Second-best Pricing for Incomplete Market Segments: Applications to Electricity Pricing

Nicolas Astier

(Stanford - Bits & Watts initiative)

IAEE session at annual ASSA Convention - January 2020

(source: www.commons.wikimedia.org)

Research question

Most of the goods we purchase every day as end consumers are priced according to simple rules, not at state-contingent prices varying by time and location of delivery.

Research question

Most of the goods we purchase every day as end consumers are priced according to simple rules, not at state-contingent prices varying by time and location of delivery.

Different kinds of transaction costs may explain such practices:

- Cognitive costs;
- Technology costs;
- Political costs.

Research question

Most of the goods we purchase every day as end consumers are priced according to simple rules, not at state-contingent prices varying by time and location of delivery.

Different kinds of transaction costs may explain such practices:

- Cognitive costs;
- Technology costs;
- Political costs.

Public utility pricing is particularly relevant as it combines all rationales.

Research question

Most of the goods we purchase every day as end consumers are priced according to simple rules, not at state-contingent prices varying by time and location of delivery.

Different kinds of transaction costs may explain such practices:

- Cognitive costs;
- Technology costs;
- Political costs.

Public utility pricing is particularly relevant as it combines all rationales.

In such a context, one quickly faces the question:

how simple should simple rates be?

Previous of results

Theory

I develop a theoretical framework to design simple price schedules under exogenous constraints within a large collection of admissible constraints. The opportunity cost of different constraints can then be assessed and compared to the cost of removing them.

Previous of results

Theory

I develop a theoretical framework to design simple price schedules under exogenous constraints within a large collection of admissible constraints. The opportunity cost of different constraints can then be assessed and compared to the cost of removing them.

Empirics - retail electricity pricing

- Time-of-use (TOU) rates, no matter their complexity, can only remove a very limited fraction of the inefficiencies occurring under a flat rate.
- In California:
  - the optimal TOU structure is shifting as the share of solar generation increases: the highest-price period has become narrower (and more expensive) and off-peak solar hours have appeared in the winter, the spring and during weekends;
  - Differentiating TOU rates by geographical zones wider than physical nodes yields small efficiency gains relative to a State-wide TOU tariff.

Outline

1. Theoretical framework
2. Application to retail electricity pricing
3. Conclusion

Outline

Framework

We consider a partial equilibrium framework with J Arrow-Debreu commodities ($J >> 1$).

Framework

We consider a partial equilibrium framework with J Arrow-Debreu commodities ($J >> 1$).

Consumer k problem:

$$\max_{(x_1, x_2, ..., x_{J+1})} U^k(x_1, x_2, ..., x_J) + x_{J+1}$$
$$\text{s.t.}$$
$$\sum_{j=1}^{J} p_j x_j + x_{J+1} \leq w_k$$

$\Rightarrow$ aggregating individual indirect demands over consumers:

$$\mathbf{x}(\mathbf{p}) \equiv (x_1(\mathbf{p}), ..., x_J(\mathbf{p}))$$

Supply:
Supply cost is $\mathbf{p}^*.\mathbf{x}$ where marginal costs $\mathbf{p}^* \equiv (p_1^*, ..., p_J^*)$ are constant (e.g. we focus on a relatively small market segment).

First-best benchmark and deadweight loss

A rate designer sets the prices $(p_1, ..., p_J)$ faced by consumers in a given market segment. A second-order Taylor approximation of the social surplus if he charges prices $(p_1, ..., p_J)$ is:

$$W(\mathbf{p}) \simeq W(\mathbf{p}^*) + \frac{1}{2}\sum_{i=1}^{J}\sum_{j=1}^{J}(p_i - p_i^*)(p_j - p_j^*)\frac{\partial x_i}{\partial p_j}(\mathbf{p}^*)$$

First-best benchmark and deadweight loss

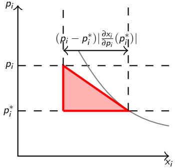
A rate designer sets the prices $(p_1, ..., p_J)$ faced by consumers in a given market segment. A second-order Taylor approximation of the social surplus if he charges prices $(p_1, ..., p_J)$ is:

$$W(\mathbf{p}) \simeq W(\mathbf{p}^*) + \frac{1}{2} \sum_{i=1}^{J} \sum_{j=1}^{J} (p_i - p_i^*)(p_j - p_j^*) \frac{\partial x_i}{\partial p_j}(\mathbf{p}^*)$$

The second term is the usual expression for deadweight losses. When Arrow-Debreu commodities are independent (i.e. $\partial_j x_i = 0$ for $i \neq j$), it simplifies to:

$$\frac{1}{2} \sum_{i=1}^{J} (p_i - p_i^*)^2 \frac{\partial x_i}{\partial p_i}(p_i^*)$$

which is simply a sum of Harberger triangles:



Second-best setting

We assume that the vector $(p_1^*, ..., p_J^*)$ is not charged to consumers due to a variety of constraints denoted by $\mathcal{C}$. Assuming the rate designer relies on linear prices, he has to solve a second-best problem:

$$\max_{\mathbf{p}} \frac{1}{2} \sum_{i=1}^{J} \sum_{j=1}^{J} (p_i - p_i^*)(p_j - p_j^*) \frac{\partial x_i}{\partial p_j}(\mathbf{p}^*)$$

s.t.

constraint $\mathcal{C}$

Second-best setting

We assume that the vector $(p_1^*, ..., p_J^*)$ is not charged to consumers due to a variety of constraints denoted by $\mathcal{C}$. Assuming the rate designer relies on linear prices, he has to solve a second-best problem:

$$\max_{\mathbf{p}} \frac{1}{2} \sum_{i=1}^{J} \sum_{j=1}^{J} (p_i - p_i^*)(p_j - p_j^*) \frac{\partial x_i}{\partial p_j}(\mathbf{p}^*)$$

s.t.

constraint $\mathcal{C}$

Different constraints $\mathcal{C}$ have been explored in the literature:

- $\mathcal{C} : (\mathbf{p} - \mathbf{p}^*).\mathbf{x}(\mathbf{p}) \geq R$ yields the problem studied by Ramsey (1927) and Boiteux (1956);

Second-best setting

We assume that the vector $(p_1^*, ..., p_J^*)$ is not charged to consumers due to a variety of constraints denoted by $\mathcal{C}$. Assuming the rate designer relies on linear prices, he has to solve a second-best problem:

$$\max_{\mathbf{p}} \frac{1}{2} \sum_{i=1}^{J} \sum_{j=1}^{J} (p_i - p_i^*)(p_j - p_j^*) \frac{\partial x_i}{\partial p_j}(\mathbf{p}^*)$$

$$\text{s.t.}$$

$$\text{constraint } \mathcal{C}$$

Different constraints $\mathcal{C}$ have been explored in the literature:

- $\mathcal{C} : (\mathbf{p} - \mathbf{p}^*).\mathbf{x}(\mathbf{p}) \geq R$ yields the problem studied by Ramsey (1927) and Boiteux (1956);
- $\mathcal{C} : (\mathbf{p} - \mathbf{p}^*) \in E$ where E is an exogenously given vector space of dimension $N << J$ is the problem studied by Jacobsen et al. (2019).

Second-best setting

We assume that the vector $(p_1^*, ..., p_J^*)$ is not charged to consumers due to a variety of constraints denoted by $\mathcal{C}$. Assuming the rate designer relies on linear prices, he has to solve a second-best problem:

$$\max_{\mathbf{p}} \frac{1}{2} \sum_{i=1}^{J} \sum_{j=1}^{J} (p_i - p_i^*)(p_j - p_j^*) \frac{\partial x_i}{\partial p_j}(\mathbf{p}^*)$$

s.t.

constraint $\mathcal{C}$

Different constraints $\mathcal{C}$ have been explored in the literature:

- $\mathcal{C} : (\mathbf{p} - \mathbf{p}^*).\mathbf{x}(\mathbf{p}) \geq R$ yields the problem studied by Ramsey (1927) and Boiteux (1956);
- $\mathcal{C} : (\mathbf{p} - \mathbf{p}^*) \in E$ where E is an exogenously given vector space of dimension $N << J$ is the problem studied by Jacobsen et al. (2019).

$\Rightarrow$ we consider the constraint $\mathbf{p} \in E$ where E is a vector space of dimension $N << J$ to be chosen among a set of admissible vector spaces.

Second-best problem of interest (unconstrained case)

Collection of feasible sets:
We start by considering the second-best problem defined by:

$\mathcal{C}$: the rate designer may only use an exogenously given number N of distinct prices in his rate schedule.

Such a situation may for example be motivated by practical considerations.

Second-best problem of interest (unconstrained case)

Collection of feasible sets:
We start by considering the second-best problem defined by:

$\mathcal{C}$: the rate designer may only use an exogenously given number N of distinct prices in his rate schedule.

Such a situation may for example be motivated by practical considerations.

Formally, if we denote $\mathcal{S}_N^J$ the set of N-set partitions of $\{1, ..., J\}$ (which we characterize as the set of the injunctive functions s mapping $\{1, ..., J\}$ to $\{1, ..., N\}$), our second-best problem of interest is:

$$\max_{s \in \mathcal{S}_N^J} \left(\max_{\bar{p}_1, \ldots, \bar{p}_N} \frac{1}{2} \sum_{i=1}^{J} \sum_{j=1}^{J} (\bar{p}_{s(i)} - p_i^*)(\bar{p}_{s(j)} - p_j^*) \frac{\partial x_i}{\partial p_j} \right)$$

Solution - independent commodities

Consider the simplest situation where (cf. paper for general case):

Assumption

$$\textit{For } i \neq j,\ \frac{\partial x_i}{\partial_{p_j}} = 0$$

Solution - independent commodities

Consider the simplest situation where (cf. paper for general case):

Assumption

For $i \neq j$, $\frac{\partial x_i}{\partial_{p_j}} = 0$

We then have:

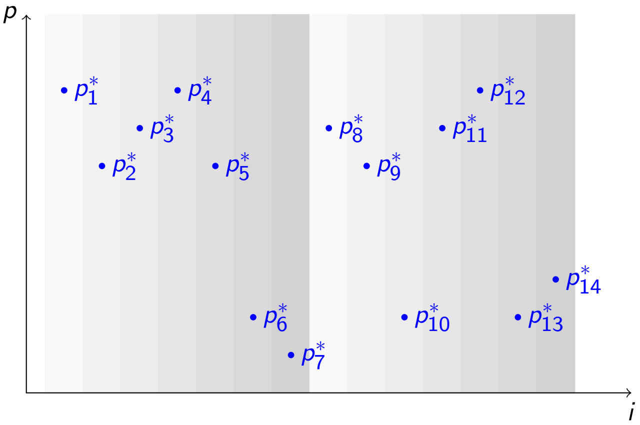
Proposition

The second-best price schedule $(\bar{p}_1, ..., \bar{p}_N)$ *is given by the N-step function that best approximates the inverse of the cumulative distribution function of first-best prices* p_j^* *weighted by* $|\frac{\partial x_j}{\partial p_j}|$*, when errors are penalized in a quadratic fashion.*

In practice, the second-best rate schedule can be computed by applying a weighted k-means algorithm to the distribution of first-best prices $\{p_i^*\}_i$ *with weights* $|\frac{\partial x_i}{\partial p_i}|$ *and using the Euclidian distance.*

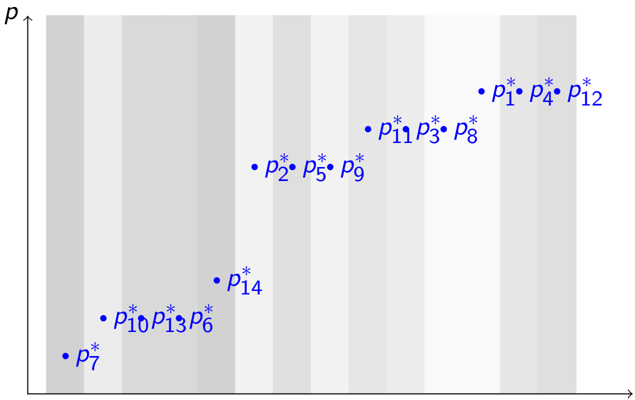
Graphical intuition

Assume for simplicity that i indexes days within a given month, that $\frac{\partial x_i}{\partial p_i} = 1$ for all i and that first-best prices vary only with respect to time as follows:



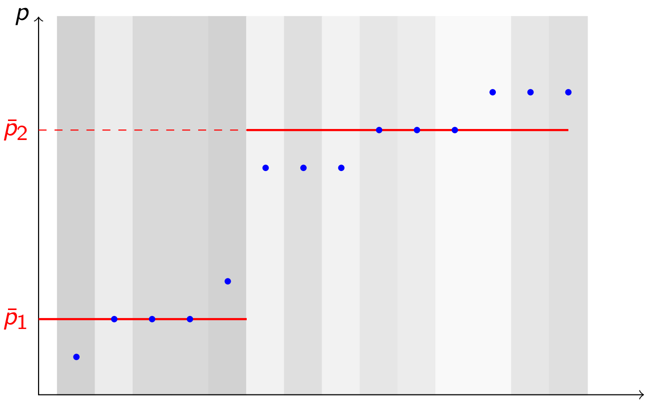
Graphical intuition

1. Build the inverse cumulative distribution of first-best prices.



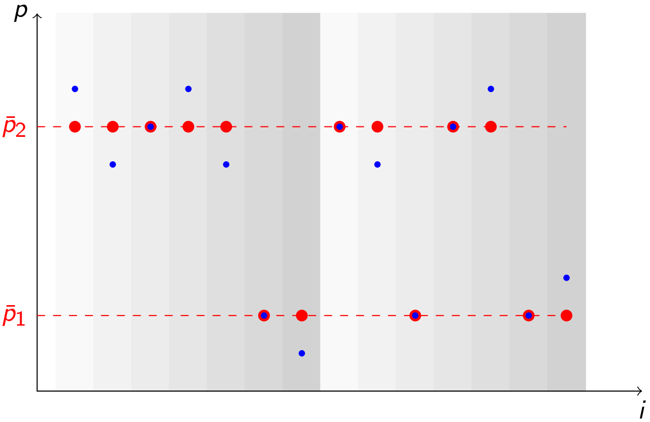
Graphical intuition

2. Approximate it by a N-step function ($N = 2$ below).



Graphical intuition

3. Obtained price schedule.



Motivation for adding further constraints

Practical, technical or political considerations may translate into a much wider family of exogenous constraints than just a limited number of prices.

Motivation for adding further constraints

Practical, technical or political considerations may translate into a much wider family of exogenous constraints than just a limited number of prices.

Our framework can seamlessly account for constraints of the type *"commodity i must be sold at the same price as commodity j"*. This family of constraints encompasses important applications such as:

- Geography: one may want the rate schedule to be homogenous over wide geographical areas;
- Time: rate stability over different periods (e.g. weeks) may be imposed;
- Contingencies: one may want to minimize the number of contingencies upon which prices can exhibit stochastic variations.

Formalization of additional second-best constraints

We enrich constraint $\mathcal{C}$ as follows:

Assumption

The additional constraints on feasible second-best prices may be formalized as the existence of a finest partition $\underline{s} \equiv \{\underline{S}_1, ..., \underline{S}_M\}$ that must be a possible refinement of the partition that ends up defining the optimal sets of composite commodities.

In other words, instead of optimizing on the full set of N-set partitions $\mathcal{S}_N^J$ of the Arrow-Debreu commodities, we now optimize the second-best rate schedule over the following set:

$$\underline{\mathcal{S}}_N^J \equiv \{s \in \mathcal{S}_N^J \,|\, \forall m \in \{1, ..., M\}, \{i_1, i_2\} \in \underline{S}_m \Rightarrow s(i_1) = s(i_2)\} \subset \mathcal{S}_N^J$$

Formalization of additional second-best constraints

We enrich constraint $\mathcal{C}$ as follows:

Assumption

The additional constraints on feasible second-best prices may be formalized as the existence of a finest partition $\underline{s} \equiv \{\underline{S}_1, ..., \underline{S}_M\}$ *that must be a possible refinement of the partition that ends up defining the optimal sets of composite commodities.*

In other words, instead of optimizing on the full set of N-set partitions $\mathcal{S}_N^J$ of the Arrow-Debreu commodities, we now optimize the second-best rate schedule over the following set:

$$\underline{\mathcal{S}}_N^J \equiv \{s \in \mathcal{S}_N^J \,|\, \forall m \in \{1, ..., M\}, \{i_1, i_2\} \in \underline{S}_m \Rightarrow s(i_1) = s(i_2)\} \subset \mathcal{S}_N^J$$

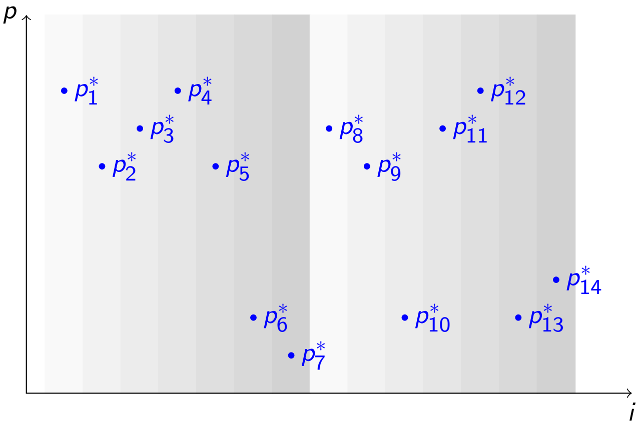
Proposition

The same approach as before made be used by replacing the underlying Arrow-Debreu commodities with auxiliary commodities built from the enforced finest partition.

Details

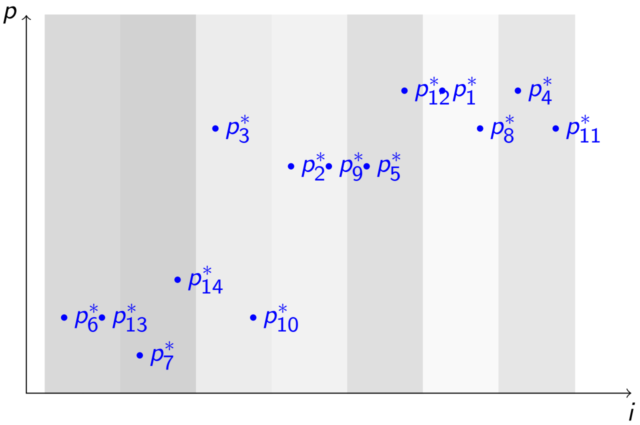
Graphical intuition

We go back to the previous example and seek to further enforce the constraint that the price schedule should be constant for a given day within the week (e.g. the same price should be charged on Mondays):



Graphical intuition

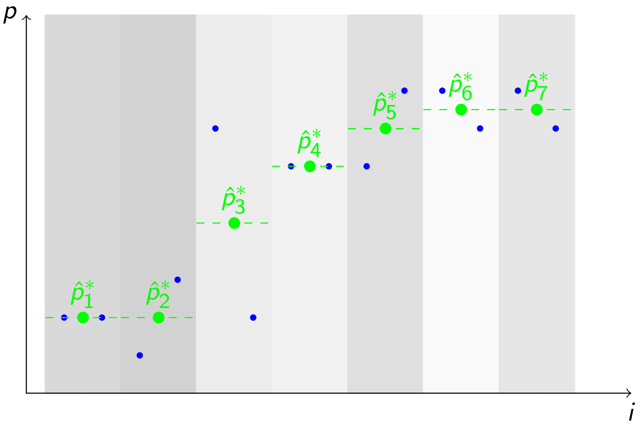
1. Build auxiliary objects based on the assumed finest partition:
$\Rightarrow$ welfare losses induced by the finest partition.



Graphical intuition

1. Build auxiliary objects based on the assumed finest partition:

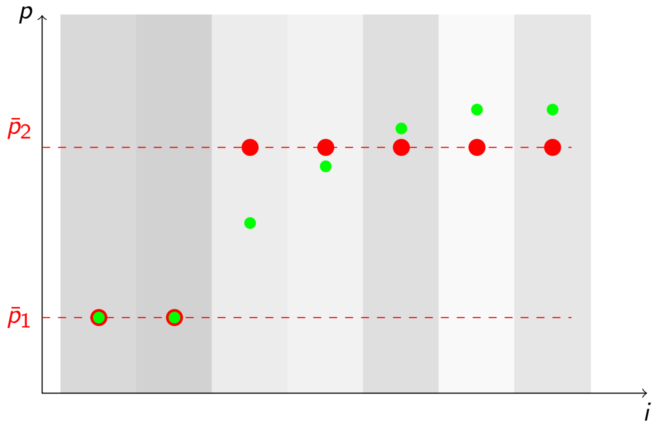
$\Rightarrow$ welfare losses induced by the finest partition.



Graphical intuition

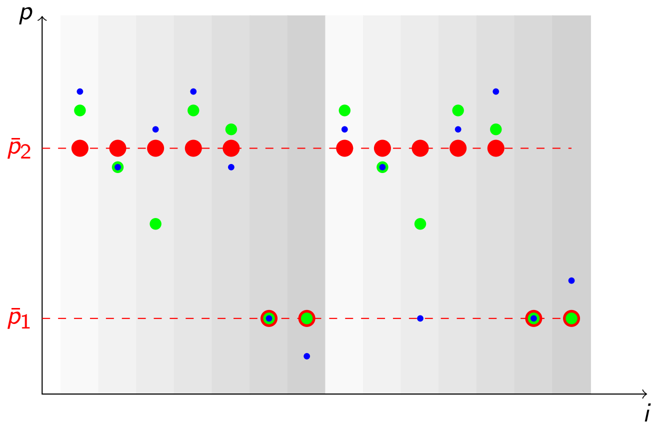
2. Approximate it by a N-step function ($N = 2$ below):

$\Rightarrow$ additional welfare losses induced by the limited number of prices.



Graphical intuition

3. Obtained price schedule.



Outline

Application to California - Background

Background

- Retail industry structure: residential consumers are served by regional monopolies over both distribution and retail. Three investor-owned utilities (IOUs), PG&E, SCE and SDG&E serve the majority of the consumers.
- Rates: retail electricity rates are set by the California Public Utilities Commission (CPUC), along with other Local Regulatory Authorities. Historically, the main challenge that had to be addressed was a relatively spread-out summer peak demand.
- Energy transition: Between 2011 and 2018, utility-scale solar photovoltaic has grown from a negligible share to about 12% of total electricity generation. Similarly, rooftop solar adoption has steadily increased.

Application to California - Background

Background

- Retail industry structure: residential consumers are served by regional monopolies over both distribution and retail. Three investor-owned utilities (IOUs), PG&E, SCE and SDG&E serve the majority of the consumers.
- Rates: retail electricity rates are set by the California Public Utilities Commission (CPUC), along with other Local Regulatory Authorities. Historically, the main challenge that had to be addressed was a relatively spread-out summer peak demand.
- Energy transition: Between 2011 and 2018, utility-scale solar photovoltaic has grown from a negligible share to about 12% of total electricity generation. Similarly, rooftop solar adoption has steadily increased.

$\Rightarrow$ *in 2015, the CPUC decided move completely California residential customers towards updated TOU tariffs by 2019-2020 notably in order to reflect this shift in the generation mix.*

Data

We focus on the service area of the three main IOUs between 2011 and 2018 and recover hourly price and quantity data from CAISO website.

Variable		Mean (std)	Min	Max
PG&E	DLAP price ($/MWh)	36.2 (18.8)	-17.3	946.4
	TAC load (GW.h)	11.5 (1.9)	7.8	21.3
SCE	DLAP price ($/MWh)	37.0 (21.9)	-28.6	1000.0
	TAC load (GW.h)	11.9 (2.6)	7.5	25.8
SDG&E	DLAP price ($/MWh)	38.1 (23.0)	-71.2	1007.5
	TAC load (GW.h)	2.3 (0.5)	1.4	4.7
Number obs.	70128			

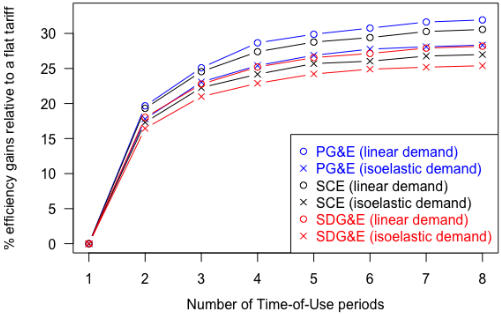
Summary statistics of data used for California (period 2011-2018)

Note: we also retrieve day-ahead hourly LMPs for the 23 sub-load aggregation points (SLAPs) within IOUs service territories to explore the spatial dimension (see paper).

Assumptions

1. we use day-ahead prices as a proxy for the distribution of first-best prices $\mathbf{p}^*$;
2. we consider each year to be a different realization of possible contingencies;
3. for simplicity, we assume Arrow-Debreu commodities to be independent;
4. in order to assess the full potential of TOU tariffs, we enforce a finest partition that can discriminate between months, types of day (weekends vs working days) and hours of the day.

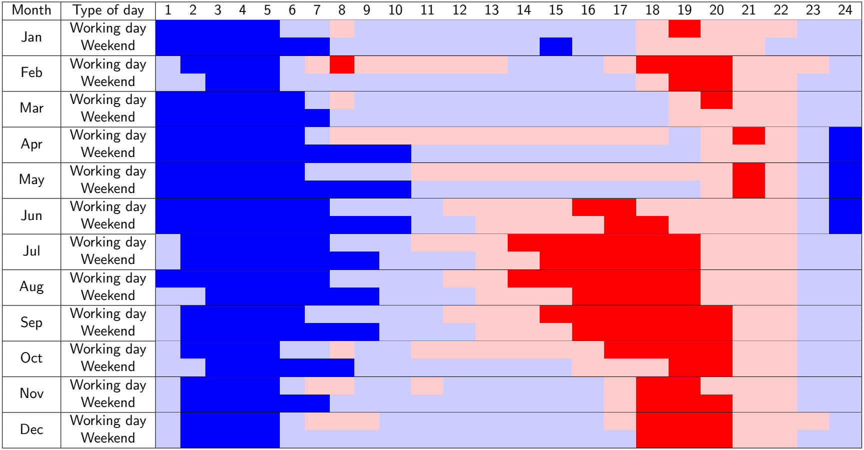
1. Efficiency gains from time-of-use rates wane quickly



Efficiency gains from increasing the number of Time-of-Use periods (2015-2018)

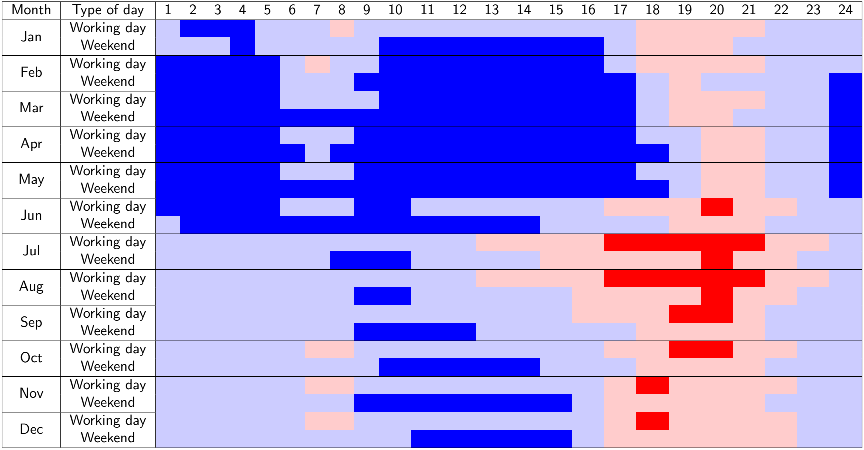
$\Rightarrow$ *achievable efficiency gains achievable with TOU rates are limited.*

2. An impressive on-going shift in the structure of supply costs - California-wide optimal TOU rate 2011-2014



Obtained California-wide TOU tariff (isoelastic demand, 2011-2014 data)

2. An impressive on-going shift in the structure of supply costs - California-wide optimal TOU rate 2015-2018



Obtained California-wide TOU tariff (isoelastic demand, 2015-2018 data)

Outline

How simple should simple rates be?

- I develop a theoretical framework to design simple rate schedules. It notably allows to easily compute the opportunity cost of a large family of exogenous "simplicity" constraints.
  $\Rightarrow$ *our framework provides a very tractable tool to assess the benefits that may arise from investing in either technology or lobbying to relax prevailing constraints*.

How simple should simple rates be?

- I develop a theoretical framework to design simple rate schedules. It notably allows to easily compute the opportunity cost of a large family of exogenous "simplicity" constraints.
  $\Rightarrow$ *our framework provides a very tractable tool to assess the benefits that may arise from investing in either technology or lobbying to relax prevailing constraints*.

- Electricity pricing provides possible applications of this framework:
  - Time-of-use rate are shown to be intrinsically limited in the efficiency gains they can achieve (at most 20-30% of the inefficiencies arising under a flat rate may be removed);
  - Critical-peak pricing does much better, but still falls significantly short of the first-best benchmark;
  - The California example illustrates that a massive shift in the generation mix can alter very significantly the optimal TOU rates, compromising their stability over time.

Back up slides

Solution of the enriched second-best problem (1/2)

We define two auxilary objects:

$$\hat{p}_m^* \equiv \frac{\sum_{i \in \underline{S}_m} \frac{\partial x_i}{\partial p_i} p_i^*}{\sum_{i \in \underline{S}_m} \frac{\partial x_i}{\partial p_i}}$$

Without loss of generality, the subsets $\{\underline{S}_1, ..., \underline{S}_j\}$ are assumed to be indexed such that $\hat{p}_1^* \leq \hat{p}_2^* \leq ... \leq \hat{p}_M^*$. We further denote:

$$W_0 \equiv 0 \text{ and } W_m \equiv \sum_{j \in \underline{S}_m} |\frac{\partial x_j}{\partial p_j}|$$

Finally, we construct the function $\hat{G}^{-1}$ as:

$$\hat{G}^{-1}(z) = \sum_{m=1}^{M} \hat{p}_m^* \mathbf{1}_{\sum_{k=0}^{m-1} W_k \leq z < \sum_{k=0}^{m} W_k}$$

Solution of the enriched second-best problem (2/2)

If we further assume that the Arrow-Debreu commodities are independent ($\frac{\partial x_i}{\partial p_j} = 0$ for $i \neq j$) we have:

Proposition

The second-best price schedule $(\bar{p}_1, ..., \bar{p}_N)$ is given by the N-step function that best approximates $\hat{G}^{-1}$, when errors are penalized in a quadratic fashion. Welfare losses may be decomposed as the sum of:

- *A first term $\frac{1}{2}\sum_{m=1}^{M}\sum_{j\in \underline{S}_m}\left(\hat{p}^*_m - p^*_j\right)^2 \frac{\partial x_j}{\partial p_j}$ measures the welfare losses arising because of the exogenous constraint of enforcing a finest partition of Arrow-Debreu states.*
- *A second term, consisting in the remaining welfare losses, measures the additional inefficiencies arising because of the limited number of prices used in the rate schedule.*

Back

Exploring different margins of efficiency gains

1. Critical-peak pricing achieves significant efficiency gains:
   Instead of a four-tier TOU rate, one could alternatively implement a simple tariff with four prices consisting in:
   - critical-peak events called at most a given number of hours per year (e.g. 200 hours);
   - a three-period TOU rate for the rest of the year.

   $\Rightarrow$ relative to a three-period TOU rate, implementing critical-peak events increases efficiency by about 40% while adding a fourth TOU period only yields of $3 - 4\%$ improvement.

2. Limited gains from spatial differentiation relying on zones:
   - Designing an IOU-specific TOU rate instead of a California-wide rate decreases deadweight losses by only about 1%;
   - Using smaller zones, namely SLAPs, enables higher but still modest gains (up to 7% when focusing on 2015-2016 only).

General case - substitution/complementarity between commodities

Allowing for $\frac{\partial x_i}{\partial_{p_j}} \neq 0$ for $i \neq j$ raises a combinatorial challenge.

In the absence of a specialized optimization routine, we suggest a two-step heuristic:

1. Define the N clusters of Arrow-Debreu commodities under the assumption that $\frac{\partial x_i}{\partial_{p_j}} = 0$ for $i \neq j$ (i.e. only keeping information about own-price elasticity);
2. Taking the composition of the obtained clusters as exogenously given, solve the linear system that characterizes the optimal second-best price levels $(\bar{p}_1, ..., \bar{p}_N)$ (taking into account the cross-elasticities).