price (set on an hourly basis) clearly reflects the changes in marginal costs on the supply side (electricity production). However, keeping prices for final consumers invariant can result in more rigidity in consumption than under the efficient level, thus generating a major market failure (Borenstein and Holland, 2005; Jessoe and Rapson, 2015).

This disparity between wholesale and retail prices has long been a major cause of inefficiency in electricity markets. On the one hand, rigidities can hinder the optimization of capacity and load factors (technical efficiency), while on the other hand, invariant prices can prevent consumers from obtaining possible reductions in the average price of their electricity bills (economic efficiency). Moreover, the system as a whole has failed to take full advantage of local natural resources (e.g., renewable sources) and to reduce the import of fossil fuels for thermal power generation.

As for DSM policies, they are based on a redistribution of load over time, shifting consumption from periods of high demand (peak demand) to periods of lower demand (off-peak demand). Although they do not necessarily reduce total energy consumption,[3] some policies may (depending on their design) involve a reduction in electricity demand, not only a shift from peak to off-peak.[4] The key element in DSM is the incentive to modify consumers' electricity usage habits. This incentive is usually translated into the variable part of the electricity bill and may be achieved through *smart meters* with two-way communication (i.e., from the smart-meter to utilities and from the smart-meter to the consumers) to enable users to monitor, control, and predict their electricity consumption.

International analyzes have proven that when users have access to information on how much they consume, they tend to react to dynamic pricing policies by reducing electricity consumption during peak hours. In fact, one study by Faruqui and George (2005) on the California market found that the necessary investments for replacing all conventional meters with smart meters could be fully offset by the demand response benefits. There is also evidence for substantial heterogeneity in preferences for smart home energy products, with younger consumers being much more likely to perceive their economic value and showing greater willingness to pay for such products (Daziano, 2020).

According to the European Commission (2019), smart meter systems in the European Union deliver an overall benefit per customer of EUR 271, plus energy savings of 7.85%.[5] Specifically, the target for 2020 was for 80% of conventional electricity meters to be replaced by smart meters (European Commission, 2009). However, only Denmark, Estonia, Finland, Italy, Malta, Spain, and Sweden reached this target (European Commission, 2019).

Based on this evidence, we propose a theoretical model in which competing retailers use time-of-use (ToU) pricing. In our model, consumers may switch between retailers, depending on the price scheme that they offer. The highlight of our model is retailers' demand functions that depend on (i) the price change between peak and off-peak consumption by the retailer and (ii) the price divergence between different retailers. The literature, which (to date) has mainly focused on understanding customers' willingness to adopt dynamic tariffs, supports the fact that DSM via dynamic pricing of electricity is capable of stimulating demand response. In particular, according to the review by Dutta and Mitra (2017), the residential sector reacts to price changes more than commercial or small industrial consumers. Meanwhile, the price responsiveness depends on socio-demographic characteristics, which are typically larger for customers with high consumption levels and those living in hotter climates. However, there has been little research on designing suitable pricing schemes and comparing flat rate tariffs to dynamic tariff schemes. Conversely, concerning retail competition, Mountain and Burns (2021) empirically confirmed that consumers who switched their electricity retailer in the previous 12 months in Australia paid 4% less than those who remained with their retailers. This supports the fact that consumers may react to the price signal, in addition to other considerations such as reputation and brand reliability. Furthermore, it proves that consumers under ToU pricing tend to pay lower annual bills than those under flat rate tariffs. In this sense, analyzing dynamic pricing from the welfare viewpoint can achieve better informed consumers and regulators, which can enhance the actual implementation of ToU pricing under retailer competition.

In this study, we calculate the resulting price schemes and calibrate the model using Spanish data, given its availability at the hourly level.[6] Our objective is to determine whether the equilibrium ToU pricing that emerges from the retail competition model makes for greater efficiency than a fixed tariff, and if so, then to what extent. We also examine how efficiency gains are distributed between retailers and consumers, and argue that the price signal to consumers under ToU pricing may be quite effective for attaining social welfare gains by modifying users' consumption patterns. Our results indicate that for intermediate values of consumers' elasticities, ToU pricing can be a win–win situation for both retailers and consumers.

Another contribution of this study is the way in which we model retailers' electricity costs. We consider these costs as endogenous, since they may change when electricity consumers have greater elasticities. This may place downward pressure on electricity prices and reduce firms' profits. The question that we address is whether it is still possible to increase firms' profits with ToU pricing, considering that their revenues may be lower. Our results may be significant for the future evolution of the European electricity market, given the growing penetration of smart meters and dynamic pricing schemes.

The remainder of this study is organized as follows. Section 2 summarizes the empirical evidence on the elasticity of demand, while our theoretical model is presented in Section 3. Sections 4 and 5 describe the data, our simulations, and the results, respectively. Finally, Section 6 presents the main conclusions and suggestions for further research.

2. The price elasticity of electricity demand

Previous literature has mainly focused on aggregate electricity demand (Section 2.1) and provided estimates of the variation in aggregate consumption when prices change. However, we are also interested in two other measures of elasticity. The first is inter-hour price elasticity (Section 2.2) and the second is the elasticity of the demand faced by the retailer (Section 2.3).

Concerning the inter-hour price elasticity, own-price elasticity expresses the change in electricity demand in a given period, for a variation of 1% in the price of electricity in the same period. Cross-price elasticity represents the change in electricity demand in a given period, for a variation of 1% in the price of electricity in a different period. Related to the elasticity of the demand faced by the retailer, own-price elasticity expresses the change in electricity demand, for a variation of 1% in the price of electricity for the same retailer in the same period. Moreover, cross-price elasticity represents the change in electricity demand, for a variation of 1% in the price of electricity for a competing retailer in the same period.

[3] When consumers face reduced prices during certain periods they tend to increase total consumption.

[4] There are some additional benefits of dynamic pricing that shift demand from peak to off-peak hours, such as avoiding capacity investments that remain idle during off-peak hours (Dutta and Mitra, 2017).

[5] These figures show the average benefit per meter point toward the long term, especially for countries that have already completed a large-scale rollout.

[6] In Spain, the deployment of smart meters started in 2011. By 2018, 98.14% of the electricity meters for consumers with contracted power levels of less than 15 kW were smart meters (Comisión Nacional de los Mercados y la Competencia, 2019).

2.1. Aggregate price elasticity

There is an important distinction between short- and long-run elasticity. In their meta-analysis of residential electricity demand elasticities, Espey and Espey (2004) reported short-run elasticities between −2.01 and −0.004 (with a mean of −0.35 and a median −0.28) and long-run elasticities between −2.25 and −0.04 (with a mean −0.85 and a median −0.81). In general, there is a large variability in the estimated values of elasticity, depending on the availability of technology enabling price signals and the price of substitute products, especially in the long-run. According to Filippini (2011), the short-run own-price elasticity for the Swiss market is lower than 1%, whereas the long-run figure is higher than 1%. Thus, although demand in terms of short-run own-price elasticity is relatively inelastic, in the long-run, it is elastic. More recent studies have corroborated these findings (Auray et al., 2019) and found higher values for these elasticities, especially as retail prices increase over time (Labandeira and López-Otero, 2017; Bueno et al., 2020).

As for Spain, there are few empirical studies on the elasticity of residential electricity demand, and none related to dynamic pricing. Blázquez et al. (2013) used econometric techniques based on household income, weather, and geographical location, among others, and found estimated own-price elasticity figures of −0.07 in the short-run and −0.19 in the long-run for the 2000–2008 period. Labandeira et al. (2006, 2012) estimated the own-price elasticity of electricity demand in Spain at −0.78 for the 1975–1995 period, while Pellini (2021) obtained values of −0.699 for the 1975–2018 period. All of these values fall within the range of the aforementioned international studies.

2.2. Inter-hour price elasticity

In general, electricity demand shows regular patterns throughout a typical 24 hour time period. Meanwhile, electricity consumption is higher during the so-called peak hours, and considerably lower in off-peak periods. Fig. 1 represents the distribution of electricity demand in four European countries (Germany, Spain, France, and the United Kingdom) for three different years (2015, 2018, and 2020).[7] For each year, we plot the demand of a representative day in the winter (the third Wednesday of January), as shown in Fig. 1(a), and another representative day in the summer (the third Wednesday of June), as shown in Fig. 1(b).

Demand patterns for the winter and summer seasons are different, but consistent across years and countries. Specifically, winter demand shows two distinct peaks (one in the morning and one in the evening), while demand in summer shows a single peak (around midday), which can be longer than the peak-time in the winter. Peaks are also smoother in the summer. Additionally, the effect of economic cycles is shown in Fig. 1, with demand levels related to economic activity per country.

Considering this pattern of electricity demand, there is scope for efficiency gains based on the shift in consumption from peak to off-peak hours induced by price differences. In fact, the success of any ToU pricing policy lies in the price elasticity of demand (Fillipini, 1995a).

DSM programs can also be price-oriented or incentive-oriented. In price-oriented systems, consumers react to different price schemes, by modifying their consumption patterns according to the electricity price, e.g., ToU, Critical Peak Pricing (CPP), Inclining Block Rates, and Real-Time Pricing. In incentive-oriented systems, consumers are rewarded if they reduce their consumption in a given period, e.g., Critical Peak Rebate. Our analysis exclusively focuses on price-oriented policies, in particular, ToU pricing.

Empirical evidence has shown that these dynamic pricing programs can reduce electricity demand during peak hours, with figures being lower for ToU programs (e.g., Darby and McKenna (2012) and Di Cosmo et al. (2014) for Ireland) and higher for CPP programs (e.g., Vesterberg and Krishnamurthy (2016) for Sweden). Moreover, ToU schemes can achieve load shifting (e.g., Breukers and Mourik (2013) for the United Kingdom and Fabra et al. (2021) for Spain). However, the success of these programs depends on demand elasticity.

Finally, King and Chatterjee (2003) reviewed the estimations for elasticities in 35 studies from the United States and other countries for domestic customers and small businesses under ToU and CPP between 1980 and 2003, and found that the average own-price elasticity was −0.3, with figures ranging between −0.1 and −0.8 (between −0.1 and −0.4 for most studies). In related research, Faruqui and George (2002) estimated average values of 0.14 (with a range between 0.07 and 0.21) for elasticity of substitution.

2.3. Retailer demand elasticity

Consumers may perceive the costs for switching from one firm to another. According to Klemperer (1995), these switching costs "give firms a degree of market power over their repeat-purchasers, and mean that firms' current market shares are important determinants of their future profits". In this sense, each firm faces a trade-off between (i) charging a lower price to attract new consumers who will remain with them in subsequent periods (investing in the market share) and (ii) charging higher prices to their existing consumers to harvest profits, at the expense of losing some of the market share in the future. As a result, switching costs can result in higher prices and welfare losses for consumers. They may also discourage new entries and diminish market competition. Wilson (2012) emphasized the importance of considering the interaction between search costs and switching costs in eight different markets. Search costs can harm competition more than switching costs. Such costs can also reduce the incentives for firms to differentiate their products.[8] Simshauser and Whish-Wilson (2017) claimed that price discrimination in which the marginal offer has a zero retail profit margin displays positive distributional efficiency effects, because it distributes the firm's cost recovery from weak (more price-sensitive) customer segments to strong (less price-sensitive) ones, which are usually high-income households.

The electricity market, after the creation of retail markets during the 1990s and early 2000s, is one of many liberalized markets in which consumers are allowed to switch retailers. In related research, Keaveney (1995) analyzed the existence of critical events that determine customers' decision to switch suppliers, while Gärling et al. (2008) found that lower switching in electricity markets is related to the fact that electricity costs constitute a small fraction of total expenditures. Harold et al. (2020) analyzed switching behavior in the energy retail markets of 27 European Union countries and found that switching in these markets is greater for consumers who have switched in at least one other retail market and have access to the Internet. In this line, Fabra and Reguant (2020) confirmed that sellers charge lower prices when buyers have a higher perceived willingness to search. The switching rate is thus an indicator of the level of competition in the retail electricity market.[9]

Ilieva and Gabriel (2014) investigated the effects of regulation in the Nordic retail market for electricity and concluded that decisions

[7] See Do et al. (2016) for a more detailed analysis of electricity demand behavior in Germany and Martin-Rodriguez and Cáceres-Hernández (2005) for such information in Spain.

[8] As Giulietti et al. (2014) showed, product differentiation can explain the price differentials between retailers and be observationally equivalent to switching costs.

[9] Of course, price is not the only variable that affects such decisions. Other considerations, such as the standard of customer service, loyalty, information search costs, and lack of economic benefits, may also affect the decision to switch retailers (Giulietti et al., 2005).

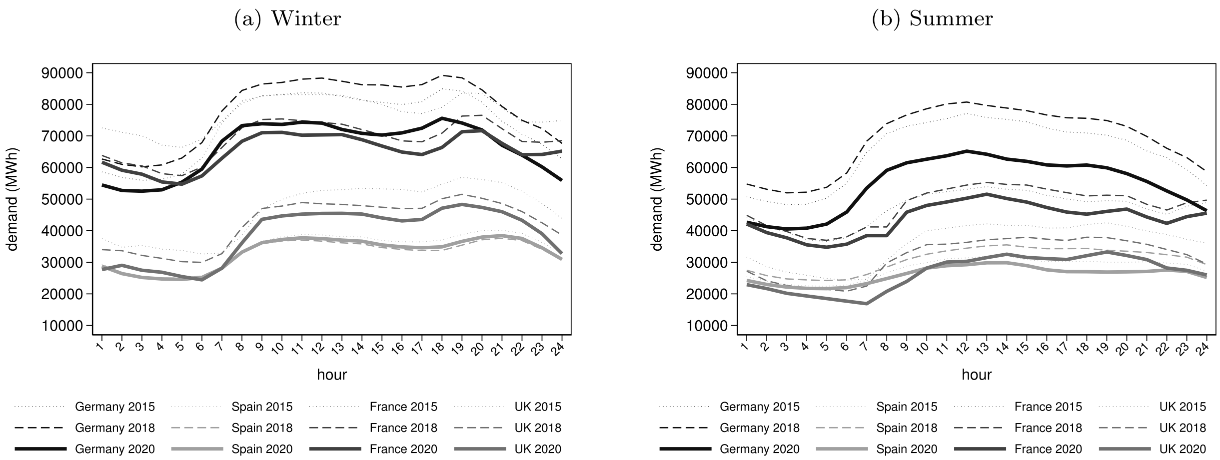

Fig. 1. Electricity demand in European wholesale markets [MWh].
Note: Germany, Spain, France, and the United Kingdom for 2015, 2018, and 2020. The third Wednesday of January (for the winter) and the third Wednesday of June (for the summer).
Source: Our own work using data from Operador del Mercado Ibérico de Electricidad (OMIE) (2019).

made by one retailer have a strong impact on the market strategy of another. Focusing on electricity distribution companies in the United States, Ros (2017) found that retail electricity competition is associated with lower electricity prices, with the mean total impact of −4.3% for residential consumers during the 1972–2009 period. These two studies addressed retail competition and found aggregate price elasticity of demand values of −0.4 and a range from −0.40 to −0.61, respectively. However, they did not consider the effect of inter-hour price elasticities or retailer demand elasticities.

In the present study, our main contribution is to model electricity prices based on both retail price elasticity and inter-hour price elasticities, in order to understand the impact of retail price competition on DSM policies.

3. The model

In this study we use a price competition model with differentiated products to characterize the optimal prices that a retail company would apply to residential consumers under ToU pricing. Differentiation is provided by the billing services of the retailer, which may not be identical and may induce some customer loyalty. This loyalty is reinforced by switching costs, which, in this context, refer to the costs that consumers face when they switch electricity retailers (see Section 2.3). In this regard, the higher the costs of shifting from one retailer to another, the more important the current market share is for future profitability.

When setting hourly prices, a retailer must realize that customers in this period (e.g., this quarter) could switch to a competitor for the following period, especially if the other company's price schedule is better suited to their needs. For instance, a customer with high electricity consumption during peak hours and little propensity to shift such consumption to off-peak hours generally prefers a retailer that offers moderate prices for peak hours, even if the price for off-peak hours is higher. The same customer may also be willing to switch retailers if the advantages of the competitor's price scheme outweighs the switching costs.

Taking this into account, we develop a model in which the service provided by retailers is heterogeneous and there are switching costs such that in the short-run customers are locked-in and it takes one period to change retailers. In this case, the regulator allows price discrimination depending on the consumption period, since companies have more information about demand and costs than the regulator.

We also consider two symmetric retailers (A and B), two periods (t and $t+1$), and two intervals (peak and off-peak). Sub-index 1 refers to peak hours, while sub-index 2 refers to off-peak hours. Consumers buying from a retailer in period t must wait until period $t+1$ to change the retailer. There is also a peak and an off-peak interval in periods t and in $t+1$. Here, consumers distribute their electricity consumption between these two intervals, depending on their preferences and the price of electricity in each interval. To formalize this decision, we assume that the representative consumer's utility function is given by $U(q) = \eta' q - \frac{q'\Theta q}{2}$, where $q = (q_1, q_2)$, q_1 is consumption during peak hours, q_2 is consumption during off-peak hours, $\eta = (\eta_1, \eta_2)$ is the vector of strictly positive parameters, and Θ is an asymmetric 2×2 matrix[10]:

$$\Theta = \begin{pmatrix} \omega_1 & \gamma_1 \\ \gamma_2 & \omega_2 \end{pmatrix} \tag{1}$$

Matrix Θ is positive and definite (equivalent to strict concavity of the utility function). Thus, the diagonal elements (ω_1, ω_2) are positive. As for the off-diagonal elements (γ_1, γ_2), they are also positive under the assumption of weak asymmetric gross substitutability between consumption during peak and off-peak hours (De Jaegher, 2009).

The representative consumer chooses q to solve:

$$\max\{\eta' q - \frac{q'\Theta q}{2} + y\} \text{ subject to } p'q + y = m \tag{2}$$

where p is the vector of prices, y is the numeraire whose price is normalized to 1, and $m > 0$ is the income. Matrix Θ and the vectors η and p satisfy the condition for an interior solution, $\Theta^{-1}(\eta - p) > 0$, and the feasibility condition, $p'\Theta^{-1}(\eta - p) \leq m$. Thus, the inverse demand functions are[11]:

$$p(q) = \eta - \Theta q \tag{3}$$

while the demand functions are:

$$q(p) = \Theta^{-1}(\eta - p) \tag{4}$$

Equivalently, denoting $\theta = \omega_1\omega_2 - \gamma_1\gamma_2$, $a_i = \frac{\eta_i\omega_j - \eta_j\gamma_i}{\theta}$, $b_i = \frac{\omega_j}{\theta}$ and $z_i = \frac{\gamma_i}{\theta}$ for $i = 1, 2$ and $i \neq j$, the demands for peak and off-peak hours are, respectively:

$$q_1 = a_1 - b_1 p_1 + z_1 p_2 \tag{5}$$

$$q_2 = a_2 - b_2 p_i + z_2 p_j \tag{6}$$

10 See Amir et al. (2017) for a generalization of the quadratic utility function in Singh and Vives (1984). We allow γ to differ between peak and off-peak hours.

11 See Lemma 4 in Amir et al. (2017).

where $b_i > z_i$. Meanwhile, firms A and B decide their pricing schemes simultaneously and non-cooperatively, considering that consumers allocate their electricity consumption in period t. This is only based on the peak and off-peak prices of their retailer. Meanwhile, consumption in t does not depend on the other retailer's prices, since consumers cannot switch the supplier in the short-run. However, since consumers can switch retailers in $t+1$, the (future) demand in $t+1$ also depends on the prices of the two retailers. Our two-firm model can be easily generalized in the case of more competitors.

As for the retailers, they are multiproduct firms, since they produce electricity during peak and off-peak hours. Additionally, since it takes one period to switch retailers, consumers cannot switch a retailer until the end of period t (period $t+1$). Hence, in period t, the short-run demand functions for firm A for peak (sub-index 1) and off-peak hours (sub-index 2) are (symmetric for firm B):

$$q_{A1}(t) = a_1 - b_1 p_{A1}(t) + b_{12} p_{A2}(t) \quad \text{(peak)} \tag{7}$$

$$q_{A2}(t) = a_2 - b_2 p_{A2}(t) + b_{21} p_{A1}(t) \quad \text{(off-peak)}, \tag{8}$$

where $a_i, b_i, b_{ij} > 0$.[12] Note that the constants a_1 and a_2 may contain the impact of the rival's prices in previous periods, which are given in period t. Additionally, Eqs. (7) and (8) represent the short-run situation in which consumers are committed to their retailer, and their only decision is consumption during peak and off-peak hours. Thus, the short-run demand during peak hours for retailer A only depends on its own peak and off-peak prices, while the same goes for off-peak demand.

Moreover, retailer prices are assumed to be the same in t and t+1 in order to reflect the trade-off between setting a high price in the short-run, and taking advantage of the lock-in effect, but losing the market share in the long-run when customers switch retailers, or setting a low price in the short-run and increasing the market share in the long-run.

Given a point on the demand curve, i.e., the pair price-quantity (q_i, p_i), the own-price short-run elasticities (no retailer switching) are:

$$\epsilon_{ii} = \frac{\partial q_i}{\partial p_i}\frac{p_i}{q_i} = -b_i \frac{p_i}{q_i} \quad \text{(i = 1, 2)} \tag{9}$$

while the cross-price short-run elasticities (no retailer switching) are:

$$\epsilon_{ij} = \frac{\partial q_i}{\partial p_j}\frac{p_j}{q_i} = b_{ij} \frac{p_j}{q_i} \quad (\text{i, j = 1, 2; i} \neq \text{j}) \tag{10}$$

Consumers may switch retailers in period $t+1$, so during period t firm A expects a future (long-run) demand function for period $t+1$ during peak and off-peak hours, respectively (symmetric for firm B):

$$q_{A1}(t+1) = A_1 - B_1 p_{A1} + B_{12} p_{A2} + D_1 p_{B1}(t) + D_{12} p_{B2}(t) \quad \text{(peak)} \tag{11}$$

$$q_{A2}(t+1) = A_2 - B_2 p_{A2} + B_{21} p_{A1} + D_2 p_{B2}(t) + D_{21} p_{B1}(t) \quad \text{(off-peak)} \tag{12}$$

where $A_i, B_i, B_{ij}, D_i, D_{ij} > 0$, and $B_i > D_i$. It is also assumed that: $p_{A1}(t) = p_{A1}(t+1) = p_{A1}$ and $p_{A2}(t) = p_{A2}(t+1) = p_{A2}$.

The last two terms represent the effect of the competitor's prices in the previous period. In this setting, firm A can lose customers in $t+1$, especially if p_{A1} is high or if p_{B1} is low in t. This formulation reflects the firm's choice between setting a low price to increase the future market share and setting a high price to exploit the fact that its customers are locked-in in the short-run. The terms of this trade-off are affected by how sensitive consumers are to the other retailer's offers. We define the long-run and inter-retailer price elasticities as follows:

Retailer l's long-run price elasticities (i = peak, off-peak) are:

$$\mathrm{E}_{li} = \frac{\partial q_{li}}{\partial p_{li}}\frac{p_{li}}{q_{li}} = -B_i \frac{p_{li}}{q_{li}} \tag{13}$$

Retailer l's long-run cross (inter-hour) price elasticities (i, j = peak, off-peak) are:

$$\mathrm{E}_{lilj} = \frac{\partial q_{li}}{\partial p_{lj}}\frac{p_{lj}}{q_{li}} = B_{ij} \frac{p_{lj}}{q_{li}} \tag{14}$$

Inter-retailer k's and l's price elasticities (i = peak, off-peak) are:

$$\mathrm{E}_{lki} = \frac{\partial q_{li}}{\partial p_{ki}}\frac{p_{ki}}{q_{li}} = D_i \frac{p_{ki}}{q_{li}} \tag{15}$$

All of the parameters of the model are positive: (i) a_1, b_1, b_{12} for peak hours and a_2, b_2, b_{21} for off-peak hours refer to the electricity demand in t; and (ii) A_1, B_1, B_{12}, D_1, D_{12} for peak hours and A_2, B_2, D_{21}, D_2, D_{21} for off-peak hours, contain information on future demand. In particular, the consumer reaction in $t+1$ to the price of the rival firm in t is linked to the retailer switching rate. In Section 4, we assign values to these parameters in order to conduct the simulations, since none of them are directly observable.

At t, firms maximize their profits for periods t and $t+1$, and their decision variables are peak and off-peak prices.[13] Therefore, the objective function for A (symmetric for firm B) is:

$$\pi_A = (p_{A1} - c_1)[q_{A1}(t) + q_{A1}(t+1)] + (p_{A2} - c_2)[q_{A2}(t) + q_{A2}(t+1)]$$

The parameters c_1 and c_2 are the unit costs for the retailing companies, which are the same for firms A and B and for periods t and $t+1$. In this case, c_1 represents the unit costs during peak hours, which correspond to the average price of the pool during the peak period. Similarly, c_2 represents the unit costs during off-peak hours, which reflect the average price of the pool during the off-peak period.

At t, firm A chooses prices p_{A1} and p_{A2} in order to maximize its profits (symmetric for firm B):

$$\max_{\{p_{A1}, p_{A2}\}} (p_{A1} - c_1)[(\alpha_1 - \beta_1 p_{A1} + \beta_{12} p_{A2}) + D_1 p_{B1} + D_{12} p_{B2}] \\ + (p_{A2} - c_2)[(\alpha_2 - \beta_2 p_{A2} + \beta_{21} p_{A1}) + D_2 p_{B2} + D_{21} p_{B1}],$$

where $\alpha_i = a_i + A_i$, $\beta_i = b_i + B_i$, $\beta_{ij} = b_{ij} + B_{ij}$ for $i = 1, 2$, $j = 1, 2$, and $i \neq j$.

Solving the first-order conditions for firm A gives the following reaction functions for firm A during the peak and off-peak periods (symmetric for firm B):

$$p_{A1} = \frac{\alpha_1 + \beta_1 c_1 - \beta_{21} c_2 + (\beta_{12} + \beta_{21}) p_{A2} + D_1 p_{B1} + D_{12} p_{B2}}{2\beta_1}$$

$$p_{A2} = \frac{\alpha_2 + \beta_2 c_2 - \beta_{12} c_1 + (\beta_{12} + \beta_{21}) p_{A1} + D_2 p_{B2} + D_{21} p_{B1}}{2\beta_2}$$

Note that in each period, the prices in the peak and off-peak intervals (both the own price and the price of the other firm) are affected by electricity production costs and by consumer behavior regarding the switching consumption between retailers and between peak and off-peak periods.

By symmetry, it follows that $p_{A1} = p_{B1}$ and $p_{A2} = p_{B2}$, so the Nash equilibrium (Eqs. (16) and (17)) for the peak and off-peak prices is:

$$p_{A1} = p_{B1} \\ = \frac{(2\beta_2 - D_2)(\alpha_1 + \beta_1 c_1 - \beta_{21} c_2) + (\beta_{12} + \beta_{21} + D_{12})(\alpha_2 + \beta_2 c_2 - \beta_{12} c_1)}{(2\beta_1 - D_1)(2\beta_2 - D_2) - (\beta_{12} + \beta_{21} + D_{12})(\beta_{12} + \beta_{21} + D_{21})} \tag{16}$$

$$p_{A2} = p_{B2} \\ = \frac{(2\beta_1 - D_1)(\alpha_2 + \beta_2 c_2 - \beta_{12} c_1) + (\beta_{12} + \beta_{21} + D_{21})(\alpha_1 + \beta_1 c_1 - \beta_{21} c_2)}{(2\beta_1 - D_1)(2\beta_2 - D_2) - (\beta_{12} + \beta_{21} + D_{12})(\beta_{12} + \beta_{21} + D_{21})} \tag{17}$$

[12] As pointed out by a reviewer, there are two effects that appear after a peak price change: (1) peak-off-peak shifting of electricity consumption and (2) electricity conservation. If the first effect dominates, then $b_{21} > 0$, whereas if the second effect dominates, then $b_{21} < 0$. In our model, we assume that the first effect dominates.

[13] We assume that the discount factor of future payoffs is 1.

4. Simulations and data

In this section, we present the purpose of the simulations (Section 4.1), the procedure for computing the social welfare or total surplus (Section 4.2), and the data used in this empirical process (Section 4.3).

4.1. General purpose of the simulations

The main purpose of our simulations is to determine whether the ToU pricing that emerges from the retail competition makes for greater efficiency than a fixed tariff, and if so, then to what extent. We also examine how efficiency gains are distributed between producers and consumers.

To carry out these simulations, the parameters related to consumers' elasticity between hours, their willingness to switch retailers, and the costs of electricity production must be calibrated. We do this by using real data from the Spanish electricity system provided by the market operator OMIE,[14] the system operator REE,[15] and the National Commission on Markets and Competition CNMC,[16] plus the results from other studies on inter-hour price elasticity (Filippini, 1995a,b) and self-selected scenarios for retailer price elasticity. We present a more detailed explanation on the parametrization of these variables in Section 4.3. In particular, we consider the data on the cost of electricity for retailers (Section 4.3.1), on inter-hour price elasticity (Section 4.3.2), and on inter-retailer price elasticity (Section 4.3.3).

The simulations are applied to the ToU model in two periods. Given the seasonal differences in electricity consumption (recall Fig. 1), we analyze one representative month in the winter (January) and one in the summer (June). The simulations are performed for 2013, the last year without ToU pricing in Spain. Since 2014, Spanish residential prices have been linked to electricity market prices. Using 2013 data, the effects of ToU pricing compared to the benchmark without dynamic pricing can be seen.

We also consider peak and off-peak retail prices for the hours of the maximum and minimum price spikes in the pool, respectively. In other words, for a given month, we find the hour in which the average price is the highest (lowest) for peak (off-peak) hours during the winter and summer. We do not average winter and summer hours together, but we treat them separately. For instance, for month m (either the winter or summer), we compute the average hourly price as $\bar{P}_h = \frac{1}{H_i}\sum_{i=1}^{H_i} P_{H_i}$ for h=1,…,24 and i=30,31. Then, we take $\max \bar{P}_h$ in order to identify the peak hours and $\min \bar{P}_h$ to identify the off-peak hours. The peak retail prices occur in hour 20 during the winter and in hour 13 during the summer, while the off-peak retail prices occur in hour 5 during both the winter and summer. The purpose of this strategy is to identify the largest possible gain in electricity consumption variation that is consistent with the empirical evidence in Section 2.2.

4.2. Methodology for computing the change in social welfare

In this study, we compute social welfare as the sum of the consumer surplus and the producer surplus. The aim is to determine under what conditions the equilibrium prices for peak and off-peak hours under the ToU scheme can lead to an efficiency gain and a win–win situation for both consumers and producers. First, we determine the effect on consumers (Section 4.2.1), and then explore the effect on retailers (Section 4.2.2). Finally, we obtain the change in social welfare (Section 4.2.3).

[14] *Operador del Mercado Ibérico de Electricidad.*

[15] *Red Eléctrica de España.*

[16] *Comisión Nacional de los Mercados y la Competencia*, formerly called *Comisión Nacional de la Energía* CNE.

4.2.1. Effect on consumers

In order to calculate the variation in consumer surplus, we consider two different situations, represented in Fig. 2. In Fig. 2(a), the average price based on ToU pricing (p_{TOU}) is lower than the regulated price (p_{TUR}), i.e., $p_{TOU} < p_{TUR}$, while the quantity of energy traded under ToU pricing (q_{TOU}) exceeds the quantity of energy traded under the regulated price (q_{TUR}), i.e., $q_{TOU} > q_{TUR}$. Note that p_{TOU} is the weighted average of equilibrium prices at different hours, whereas p_{TUR} represents the fixed price that consumers pay when there is no price discrimination (our benchmark).

In Fig. 2(a), the triangle ABC, computed as $\frac{(p_{TUR}-p_{TOU})\cdot(q_{TOU}-q_{TUR})}{2}$, represents the decrease in deadweight loss. The rectangle DABE, computed as $q_{TUR}\cdot(p_{TUR}-p_{TOU})$, is a transfer from the retailer to the consumers, and is therefore not an efficiency loss. The change in the consumer surplus is the sum of the areas ABC and $DABE$: $\frac{(p_{TUR}-p_{TOU})\cdot(q_{TOU}-q_{TUR})}{2} + q_{TUR}\cdot(p_{TUR}-p_{TOU})$, which is positive (gain). Fig. 2(b) represents the opposite case, where $p_{TOU} > p_{TUR}$ and $q_{TOU} < q_{TUR}$ and the change in the consumer surplus is $-[\frac{(p_{TOU}-p_{TUR})\cdot(q_{TUR}-q_{TOU})}{2} + q_{TOU}\cdot(p_{TOU}-p_{TUR})]$, which is negative (loss). In sum, consumer surplus increases when average prices drop, as represented in Fig. 2(a), and decreases when average prices rise, as shown in Fig. 2(b).

4.2.2. Effect on retailers

The change in profits for the retailer is computed as the change in revenues minus the change in costs ($\Delta profit = \Delta revenue - \Delta costs$). The change in revenues is the difference between revenues under the ToU scheme and those under the regulated tariff ($\Delta revenue = p_{TOU}\cdot q_{TOU} - p_{TUR}\cdot q_{TUR}$). The change in costs takes into account the endogeneity of the pool price, which is higher than the actual value when the quantity of energy reduces as a result of ToU prices, or lower otherwise. We use $p_{PoolToU}$ to denote the average pool price under a ToU scheme, i.e., when the quantity demanded is q_{TOU}, and by p_{Pool}, i.e., when the original average pool price that corresponds to a quantity of energy q_{TUR}. Therefore, the change in costs is computed as $p_{PoolToU} * q_{TOU} - p_{Pool} * q_{TUR}$. To obtain the corresponding $p_{PoolToU}$ for each scenario, we use the original supply curve and find the intersection with the new demand after implementing our ToU model.

4.2.3. Change in social welfare

In this section, we compute the change in social welfare as the sum of the variations in consumer surplus and retailer profits.

When the ToU average price is higher than the regulated price, the deadweight loss is larger and the gain for the retailer fails to offset the loss for consumers. In this case, ToU pricing can result in a loss of efficiency, after which social welfare decreases. This loss is a consequence of retailers' market power stemming from the low elasticity of demand.

When the ToU average price is lower than the regulated price, the lower revenues of retailers may decrease profits by less than the gain for consumers, thus increasing social welfare. A third and more interesting possibility from a policymaking perspective is that under ToU pricing, lower revenue for retailers is offset by lower cost. In this case, both consumer surplus and retailer profits increase, resulting in an increase in social welfare and a win–win situation for both consumers and retailers.

4.3. Data

This section presents the data used in the simulations. Specifically, we consider the data on the cost of electricity for retailers (Section 4.3.1), on inter-hour price elasticity (Section 4.3.2), and on inter-retailer price elasticity (Section 4.3.3).

4.3.1. Data on the cost of electricity for retailers

We assume that the cost of electricity for a retailer in each period (c_1 for peak hours and c_2 for off-peak hours) is the final electricity

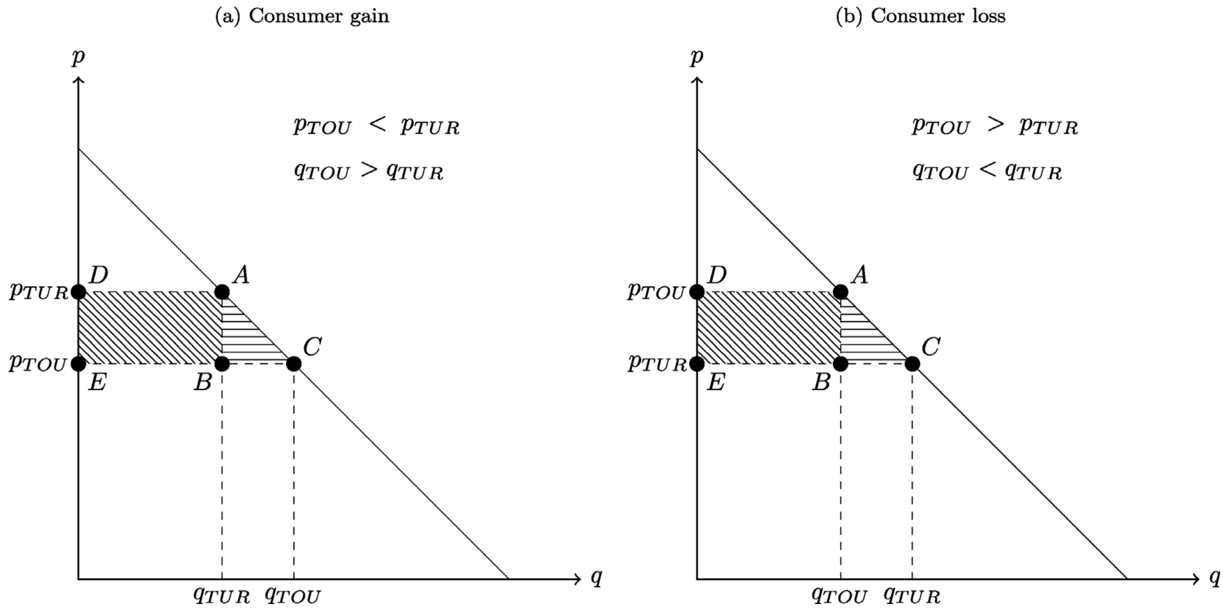

Fig. 2. Consumer surplus.

Table 1
Descriptive statistics of the final electricity wholesale price [EUR/MWh].
Source: Our own work using the pool data from Operador del Mercado Ibérico de Electricidad (OMIE) (2015, 2019).

Season	Mean	Median	Std. deviation	Skewness	Kurtosis
Winter-peak	89.61	91.15	12.28	−1.06	3.53
Winter-off-peak	33.19	33.43	15.37	−0.16	2.04
Summer-peak	60.49	63.72	9.23	−0.89	3.81
Summer-off-peak	40.69	44.04	11.70	−0.53	1.92

Note: Winter-January 2013, peak-hour 20, off-peak-hour 5. Summer-June 2013, peak-hour 13, off-peak-hour 5. Peak prices correspond to the parameter c_1 in Eqs. (16)-(17), while off-peak prices correspond to the parameter c_2.

wholesale price reported by the market operator OMIE. This price includes the day-ahead market, intraday markets, adjustment services and capacity payments.

Table 1 summarizes the main descriptive statistics of the final electricity wholesale price used in the simulations. According to the data, there is a greater dispersion of prices in the winter, with a greater peak/off-peak difference. Meanwhile, negative asymmetry is observed for all prices, with leptokurtic distribution for peak hours and platykurtic distribution for off-peak hours, both in the winter and the summer.

4.3.2. Data on inter-hour price elasticity

In this section, we use the short-run own-price elasticities obtained by Filippini (1995a,b) for peak and off-peak periods. These elasticity values come from actual pricing experiments with ToU rates conducted in Switzerland. They also represent possible responses of retail customers if they perceive the price signal. Since these elasticities are factored into the average ranges provided by the literature (between −0.1 and −0.8, see Section 2 for more details) and are close to the −0.78 reported by Labandeira et al. (2006) for Spain, they are useful for a discussion on the effect of elasticities. It should be noted that we do not claim that the evidence from Switzerland in the 1990s is applicable to today's elasticities in Spain. The objective is to obtain a variation range for the elasticities. In any case, more recent studies have provided elasticities in the same range. In particular, Boogen et al. (2021) found that the short-run price elasticity of residential electricity consumption in Switzerland was approximately −0.7 in 2015 and 2016. Concerning Spain, a more recent study found a value of −0.699 for the electricity price-elasticity for the 1975–2018 period (Pellini, 2021).

For cross-price demand elasticities, we select the values that are lower than own-price demand elasticities.[17] Matrix 18 presents the own-price and cross-price elasticity values. Note that demand is more elastic during off-peak hours for both own-price changes and cross-price elasticity.

$$\epsilon_{ToU2} = \begin{bmatrix} \epsilon_{11} & \epsilon_{12} \\ \epsilon_{21} & \epsilon_{22} \end{bmatrix} = \begin{bmatrix} -0.60 & 0.20 \\ 0.30 & -0.79 \end{bmatrix} \tag{18}$$

Given a point in the demand curve, i.e., a price-quantity pair (q_i, p_i),[18] and given the values for own- and cross-price elasticities, we calibrate the parameters of the short-run demand function (when switching retailers is not possible).

Eqs. (9) and (10) relate parameters b_i and b_{ij} to the price elasticities. Finally, parameter a_i represents the maximum amount of energy demanded in period t for each hour, i.e., the energy demanded at zero price in the hourly aggregate demand curve. A summary of the calibration of these parameters can be found in Tables A.9 and A.10 in Appendix.

4.3.3. Data on inter-retailer price elasticity

In order to calculate the coefficients B_i and D_i from demand Eqs. (11) and (12), we use price elasticities when consumers are not

[17] Initial simulations were performed with those reported in Filippini (1995a,b). However, we did not obtain interior solutions. Thus, we use the lowest possible values, which are consistent with the regularity conditions of the model.

[18] We consider that 25% of the aggregate demand stems from the residential sector, as reported by Instituto para la Diversificación y Ahorro de la Energía (IDAE) (2011).

Table 2
Simulated scenarios and retailer elasticities.

Scenario	Description	E_{A1}	E_{A2}	E_{AB1}	E_{AB2}
Benchmark	Actual regulated electricity prices applied in Spain for the period reported (observed prices).	–	–	–	–
Scenario 1	Very high elasticity (very low switching costs)	−3.5	−4.0	2.9	3.21
Scenario 2	High elasticity	−3.0	−3.5	2.4	2.71
Scenario 3	Medium/High elasticity	−2.7	−3.24	2.1	2.45
Scenario 4	Medium elasticity	−2.0	−3.0	1.4	2.21
Scenario 5	Low elasticity (high switching costs)	−1.5	−2.0	0.9	1.21

Note: E_{A1} = retailer peak-price elasticity, E_{A2} = retailer off-peak-price elasticity, E_{AB1} = inter-retailer peak-price elasticity, E_{AB2} = inter-retailer off-peak-price elasticity; $E_{A1A2} = \epsilon_{12}$; $E_{A2A1} = \epsilon_{21}$, and $E_{A1B2} = E_{A2B1} = 0$.

locked-in and can change retailers, i.e., the retailer and inter-retailer price elasticities. Eqs. (13) and (15) allow us to compute the relevant coefficients.

For the sake of simplicity in parameter selection, we consider that the demands in t and $t+1$ are equivalent, except that in t+1, consumers may change suppliers. Thus, $D_i = B_i - b_i$. We also assume that $b_{12} = B_{12}$ and $b_{21} = B_{21}$. Moreover, we assume that the effect of inter-hour cross-price elasticities when choosing a retailer (i.e., the other retailer's price in off-peak hours when choosing consumption for peak hours and vice versa) is negligible. Hence, D_{12} and D_{21} are zero.[19]

We consider five scenarios with different retailer and inter-retailer price elasticities.[20] Table 2 describes the varying elasticities for our five scenarios. The benchmark case is the actual regulated electricity prices applied in Spain for the period under study. We model the "very low switching costs" scenario as Scenario 1 and the "high switching costs" scenario as Scenario 5. We also propose three intermediate scenarios, i.e., Scenarios 2 to 4, with retailer and inter-retailer elasticity values that are lower than those in the "very low switching costs" scenario and higher than those in the "high switching costs" scenario. A summary of all of the parameters calibrated for the simulations can be found in Tables A.9 and A.10 in Appendix.

5. Results and discussion

Here, we present the results of the simulations for ToU optimal prices, based on our theoretical model. First, we explore the total efficiency gains (Section 5.1), and then the effect of ToU pricing on the cost of electricity (Section 5.2).

5.1. Total efficiency gains

In this study, we modeled the five scenarios with the different retailer and inter-retailer price elasticities presented in Table 2 and analyzed the change in social welfare under ToU pricing, compared to the benchmark case. We used the same values for the short-run elasticities as in Matrix 18 and the final electricity wholesale prices presented in Table 1, as a proxy for the cost of electricity during the peak and off-peak periods. In sum, we used the calibrated parameter values presented in Tables A.9 and A.10 in Appendix. The endogenous variables of our model are ToU prices and quantity values for the peak and off-peak periods.

Note that relatively low switching costs (relatively high inter-retailer price-elasticity) are necessary for the consumer expenditures to be lower than the benchmark. Then, the question is under what conditions is it possible to increase firms' profits with ToU pricing, considering that their revenues will inevitably be lower when there are higher elasticities. Increases in profits may come from reductions in firms' costs. Furthermore, when pool prices are endogenous and react to consumers' demand behavior, ToU pricing (given that it transfers consumption from peak to off-peak periods) represents an efficiency gain that translates into lower costs for firms. Determining whether this decrease in costs is enough to offset the decrease in revenue is the objective of our simulation. It is important to note that we consider that electricity costs are endogenous, pool prices may change as a result of ToU pricing.

Table 3 presents the relevant prices from simulating our model, while Table 5 presents the impact on social welfare (consumer surplus plus firms profits), compared to the benchmark, for a representative month in winter. The retailer and inter-retailer elasticities are taken from Table 2, while the inter-hour price elasticities from Filippini (1995a,b).

The first important result in Table 3 is that all scenarios improve cost efficiency, since average wholesale pool prices are lower than actual prices. This effect comes from consumers reacting to price signals and transferring consumption from peak to off-peak periods. However, a closer examination of the retail prices revealed that only Scenarios 1 and 2 achieve lower average retail prices than the benchmark of regulated tariffs. Meanwhile, in Scenarios 3 to 5, retailer and inter-retailer elasticities were too low for price schemes to be lower than the benchmark.

Regarding the substitution of electricity consumption between the peak and off-peak hours for one hour, Table 4 shows a clear peak-shaving effect (between 1.17 and 1.26) with respect to the benchmark scenario (1.66). Within the scenarios, there is no clear pattern. However, we found that in the scenarios in which the average price is higher than the benchmark price, the peak-shaving is larger.

According to the social welfare analysis in Table 5, Scenarios 1 to 4 achieve positive social welfare gains, whereas only Scenario 5 leads to losses. The gains obtained in Scenario 1 (very high elasticity) are exclusively from the increase in consumer surplus, in comparison to the benchmark. When elasticities are high, consumers can take full advantage of ToU pricing, react to prices, and change retailers more easily. This also indicates that the optimal prices by retailers are lower in response to low customer loyalty.

However, in Scenario 5, elasticities are low, and optimal retail prices and revenues are correspondingly high. In this case, the low elasticities give market power to retailers, with the resulting deadweight loss yielding a lower social welfare than in the benchmark case of regulated tariffs.

In Scenarios 3 and 4, the social welfare gains come from the increase in firms' profits. In both scenarios, there is a cost reduction, as a consequence of ToU pricing (consumers transfer part of their consumption at peak periods to off-peak periods), which is not translated into lower retail prices. Indeed, the lower elasticities in these scenarios (compared to Scenarios 1 and 2) increase the loyalty of customers. Hence, optimal retail prices are higher and consumer surplus is lower than in the benchmark case.

Scenario 2 is particularly interesting because it presents a win–win situation in which both producers and consumers are better off, with positive variations in consumer surplus and firms' profits, compared

[19] Taylor et al. (2005) found that cross-price elasticities are generally in an order of magnitude that is smaller than own-price effects, while Borenstein and Holland (2005) and Holland and Mansur (2006) assumed that cross-price elasticities between demands in different periods are zero.

[20] Note that we hold the same values for the inter-hour elasticities (recall Matrix 18), with the same electricity costs (recall Table 1) in all of them.

Table 3
Simulations for ToU prices. Two periods: peak vs. off-peak, winter.
Source: Our own work using the actual regulated tariff from Comisión Nacional de los Mercados y la Competencia (2014) and the pool data from Operador del Mercado Ibérico de Electricidad (OMIE) (2015, 2019).

	Retail price [EUR/kWh]			Pool price [EUR/MWh]		
	Average	Peak	Off-peak	Average	Peak	Off-peak
Benchmark	0.150938	–	–	63.82	89.61	33.19
Scenario 1	0.140111	0.163880	0.118773	61.75	83.03	42.65
Scenario 2	0.149338	0.173090	0.128048	60.89	81.96	42.00
Scenario 3	0.155474	0.179651	0.133925	60.31	80.96	41.91
Scenario 4	0.167900	0.198009	0.142754	58.60	78.88	41.66
Scenario 5	0.196673	0.221820	0.174722	54.35	76.55	34.98

Note: Winter-January 2013, peak-hour 20, off-peak-hour 5. Short-run price elasticities are from Filippini (1995a,b) (see Matrix (18)), while other price elasticities are from Table 2.

Table 4
Peak/Off-peak price and quantity ratios, winter.
Source: Our own work using the actual regulated tariff from Comisión Nacional de los Mercados y la Competencia (2014) and the pool data from Operador del Mercado Ibérico de Electricidad (OMIE) (2015, 2019).

	Price ratio	Quantity ratio
Benchmark	1	1.66
Scenario 1	1.38	1.26
Scenario 2	1.35	1.25
Scenario 3	1.34	1.25
Scenario 4	1.39	1.17
Scenario 5	1.27	1.22

Note: Winter-January 2013, peak-hour 20, off-peak-hour 5. Short-run price elasticities are from Filippini (1995a,b) (see Matrix (18)), while other price elasticities are from Table 2. Prices from Table 3.

Table 5
Welfare analysis for ToU pricing. Two periods: peak vs. off-peak, winter. [kEUR].
Source: Our own work using the actual regulated tariff from Comisión Nacional de los Mercados y la Competencia (2014) and the pool data from Operador del Mercado Ibérico de Electricidad (OMIE) (2015, 2019).

	ΔConsumer surplus	Retailer ΔRevenue	ΔCost	ΔProfits	ΔSocial welfare
Scenario 1	1,784	−915	34	−950	834
Scenario 2 (win–win)	260	−19	−376	357	617
Scenario 3	−731	531	−645	1,177	446
Scenario 4	−2,681	1,505	−1,277	2,781	100
Scenario 5	−6,922	3,304	−2,662	5,966	−956

Note: Winter-January 2013, peak-hour 20, off-peak-hour 5. Short-run price elasticities are from Filippini (1995a,b) (see Matrix (18)), while other price elasticities are from Table 2. Prices are from Table 3.

to the benchmark case. In this scenario, elasticities are high and the optimal average ToU prices are slightly lower than in the benchmark case (EUR/MWh 149.34 vs EUR/MWh 150.94). This explains the higher consumer surplus and the lower revenues for firms. The high elasticity also means that consumers react to price signals by reassigning consumption between peak and off-peak periods, leading to a cost reduction that offsets the reduction in firms' revenues.

The same analysis for a representative summer month is shown in Tables 6, 7, and 8. Table 6 reveals that Scenarios 1 to 3 give lower retail prices than in the benchmark case, but average pool prices are higher, which is different from the outcome for the winter. This is because the load curve in the summer is flatter than that in the winter (i.e., there is less difference between peak and off-peak prices), which reduces the possibilities of obtaining cost reductions by shifting consumption from peak to off-peak periods.

Table 7 also shows a clear peak-shaving effect (between 1.17 and 1.27) with respect to the benchmark scenario (1.45). As in the winter, there are scenarios in which the average price is higher than the benchmark price and the peak-shaving effect is larger. In sum, the peak-shaving effect is similar in the winter and the summer, but the peak to off-peak price ratio is lower in the summer. Our findings are consistent with those of Faruqui et al. (2017).

As shown in Table 8, in Scenario 3 (medium/high elasticities), ToU pricing is a win–win situation, compared to the benchmark of regulated tariffs. The slight decrease in the average retail price (0.08%), compared to the benchmark case, increases demand, consumer surplus, and firms' revenues (the increase in demand offsets the decrease in retail price for the given values of the elasticities). The increase in demand also drives the pool price up and increases retailers' costs. In this scenario, the variation in revenues offsets the higher costs, resulting in higher profits for the firms. Meanwhile, ToU pricing is preferred by both consumers and firms, which are better off than in the benchmark case of a regulated tariff. Note that, in this case, the welfare gains do not mainly come from a shift in consumption from peak to off-peak periods that decreases costs, as in the simulation for winter. Instead, it is based on the fact that a slightly lower price is able to increase firms' revenues by spurring demand.

In Scenarios 4 and 5, the increases in average retail prices with ToU pricing (10.9% and 27.6%, respectively) lead to a substantial decrease

Table 6
Price simulations according to ToU. Two periods: peak vs. off-peak, summer.
Source: Our own work using the actual regulated tariff from Comisión Nacional de los Mercados y la Competencia (2014) and the pool data from Operador del Mercado Ibérico de Electricidad (OMIE) (2015, 2019).

	Retail price [EUR/kWh]			Pool price [EUR/MWh]		
	Average	Peak	Off-peak	Average	Peak	Off-peak
Benchmark	0.138658	–	–	50.77	60.49	40.69
Scenario 1	0.124219	0.134550	0.114884	51.77	60.10	44.25
Scenario 2	0.132796	0.143650	0.123032	51.40	59.92	43.73
Scenario 3	0.138552	0.150134	0.128212	51.23	59.92	43.47
Scenario 4	0.153768	0.168347	0.136126	50.05	58.02	43.42
Scenario 5	0.176946	0.191649	0.164255	47.87	56.99	39.99

Note: Summer-June 2013, peak-hour 13, off-peak-hour 5. Short-run price elasticities are from Filippini (1995a,b) (see Matrix (18)), while other price elasticities are from Table 2.

Table 7
Peak/Off-peak price and quantity ratios, summer.
Source: Our own work using the actual regulated tariff from Comisión Nacional de los Mercados y la Competencia (2014) and the pool data from Operador del Mercado Ibérico de Electricidad (OMIE) (2015, 2019).

	Price ratio	Quantity ratio
Benchmark	1	1.45
Scenario 1	1.17	1.27
Scenario 2	1.17	1.26
Scenario 3	1.17	1.25
Scenario 4	1.24	1.17
Scenario 5	1.17	1.21

Note: Summer-June 2013, peak-hour 13, off-peak-hour 5. Short-run price elasticities are from Filippini (1995a,b) (see Matrix (18)), while other price elasticities are from Table 2. Prices are from Table 6.

in consumer surplus. This cannot be offset by the gains in firms' profits, resulting in lower social welfare.

Finally, a comparison of the prices that lead to social welfare gains (the sum of consumer surplus and profits is higher) in both the winter and the summer reveals that such social welfare gains can be obtained, even when ToU prices are higher than the benchmark. However, to obtain a win–win situation (in which both consumer surplus and profits are higher), average ToU prices must be lower than actual prices.

5.2. The effect of ToU pricing on the cost of electricity

In order to isolate the effect of ToU pricing on cost efficiency, we analyzed what would happen if the ToU average price was the same as the actual retail price (i.e., the benchmark price). Would this lead to lower costs? To answer this question, we maintained the inter-hour elasticity figures from Matrix (18), and changed the remaining elasticities so that the ToU scheme replicates the actual average price.

Note that even if average prices under the ToU scheme are the same as in the benchmark case, there is an effect on pool prices and the cost of electricity, due to the different consumption pattern. Thus, we analyzed the effect of ToU pricing on electricity market prices in the pool.

Fig. 3 shows the actual wholesale electricity prices in the benchmark (white blocks) and the simulated electricity wholesale prices under the ToU scheme (gray blocks) for both the winter (thin lines) and the summer (thick lines). The blocks represent peak, mean, and off-peak prices. This figure also shows that, despite average retail prices being the same, peak electricity prices are lower and off-peak prices are higher under the ToU pricing scenario. This effect is present both in the winter and the summer, although it is greater in the winter because the peak/off-peak gap is wider. In the winter, since the decrease in the peak electricity price more than offsets the increase in the off-peak price, mean prices under the ToU scheme are lower than the actual values (EUR/MWh 61.00 vs. EUR/MWh 63.82). However, in the summer, the average wholesale electricity prices under the ToU scheme are slightly higher than the actual prices (EUR/MWh 51.23 vs. EUR/MWh 50.77), which indicates that ToU pricing does not necessarily reduce wholesale electricity prices, despite reducing the peak/off-peak ratio.

6. Conclusions and policy implications

Energy demand management plays a key role in balancing intermittent generation from renewable energy sources. Thus, this study focused on the design of optimal electricity prices for final residential consumers. A key element in improving the efficiency of the electricity system included designing pricing policies that reflect actual generation costs. In this regard, prices with hourly differentiation serve two purposes. On the one hand, they make the system easier to manage by increasing the price signal during peak periods, when energy is more expensive to produce. This can encourage customers to change their consumption patterns, which may also reduce the need for investment in power plants to meet peak demand. On the other hand, the difference in prices contributes to the efficiency of the system by shifting consumption from hours when generation is more costly to hours when it is less expensive, lowering the average wholesale price of electricity.

This study also highlighted the function of the retail market, by combining a theoretical model with simulations based on real data from Spain. The standout feature of our model is that it considers consumers who react to prices by not only changing consumption from peak to off-peak periods, but also by switching retailers. In this model, optimal retail prices and the effect of ToU pricing on welfare were based on the values of elasticities. As expected, we found that the lower the elasticities, the lower the consumer surplus and social welfare, and the higher the retailers' profits. More interestingly, we found intermediate levels of elasticities at which both the consumer surplus and firms' profits were higher than the benchmark figures. For these elasticity values, ToU pricing is a Pareto improvement (a win–win policy).

Our empirical work started by computing the optimal pricing schedule according to the ToU, with a tariff in two periods and endogenous electricity costs. In this regards, we considered a market with two retail companies and inter-hour price elasticities taken from the literature. This indicates that the residential electricity demand for each of the defined periods depends on the prices of the periods themselves and the prices of the rest of the hours. We also incorporated switching costs into our model, since consumers may react to prices by deciding to switch retailers. We then simulated several scenarios with different elasticity values and compared them to the benchmark of a regulated tariff.

We found that the cost for consumers (economic efficiency) is lower when both inter-hour and retailer price elasticities increase. For scenarios with high enough elasticities, we observed peak-shaving and lower average prices for consumers in both the winter and the summer, with even lower prices as elasticities increase. Conversely, when retailer price elasticities are low (the "high switching costs" scenario), the highest cost (lowest economic efficiency) emerges.

Table 8
Welfare analysis according to ToU. Two periods: peak vs. off-peak, summer. [kEUR].
Source: Our own work using the actual regulated tariff from Comisión Nacional de los Mercados y la Competencia (2014) and the pool data from Operador del Mercado Ibérico de Electricidad (OMIE) (2015, 2019).

	Consumer	Retailer			ΔSocial
	surplus	ΔRevenue	ΔCost	ΔProfits	welfare
Scenario 1	2,152	−1,154	539	−1,693	459
Scenario 2	862	−366	279	−645	217
Scenario 3 (win–win)	15	129	120	9	24
Scenario 4	−1,733	1,107	−320	1437	−305
Scenario 5	−5,243	2,628	−1,215	3843	−1,400

Note: Summer-June 2013, peak-hour 13, off-peak-hour 5. Short-run price elasticities are from Filippini (1995a,b) (see Matrix (18)), while other price elasticities are from Table 2. Prices are from Table 6.

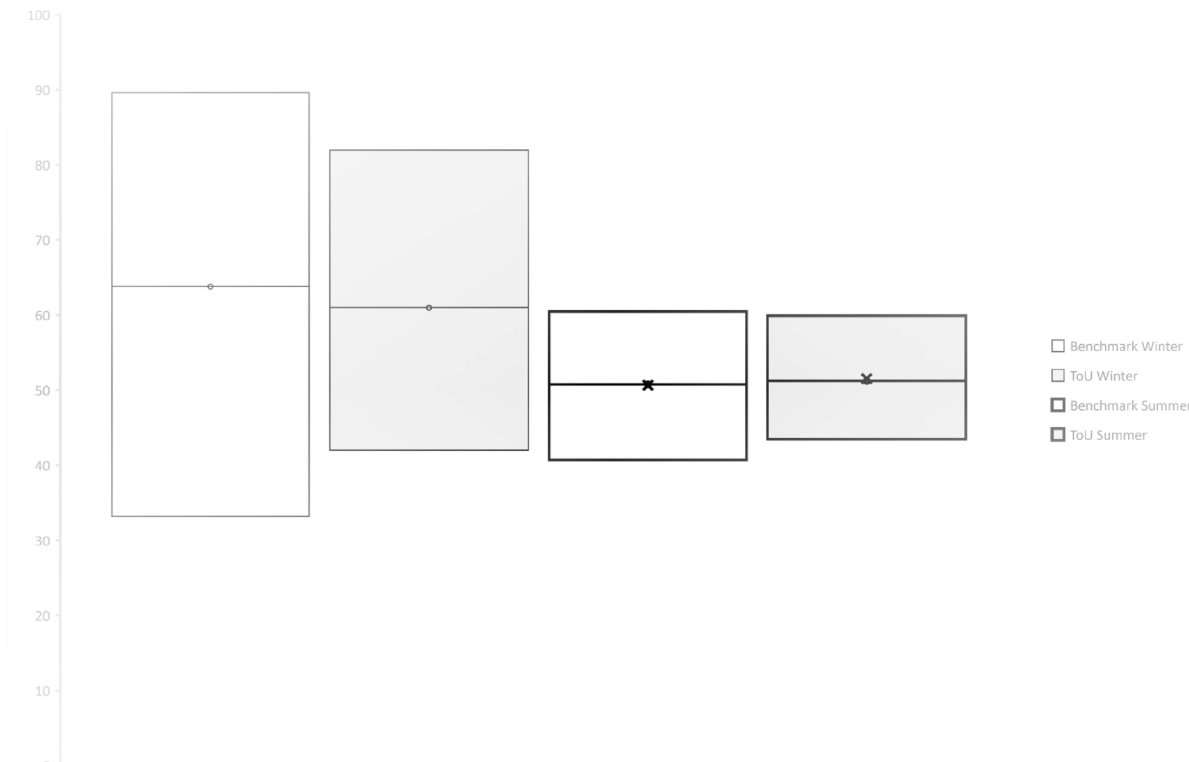

Fig. 3. Electricity prices with endogenous costs [EUR/MWh]. Actual prices (white blocks) vs. ToU prices (gray blocks), winter (thin lines) and summer (thick lines). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

When retailers optimally choose ToU prices, welfare gains are most likely found, unless elasticities are low. Moreover, for intermediate elasticity values, it is possible to achieve a win–win situation, which is preferred by consumers and retailers over the benchmark case of a regulated tariff. In other words, it is possible for retailers to increase profits, despite the fact that ToU pricing may reduce electricity prices. We also performed an analysis in which we only considered the surpluses of the participants in this market, without taking into account the externalities associated with electricity consumption. Therefore, our framework did not provide answers to certain questions related to optimizing energy consumption. In this regard, another framework will be necessary to analyze these issues.

Since the application of ToU electricity prices to residential customers is currently limited, their impact on the future and their potential effects on consumers' behavior are still unknown. In this regard, the simulations presented in this study are a first step, with field studies on consumers' reactions to inter-hour and retailer prices necessary in future research. Furthermore, in our study, retail competition was modeled on prices without explicitly considering additional services that provide product differentiation, including price structures that ensure against price fluctuations. However, note that we assumed that there is a product differentiation in the way that demand functions are modeled. Without product differentiation, competition on prices would yield a Bertrand result. Thus, we implicitly allowed the representative consumer to have heterogeneous preferences for these services provided by retailers and/or switching costs, so that a price increase by a retailer does not imply that it loses all of its customers. In fact, the elasticity values may reflect consumers' preferences for these additional services that a retailer may provide. In other words, the more valuable the services of a particular retailer from the consumers' point of view, the less elastic its demand.

Finally, our model could be extended in further research, e.g., by increasing the number of retailers (there were only two in the current model), by differentiating companies according to their market share, and by introducing individual consumer heterogeneity (we assumed that there were no differences between consumers and that they all faced the same price schedule), price schemes broken down into periods (not just peak and off-peak), or market uncertainty in order to enrich the menu of contracts of consumers averse to price volatility. In any event, our model illustrated the potential of ToU pricing to achieve welfare gains and even win–win situations in which both consumers and retailers are better off than under a regulated tariff.

Table A.9
Calibration of the parameters of the model for winter (mean values).

Parameter	Data (source)	Equation	Values Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Demand parameters:							
b_1 b_2	Short-run price elasticity	(9)	17.45 13.82	17.45 13.82	17.45 13.82	17.45 13.82	17.45 13.82
b_{12} b_{21}	Cross short-run price elasticity	(10)	5.82 5.25	5.82 5.25	5.82 5.25	5.82 5.25	5.82 5.25
B_1 B_2	Long-run price elasticity	(13)	101.81 69.99	87.26 61.24	78.54 56.69	58.17 52.49	43.63 34.99
B_{12} B_{21}	Long-run inter-hour price elasticity	(14)	5.82 5.25	5.82 5.25	5.82 5.25	5.82 5.25	5.82 5.25
D_1 D_2	Inter-retailer price elasticity	(15)	84.35 56.16	69.81 47.42	61.08 42.87	40.72 38.67	26.18 21.17
$D_{12} = D_{21}$	Inter-hour inter-retailer price elasticity	Negligible by assumption	0	0	0	0	0
$a_1 = A_1$ $a_2 = A_2$	Electricity at price=0 (OMIE)	(7), (11) (8), (12)	6146.50 3934.88	6146.50 3934.88	6146.50 3934.88	6146.50 3934.88	6146.50 3934.88
Cost parameters:							
c_1 c_2	Electricity price (OMIE)	–	89.61 33.19	89.61 33.19	89.61 33.19	89.61 33.19	89.61 33.19

Table A.10
Calibration of the parameters of the model for summer (mean values).

Parameter	Data (source)	Equation	Values Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Demand parameters:							
b_1 b_2	Short-run price elasticity	(9)	15.99 14.51	15.99 14.51	15.99 14.51	15.99 14.51	15.99 14.51
b_{12} b_{21}	Cross short-run price elasticity	(10)	5.33 5.51	5.33 5.51	5.33 5.51	5.33 5.51	5.33 5.51
B_1 B_2	Long-run price elasticity	(13)	93.30 73.47	79.97 64.29	71.97 59.51	53.31 55.10	39.99 36.73
B_{12} B_{21}	Long-run inter-hour price elasticity	(14)	5.33 5.51	5.33 5.51	5.33 5.51	5.33 5.51	5.33 5.51
D_1 D_2	Inter-retailer price elasticity	(15)	77.30 58.95	63.98 49.78	55.98 45.00	37.32 40.59	23.99 22.22
$D_{12} = D_{21}$	Inter-hour inter-retailer price elasticity	Negligible by assumption	0	0	0	0	0
$a_1 = A_1$ $a_2 = A_2$	Electricity at price=0 (OMIE)	(7), (11) (8), (12)	5174.67 3794.75	5174.67 3794.75	5174.67 3794.75	5174.67 3794.75	5174.67 3794.75
Cost parameters:							
c_1 c_2	Electricity price (OMIE)	–	60.49 40.69	60.49 40.69	60.49 40.69	60.49 40.69	60.49 40.69

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix. Summary of the calibrated parameters

See Tables A.9 and A.10.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econmod.2023.106215.

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