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BEHAVIORAL CONSIDERATIONS FOR EFFECTIVE TIME-VARYING ELECTRICITY PRICES

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Behavioral Considerations for Effective Time-Varying Electricity Prices

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Abstract

Wholesale prices for electricity vary significantly due to high fluctuations and low elasticity in short-run demand. End-use customers have typically paid flat retail rates for their electricity consumption, and time-varying prices have been proposed to help reduce peak consumption and lower the overall cost of servicing demand. Unfortunately, the general practice is an opt-in system: a default rule in favor of time-varying prices would be far better. A behaviorally informed analysis also shows that when transaction costs and decision biases are taken into account, the most cost-reflective policies are not necessarily the most efficient. On reasonable assumptions, real-time prices can result in less peak conservation of manually controlled devices than time-of-use or critical-peak prices. For that reason, the trade-offs between engaging automated and manually controlled loads must be carefully considered in time-varying rate design. The rate type and accompanying program details should be designed with the behavioral biases of consumers in mind, while minimizing price distortions for automated devices.

1 Introduction

Electricity in the United States is typically bought and sold in wholesale markets at a fluctuating price, but sold to end-use consumers in a way that obscures the true hourly cost. Despite increased attention to time-varying rates and widespread recent deployment of smart meters, the vast majority of U.S. consumers still pay a fixed price (per kWh) for electricity. Demand flexibility could help reduce electricity prices during peak hours, which can have dramatic effects on total annual costs. As penetration of renewable resources grows, grid operators will increasingly seek to use elastic demand to promote more efficient outcomes. There are opportunities for significant economic gains and also environmental benefits (including reductions in carbon emissions).

Alert to those opportunities, Allcott and Mullainathan [1] suggest that behavioral science could be enlisted to produce significant improvements in the energy sector, and Pollitt et al.[2] have suggested that behavioral economics could be an effective tool to increase the responsiveness of demand. Despite system-level welfare benefits and documented individual benefits, however, relatively few customers have opted-in to time-varying prices in the electricity sector. A different design, with opt-out defaults, would be likely to increase participation substantially.

Existing empirical studies measure the effects of time-varying rates on electricity consumption. The high level of heterogeneity in program results suggests that program design and behavioral details greatly affect the overall impact of such rates on electricity use. Recent research shows that customers reduce peak consumption when they are defaulted to a time-varying rate, even when they would not have opted-in to the same rate option [3]. In light of this and similar studies, Faruqui et al. (2014) argue that default time-varying

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rates could help reduce peak consumption and save consumers money [4]. However, arguments continue with respect to the most effective time-varying policies for rate design.

The remainder of the introduction of this paper provides some additional background on electricity tariffs, in Subsection 1.1. Section 2 presents research on current electricity tariffs in the United States. Section 3 discusses the relevant literature in the field, encompassing behavioral economics, empirical studies, and industry/consulting analyses. Section 4 introduces an analytical framework for consideration of time-varying prices in the electricity sector, which helps show why the cost-reflective tariff is not necessarily optimal in the presence of information costs and decision biases. Because of the high proportional cost of information in electricity markets, compared to the value of consumption decisions, outcomes can be profoundly affected by the electricity tariff. Thus, contrary to results based only on traditional economic analysis, a real-time price might not maximize efficiency. Section 5 examines some of the trade-offs between rate designs for automated versus manually controlled devices. Section 6 details a policy recommendation for flexible rate defaults to enable responsive demand, using the best available evidence.

1.1 Background: Electricity Tariffs

Electricity is typically bought and sold in wholesale markets on a per-unit (kWh or MWh) basis provided during 15-minute or hour-long periods. These wholesale markets are operated by Independent System Operators (ISOs) or Regional Transmission Operators (RTOs). The ISO receives supply bids from generators and demand bids from utilities, who forecast the demand of their customers and place bids on their behalf; the ISO calculates the optimal dispatch given supply and demand bids and relevant system and transmission constraints.

Because the demand for electricity changes in every period, but is highly inelastic, the price for electricity fluctuates significantly across all periods. Furthermore, the supply curve is non-linear, increasing sharply at high demand. Practical constraints can also raise the price for electricity, since many generators cannot ramp up their output quickly; others that can, like natural gas generators, tend to have higher marginal costs. For these reasons, hourly electricity prices feature high temporal variability and exceedingly high spikes (>10x the average) during some periods of the year.

We collected price data for 2014 and 2015 in the Austin, Texas Load Zone, which highlights the variability in wholesale electricity prices. The mean price paid for electricity in Austin during that time was $32 / MWh, and the maximum price paid in a single period was $5,442 / MWh. Figure 1 displays the contribution to total two-year energy costs of each hourly period as a cumulative distribution. Just under half of the total energy costs were incurred during 20% of total hours, and just 2% of hours were responsible for over 20% of total energy costs. The extreme steepness of the graph in the most expensive hours indicates the significance of their overall contribution to total system costs.

Despite the temporal variability of wholesale electricity prices, customers have typically paid fixed, regulated rates to the utility for retail consumption. While some states allow customers to purchase their electricity from competitive retail electric providers, the vast majority of customers still use the regulated incumbent utility. For residential customers, a regulated utility provides default service in every state except for Texas. In the 13 states with deregulated electricity sectors, around 50% of commercial and industrial customers and 80% of residential customers remain on the default service [5]. Pricing plans provided by competitive retail providers may ultimately encourage demand shifting and peak conservation. However, we focus mainly on the tariffs applied to regulated utilities. There are two reasons for this. First, the vast majority of U.S. customers pay for electricity according to regulated rates, and they will continue to do so in the foreseeable future. No new state has deregulated its electricity markets since 2001, and the fraction of customers buying electricity from competitive (non-regulated) providers has barely increased since 2007 in the deregulated states [5]. Second, the regulated rate provides an important benchmark, because it typically serves as the default and as a competitive baseline for consumers to compare competitive suppliers' rates. The electricity pricing tariffs set for customers by the incumbent regulated utility will continue to have outsized efforts on the market and on peak-demand management.

Regulated rates represent pricing options offered to residential, commercial, and industrial customers in the given utilitys service area. These rates are typically designed by the utility, subject to the approval of a state regulatory body like a Public Utilities Commission (PUC) or Department of Public Utilities (DPU). The customer classes are divided by type and by size, and each class may be offered different rates options

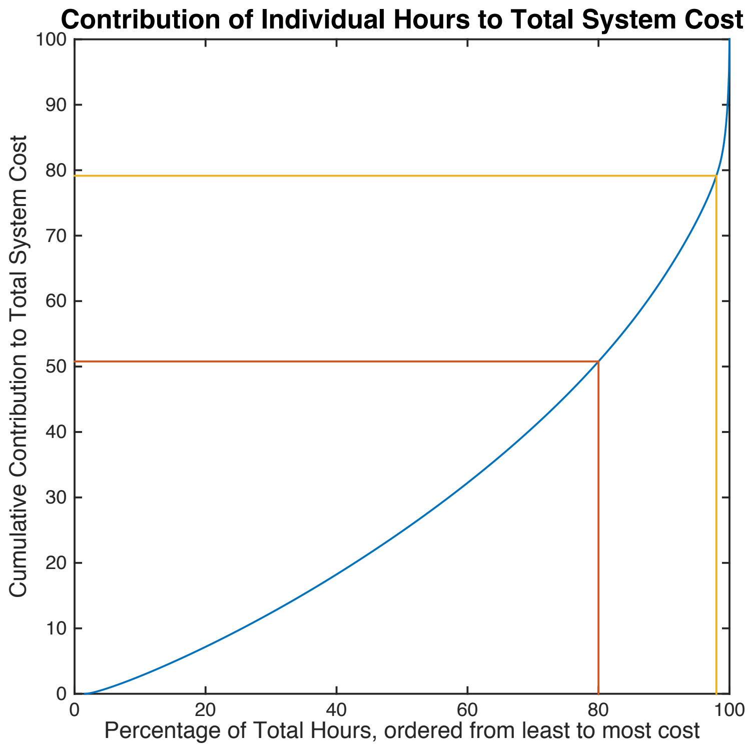

Figure 1: Contributions of individual hours to total energy costs in Austin, TX. The red and yellow lines represent the contribution of the 20% and 2% most expensive hours. Demand and market price data obtained from ERCOT

and a default rate. The rate can be divided, for assessment purposes, into two components. The first, the energy charge, is assessed for the procurement of electricity by the utility on behalf of the consumer. The second, the distribution charge, is assessed for costs associated with building and maintaining electricity distribution, and possibly also for costs related to meter-reading and customer assistance and billing.

There are several methods currently in use for charging electricity consumers based on their energy use. The five most common are as follows:

1. **Fixed Price (FP):** The electricity price is constant over all hours in the month, for a fixed period of time. It may be reassessed, for instance, every three months or every six months, to allow for seasonal and long-term changes in energy costs. An example customer on a fixed price could pay $.08 / kWh for the energy portion of all energy consumed in a given month.

2. **Time-of-Use Price (TOU):** The electricity price varies according to a set daily schedule. An example customer on a TOU rate could pay $.06 / kWh during off-peak hours, and $.15 / kWh during peak hours, for instance set as 3 p.m. to 9 p.m. on weekdays.

3. **Critical-Peak Price (CPP):** The electricity price increases during declared critical-peak hours, decided by the utility with a required notice period, e.g. 6 hours or the previous business day. An example customer on a CPP rate could pay $.07 / kWh during off-peak hours, and $.25 / kWh during the declared critical-peak hours.

4. **Time-of-Use with Critical Peaks (TOU + CPP):** This rate has the features of both TOU and CPP rates. For example, a customer could pay $.06 / kWh during off-peak hours, $.15 / kWh during scheduled peak hours, and $.25 / kWh during the declared critical-peak hours.

5. **Real-Time Price (RTP):** This rate tracks the wholesale spot price of electricity for each hour in

which electricity is consumed. For example, a customer could pay \$.038 / kWh from 1 p.m. - 2 p.m. on some Tuesday, \$.042 / kWh from 2 p.m. - 3 p.m., and \$.095 / kWh from 4 p.m - 5 p.m.

TOU, CPP, TOU + CPP, and RTP tariffs are all different forms of time-varying prices (TVPs), and occasionally we refer to them collectively in this fashion.

Besides energy charges, customers typically pay other fees for the distribution of electricity. Distribution charges are frequently assessed to consumers as a demand charge on a /kW basis, reflecting either the customer's peak consumption during a month or their coincident consumption during the system peak. In practice, this can also spur peak energy reductions, but based on the applicable economic theory, demand charges should only account for costs related to capacity or distribution [6]. The theoretical analysis and policy recommendations here are focused on energy charges. However, efforts to make distribution charges more reflective of costs could also help shift demand away from peak hours, and the principles described here could help inform rate design for those distribution charges. More detailed information regarding tariff structures can be found in reports by the Environmental Defense Fund [7] and by EPRI [8].

Time-varying rates typically require a "smart" meter that can transmit data instantly to the utility or that can log hourly data over the course of the month. For that reason, the historical prevalence of fixed prices might be partly an accident of history: only recently have digital meters, which can monitor consumption in real-time, become widely available, allowing for the widespread introduction of time-varying prices. Smart meters have been installed at a very high rate in recent years in the U.S., stemming initially from funds allocated for grid modernization as part of the American Recovery and Reinvestment Act of 2009 [9]. According to data from the Energy Information Agency (EIA), 105 million electricity consumers had digital meters installed by 2013 [10]. By 2014, AMI smart meters, which monitor consumption at least once every hour, represented 40% of all U.S. electricity meters. AMR meters, which allow for remote monitoring and which often have hourly read capabilities, represent an additional 32% of all meters [11]. Available metering infrastructure increasingly allows for the introduction of variable rates.

Broadly, there are two classes of benefits that policy-makers or analysts consider when promoting time-varying rates. The first set of benefits is based on increasing economic efficiency. A more cost-reflective rate could encourage conservation during high-priced periods or substitution of consumption towards lower priced periods. Consumer response to time-varying rates could help reduce overall system costs, especially since a large portion of total system costs are incurred during a few peak hours, but a thorough understanding of human behavior is necessary to maximize the efficiency benefits of time-varying rates. The second set of benefits is distributional: currently, consumers who use electricity at lower-priced hours pay more than the average cost to procure the electricity they use. For that reason, there are substantial cross subsidies in electricity, where consumers with low-coincident demand subsidize the higher energy costs of consumers whose demand tends to be more closely timed with system peaks.

2 Current Policies and Tariffs

Researchers and analysts continue to make the case for time-varying prices, and utilities in the United States are increasingly including TVP as a possible rate option. However, very few utilities have implemented TVPs as the default rate; for that reason, overall participation in TVPs is low. The 10 largest U.S. utilities, as identified using EIA data [11], service 20% of all U.S. electricity customers. Nine of the ten offer at least some form of time-varying price to the majority of their customers, but nearly all of the time-varying rates, except for those aimed at the largest customers, are offered as alternative tariffs, attracting customers on an opt-in basis only. Of the ten largest utilities, *none* has default (opt-out) time-varying prices for residential customers. Studies suggest that enrollment vastly increases when a TVP is introduced as the default rate, and analysts from the Brattle Group argue that TVPs will ultimately need to be introduced as defaults in order to strengthen their effects on electricity consumption [4].

Furthermore, while utilities frequently offer at least a TOU rate on an opt-in basis, they rarely offer other TVP rates. Only four utilities offer opt-in CPP, and only one offers opt-in RTP, but not to residential customers. This discrepancy–frequent offer of opt-in TOU rates, but rare opportunities for opt-in CPP or RTP–does not seem to be supported by any comparative studies of welfare benefits or of customer preference. It is not entirely clear why large utilities are so likely to offer opt-in TOU versus other time-varying rates

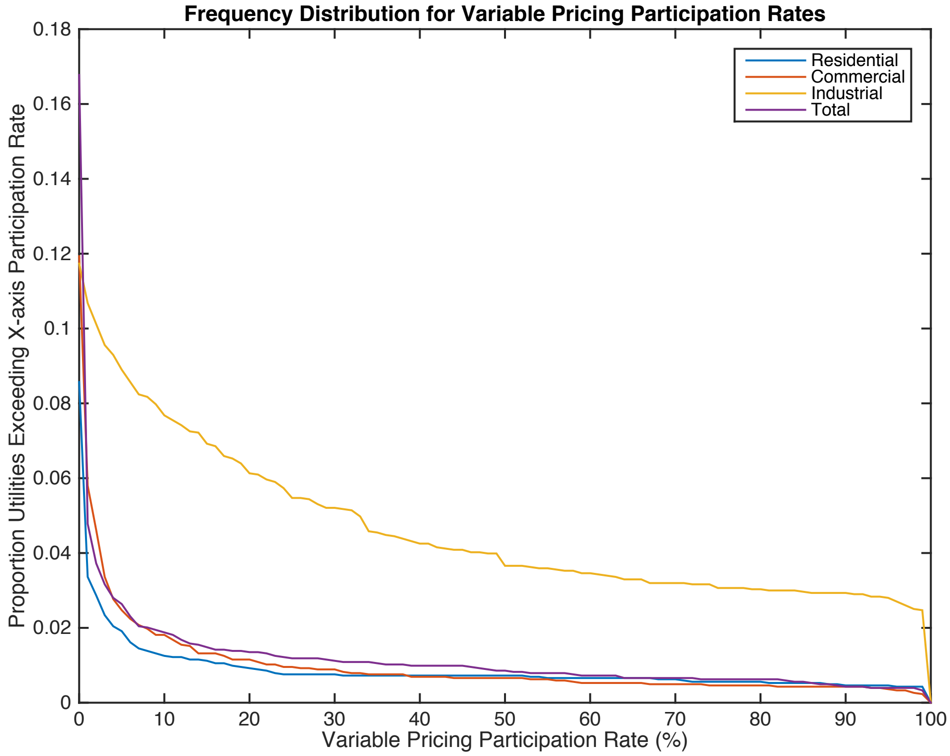

Figure 2: Fraction of U.S. utilities exceeding varying levels of customer participation in time-varying rates, using data from the EIA [11].

(especially CPP). Appendix Section 8.1 details the default rate types for each of these utilities, alternative rate options, and sources used for finding available tariff policies.

Additionally, we gathered EIA data [11] from 2014 to analyze TVP participation by all U.S. utilities. For the purpose of analyzing this data, all time-varying rates (TOU, CPP, TOU+CPP, and RTP) are counted in the same way, because the EIA's survey does not differentiate between various time-varying prices. The results show that customer participation in TVP is driven by high participation in a small portion of utilities. Figure 2 displays the proportion of utilities that achieve various participation rates in time-varying prices. Of the 3038 utilities in the U.S., only 8.6%, 11.9%, and 11.7% have TVP offerings for residential, commercial, and industrial customers, respectively. However, these programs do not tend to be successful. Only 1.9%, 2.5%, and 8.8% of utilities achieve at least 5% participation, and only 0.72%, 0.66%, and 3.7% of utilities achieve at least 50% participation in TVP, for residential, commercial, and industrial customers, respectively. Overall, 3.56%, 6.79%, and 10.13% of U.S. residential, commercial, and industrial electricity consumers are exposed to some form of TVP.

Figure 3 presents similar results on customer participation in time-varying prices, for each customer rate class, for each of the 100 largest utilities. This visualization suggests the same conclusion: participation in TVP is clustered among a very small number of high-performing utilities. The overall heterogeneity of customer participation reflects the importance of requirements, default tariffs, and program details in impacting TVP participation. The mere introduction of a TVP is not sufficient to generate participation among customers.

The standing assumption of many economics and policy researchers is that commercial and industrial customers are increasingly exposed to real-time prices, especially large consumers [12]. However, most utilities still do not have mandatory or default time-varying prices for commercial and industrial customers. The proportion of large customers enrolled in time-varying prices is still quite low, despite the fact that they have been shown to respond to TVP [13] [14]. For large customer in PJM, average cost savings were estimated at $14,000 per month for customers that enroll in TVP [15]. The dichotomy between likely welfare benefits

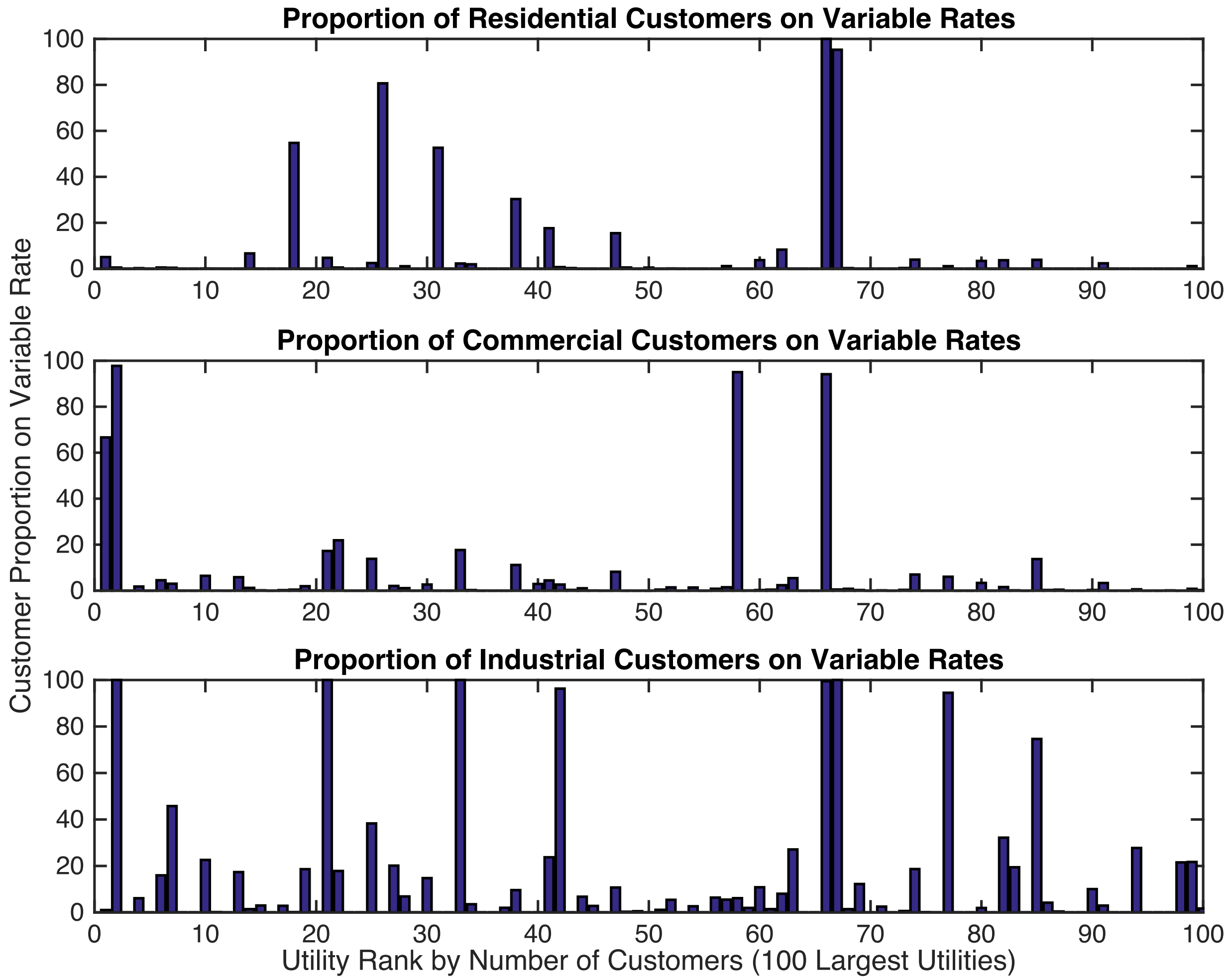

Figure 3: Proportion of each customer class on time-varying rates, using data from the EIA [11].

and low policy adoption suggests that further work is needed to identify political and economic reasons for the continued low adoption of TVP amongst commercial and industrial customers.

Overall, the evidence shows that the proportion of customers enrolled in TVP is exceedingly low and not well disbursed among utilities. There is significant room to expand enrollment in TVP, either through default or mandated rates. Behavioral research and the evidence from high-enrollment utilities suggest that defaults can be an effective means of spurring enrollment. Furthermore, few utilities have implemented successful programs with high levels of enrollment, so there is a lot of blank space for designing behaviorally informed programs that effectively reduce peak demand.

3 Behavioral Economics and Time-Varying Prices

Time-varying prices can provide efficiency and distributional benefits for electricity consumers, reducing cross-subsidies and reducing the overall cost paid for electricity on the grid (and providing environmental benefits in the process). But the benefits of time-varying prices are ultimately contingent on the number of customers that enroll in time-varying rates, the short-term elasticity of their demand in response to rates, and information deficits and behavioral biases that affect their response to the time-varying rates.

Time-varying rates are increasingly offered by utilities, but usually on an opt-in or voluntary basis, which (as we have seen) has not spurred significant adoption. Even with increased adoption rates, it is reasonable to worry that consumers might exhibit low responses to time-varying electricity demand due to information costs or behavioral biases. In principle, behaviorally informed approaches could help reduce energy costs and ease the integration of renewable resources by increasing the responsiveness of demand [2] or by reducing the effects of information costs or behavioral biases associated with demand consumption. Furthermore, the high variance in pilot and study results suggests that program details can have a major effect on consumer response. If high transaction costs and behavioral biases limit the adoption of time-varying prices, or affect consumer response to these prices, there is hope that more effective policies can be initiated to reduce these costs and biases.

Ideas from behavioral economics can help inform efforts to change electricity tariffs to align consumption with the true costs and benefits of electricity purchases. Behavioral issues affect two different decisions made by electricity consumers in the context of time-varying rates:

1. Default Bias: The initial rate choice, such as FP or TOU, if multiple options are present.
2. Consumption Bias: Electricity consumption choices in real-time, e.g. whether to run the dishwasher or turn off lights.

Both of these behavioral issues are explored in more detail below. Behavioral biases also could affect set-point decisions for automated devices, such as an acceptable A/C temperature range, when those devices are set to automatically respond to time-varying rates. This could have impacts on the value of automatically controlled devices, and it is covered briefly in Section 5.

3.1 Default Bias

When customers are confronted with a menu of rate options, decision biases can affect rate choice. For example, the decision to switch away from a default rate might be affected by inertia or a lack of information, or customers might be drawn to simpler rates that are welfare-dominated. Experts have repeatedly documented default effects on consumer choices and behavior, in areas as diverse as retirement savings participation [16],[17], organ donation [18], car purchase options [19], and the selection of a 'green' energy option for electricity [20].

Default effects can be explained by the power of inertia and the costs of effort when the costs of gathering information or making a complicated, active decision are high relative to the importance of the decision [21] [22] [23]. To overcome a default, customers must be willing to incur an "effort tax." There are costs involved with actually making a switch to a new electricity rate (paperwork, etc.), and there are additional costs involved with gathering consumption data and weighing the decision about whether an alternative rate is preferred. Furthermore, humans frequently perceive a default to be the recommended option; the informational signal that it contains might be especially strong if the customer is unfamiliar with the context [24], as is the case with electricity pricing.

Reference dependence also contributes to the default effect [23] because consumers frame decisions in terms of the default and avoid potential losses compared to the default case, which serve as the reference. "Loss aversion" therefore interacts with the default rule, which establishes certain effects as losses or gains [25]. Behavioral psychology suggests that careful framing could help improve adherence to a new default in the rate-setting context. For instance, if a utility sets a TVP as the default rate, and tries to minimize defection, it can remind consumers in its framing of the default rate that a) time-varying prices help reduce total electricity costs for the utility and b) the average consumer would spend more money on a fixed price than the default TVP (because of the additional risk carried by the utility in the case of a fixed price), establishing the new default TVP as the reference rate.

Large-scale studies in the electricity sector suggest, as expected, that consumers are much more likely to partake in a TVP when it is the default option. In a study of 174,000 households, Cappers et al. randomly sorted customers into opt-in and opt-out groups. They found that 19.5% of randomly sampled customers would opt-in to TOU rates, but that 98% would remain on the TOU rate when it was offered as a default [3]. Furthermore, in a survey of nine such studies by Faruqui et al., opt-in residential TOU programs achieve 28% participation on average, while default residential TOU programs achieve 85% participation [4], on average. The difference is striking.

A change in defaults can clearly sway consumers towards a time-varying rate option, but the ultimate benefits of the plan depend on follow-on consumption behavior. The analysis of the SMUD trial suggests that change of default does indeed affect follow-on behavior. The study teased out the consumption patterns of complacent consumers who did not opt-out of a default TOU price, but who statistically would not have opted in to an opt-in TOU either, and found that they had statistically significant reductions. The complacent consumers reduced their on peak energy consumption about a fifth as much as the consumers who opted-in [3]. Due to the additional response of the complacent consumers for the default TOU tariff, the overall reduction was significantly larger when the TOU price was offered as the default.

A word of caution: Another study failed to find statistically significant follow-on effects amongst the treatment group subjected to default time-varying prices. While the ComEd Customer Application Program did experience peak reduction effects of 22% and 11% for the responding customers in its CPP and TOU programs, respectively, a large number of customers defaulted into each program had no response; thus, the average peak-reduction effect was statistically insignificant [26]. This suggests two possibilities. First, the ComEd program could have simply been too small to achieve statistical power. Alternatively, these divergent effects could illustrate the importance of program details, including messaging. Simply defaulting customers into a TVP may not be enough. Effective messaging, guided by principles of behavioral economics (for example, by engaging intrinsic motivators and utilizing peer comparisons or follow-on feedback), might be necessary to reduce behavioral biases and to induce consumption response.

3.2 Consumption Bias

Once customers are exposed to time-varying prices, behavioral biases can affect actual consumption decisions. Several behavioral tendencies could lead to bias in electricity consumption decisions, such as inattention, decision fatigue, present bias, or hidden costs (often called shrouded attributes). Customers are not accustomed to paying much attention to electricity prices, so they could display inertia and fail to increase their attention in response to a time-varying price. Customer consumption might also be affected by a lack of information or by transaction costs for gathering and acting on price information. Transaction costs for electricity consumption decisions may be very high compared to the small price of short-term consumption decisions in the majority of purchase periods (turning on a light, running the dishwasher, etc.).

One of the striking features of a longitudinal assessment of time-varying price trials is the heterogeneity of measured effects across different trials. For example, a 2011 survey of 109 pilot programs found that consumers reduced peak demand by between 2 and 35%. Part of this is undoubtedly due to the price effect, since studies feature a range of peak/off-peak ratios. In that survey, however, Faruqui and Palmer calculate that a logarithmic regression of pilot study peak effects explains only 53% of the variation in consumer response [27]. This implies that up to nearly half of the measured effects of time-varying prices could be explained by something other than price. For small ratios between peak and off-peak prices, this variation is especially pronounced, with some studies achieving 5x the response of others despite similar price structures.

Another way to examine the range of consumer responses to time-varying prices, taking price effects into account, is to consider the variance in consumption elasticity or elasticity of substitution across studies. Elasticity of substitution refers to the substitution between energy use during high price periods and energy use during low price periods, as the percentage change in the ratio of electricity usage between time periods, due to a one percent delta in the ratio of those period's electricity prices. Surveys by the Electric Power Research Institute (EPRI), have measured elasticity of substitution amongst surveyed programs (a smaller subset than in [27], based on high-quality programs as identified by EPRI) ranging from 0.05 to 0.11 for programs that do not include automated technology, and ranging from 0.10 to 0.25 for programs including automated technology [26] [28]. Even among high-quality programs, customers responded twice as much to some programs as others, or five times as much when automated devices were included.

This variation in demand effects could lead to two different hypotheses. Either (1) there is large inherent variation in the average consumer profile in different areas or (2) program details can have a large effect on consumer response, for instance due to aspects of customer behavior that program designers might not appreciate. The first hypothesis may explain a portion of the effects, but geographic trends in consumer response are not apparent. Within individual studies, researchers have failed to identify certain consumer traits or features that correspond to increased participation [26].

The second hypothesis suggests that because of behavioral biases and transaction costs that affect decision-making, program details can have a profound effect on consumer response to time-varying prices. There are many reasons to believe that the second hypothesis is correct. For instance, different CPP programs might observe various substitution elasticities due to a difference in messaging type (i.e. email or text) or message content during critical peak periods. Information about neighbor/peer consumption during peak periods can help reduce energy use during those times, as it does more generally in terms of efficiency and conservation [29]. Furthermore, heterogeneity across device types can affect the bias level for consumption decisions. Theoretically, an automated device that responds algorithmically to prices and to its estimated probability distribution of future prices will be essentially unbiased in the way it consumes electricity. Practically, survey studies by both Faruqui and Palmer and by EPRI find larger demand reduction effects when a time-varying price is paired with enabling technology for notification or automated price response [26] [27] [28].

To be sure, some researchers have argued that variability in results is due to scientific uncertainty and will fade away over time. Paul Joskow writes, "Using randomized trials of smart grid technology and pricing, with a robust set of treatments and the 'rest of the distribution grid' as the control, would allow much more confidence in estimates of demand response, meter and grid costs, reliability and power quality benefits, and other key outcomes." [30]. However, the outcome variability amongst different tests is longstanding, even after more than 100 pilots [27]. Variance in estimates of demand response is likely to remain large because program design details and their behavioral implications have significant effects on the measured response.

In considering framework models for behavioral economics, it is typical to assume potential heterogeneity of decisional biases across customers. In analyzing consumption bias, however, it is clear that biases are heterogeneous not only across consumers, but also for single consumers, based on the automated capabilities of devices through which they consume. In Section 5, we will discuss how targeted default rates based on device type can reduce consumption biases and increase customer response to time-varying rates.

3.3 Research Gaps

A review of the literature suggests several unresolved issues with regard to the economics and policy of time-varying electricity prices. The backdrop of behavioral economics has informed policy design in energy efficiency, and some of the same lessons can be used in designing effective time-varying electricity rates. Empirical studies measure the effects of time-varying rates on consumption, which inherently takes into account the biases that affect consumption. However, there is still high variability in measured results, which suggests that program details affect consumption bias and the eventual level of customer response.

Critically, there is an ongoing disagreement about the optimal policy for rate design. On one hand, policy researchers and industry analysts tend to favor TOU and CPP prices, because they are simpler for customers and because they introduce less price variance. They are also politically more feasible for these very reasons [4]. Most empirical tests come from utility pilots, and there is only one example that includes a RTP rate, as an opt-in rate [26] [27]. Utility buy-in seems unlikely for RTP.

Economists argue that real-time prices are more efficient than TOU and CPP rates, because they are more cost-reflective of wholesale electricity prices. For example, Hogan calculates that a TOU price has only 23% of the reflective cost variance in the PJM markets, missing out on a substantial portion of the benefits of a RTP [31]. However, even putting aside the political issues associated with an RTP, they may not ultimately be the most efficient tariff from a purely economic perspective. The effects of rate type on behavioral biases are not well known, and when decisional biases are taken into account, it is no longer clear that an RTP is the most efficient policy.

Section 4 develops a basic analytical framework to analyze the potential benefits and limitations of time-varying rates for electricity, following from the basic economic model proposed by Allcott and Sunstein [32]. This model helps explain why electricity pricing might not be first-best when behavioral biases are taken into account. Section 4.1 describes the analytical model, and Section 4.2 provides a theoretical counter-example where the cost-reflective RTP is not the most efficient rate.

4 Analytical Model

4.1 The Regulator's Decision

This section presents a generalized model of the regulator rate-setting decision and consumer decisions in the face of behavioral biases. The framework for consumer decision bias is based on the model previously proposed by Allcott and Sunstein [32], and similarly to the reduced-form model proposed by Mullainathan, Scwartztein, and Congdon [33]. This suggests that the theoretically optimal policy option, passing through the wholesale price of electricity in a time-varying, cost-reflective tariff, is not necessarily optimal if transaction costs and decisional biases affect consumption decisions. The model also helps show just how difficult implementing methods to remove and regulate internalities can be, given the constraints and heterogeneity of biases in the electricity sector.

Let p_t represent the wholesale price paid for one unit of electricity (kWh) during time period t. Then, let $\tilde{p}_{it}$ represent the per-unit rate paid by customer i for electricity during period t. The regulatory tariff maps wholesale prices to the electricity rates paid by consumers. It is typically developed by the utility, but is ultimately approved by a regulator, such as the state Public Utility Commission (PUC). The tariff is thus a function that maps the wholesale price to the retail price for each customer i for the T-length vector of time periods under consideration, i.e. $u_i : \mathbb{R}_T \to \mathbb{R}_T$. Then, in a given period t, the corresponding element of the function $u_i(\cdot)$ is $u_{it}(\cdot)$, and $\tilde{p}_{it} = u_{it}(p_t)$.

Note that the actual rate paid by an electricity consumer will feature additional charges, including perhaps a fixed monthly charge for service, a distribution-systems charge, or a fixed demand charge. While some of these charges might be used in practice to cover the costs of procuring energy for the customer, as a matter of proper accounting they should be kept distinct. This function makes this claim explicit, by considering the rate paid for energy consumed to be a function of only the time-series of wholesale prices. In many state jurisdictions, for instance those with some retail electric providers, the line between energy charges and other charges is clearly drawn in this way.

This type of function could represent the various rate types described in Section 1.1. For instance, the RTP is described as $u_{it}(p_t) = \{p_t\}$, the sequence of wholesale prices $\forall t$, the CPP as $u_{it}(p_t) = \{a_t | a_t = H \text{ if } p_t > \alpha,\ a_t = L \text{ otherwise}\}$ for some threshold α, with $H > L$, and the TOU rate as $u_{it}(p_t) = \{e_t\}$, a constant price in each period, but with prices varying across periods.

The consumer i consumes q_{it} units of electricity during period t and obtains utility v_{it}, also called the 'true' or 'experienced' utility. In practice, however, the consumer faces some additional biases and transaction costs, so the consumer's behavioral utility in period t is given by $d_{it} = v_{it} - b_{it}$, where b_{it} accounts for behavioral biases, such as inertia. The term b_{it} also accounts for reducible transaction costs, i.e. transactions or information gathering that could be achieved at a lower level, but are not because of behavioral biases or ineffective defaults. For instance, we assume that the general RTP framework does not include automatic notifications about high prices; if customers prefer notifications but do not opt-in to them, for instance due to default bias, then extra costs they incur as part of information gathering can be included in b_{it}.

The regulator's goal is to choose some tariff policy u_i^*, which solves the following optimization problem:

$$\max_{u_i} \quad \sum_t \Big(\sum_i v_{it}(q_{it}) - c_t(Q_t)\Big) \tag{1}$$

Here, $Q_t = \sum_i q_{it}$ and q_{it} is the amount of energy consumed by customer i in period t, according to the decision process described in (2). The cost function $c_t(\cdot)$ represents the total system cost in period t as a function of the quantity of energy demanded. We assume that the supply side of the market is competitive, i.e. the market price accurately reflects the marginal cost of production, so $p_t = \frac{dc_t}{d\hat{q}_{it}}$. The quantity of consumption q_{it} is the result of a mapping of the difference between price and decision utility to a specific quantity demanded, i.e. the consumer makes the apparently optimal consumption decision given the price and their consumption utility, which may be biased or affected by transaction costs.

$$q_{it} = \quad \arg\max_q \quad d_{it}(q) - q\tilde{p}_{it} \tag{2}$$

Note that the consumer is a price taker, so their consumption level has no effect on the market price p_t and no indirect effect on the tariff price $\tilde{p}_{it}$. Given the standard assumption that $d_{it}(q)$ is increasing and concave in q, the consumer will choose to consume at the level q_{it} such that $\frac{dd_{it}}{dq}|_{q_{it}} = \tilde{p}_{it}$.

Assume that the cost for procuring electricity is increasing and convex in Q_t (which is a reasonable assumption for the electricity supply stack). Also assume that the experienced or 'true' utilities of the consumers are increasing and concave in q_{it}. Then, the social welfare in Equation 1 is similarly maximized when each consumer i consumes q_{it} during period t such that $\frac{dv_{it}}{dq}|_{q_{it}} = \frac{dc_t}{dq}|_{q_{it}}$, i.e. the standard efficient market clearing quantity where marginal utility equals marginal cost at the equilibrium.

Then, if $d_{it}(x) = v_{it}(x)\ \forall x, i, t$, i.e. if for all customers $b_{it} = 0\ \forall i, t$, the optimal tariff is clearly the cost-reflective, time-varying wholesale price $\tilde{p}_{it} = \frac{dc_t}{dq} = p_t\ \forall i, t$. Under this set of assumptions, the real-time price is unequivocally the optimal tariff design.

However, based on the internalities model proposed by Allcott and Sunstein [32], it is clear that a pass-through of the real-time wholesale price is no longer the optimal policy during period t if $\exists\ i$ s.t. $b_{it} \neq 0$. Assume that during this period the optimal quantity that could be chosen by a consumer i is $\hat{q}_{it}$, so $\frac{dv_{it}}{dq}|_{\hat{q}_{it}} = \frac{dc_t}{dq}|_{\hat{q}_{it}}$, i.e. at the optimal quantity the consumer's marginal experienced benefit equals the marginal cost. Then, the optimal tax/subsidy η_{it} for the specific player in a competitive market is such that $\eta_{it} = \frac{dd_{it}}{dq}|_{\hat{q}_{it}} - \frac{dv_{it}}{dq}|_{\hat{q}_{it}}$. In other words, consumer i is charged $\tilde{p}_{it} = p_t + \eta_{it}$ and therefore has quantity demanded q^*_{it}, the efficient quantity that maximizes social welfare.

Therefore, when consumers have behavioral biases or reducible transaction costs, the pass-through of the real-time price is not necessarily the optimal tariff. As a response, the idea of providing a tax or subsidy seems politically fraught in any realm. In any case, it is not of practical use in correcting behavioral biases associated with electricity consumption. Consumer demand is extremely inelastic in the short-term, so taxes aimed at reducing consumption during peak periods may only have small effects on overall quantity demanded, unless the tax is very high. Moreover, it is difficult to separate the effects of behavioral biases and transaction costs for obtaining access to price information, since these costs are small and non-monetary. Furthermore, there is already a large amount of political opposition to cost-reflective prices, because of the risk to consumers in more variable prices; it is probably not feasible to increase price variance beyond the variance that would already occur from cost-reflective prices. However, because customer demand for electricity may have significant nonlinearities, price variance from a TVP might be very helpful for reducing behavioral biases, if high-prices attract consumer attention.

Given the presence of behavioral biases and transaction costs in electricity consumption decisions, pass-through of the wholesale real-time price is unlikely to be the first-best policy for tariff design. One of the main goals of any tariff policy must be to reduce potential biases and associated information costs that affect the quantity of electricity consumed. In considering time-varying prices, the regulator must consider both the potential benefits of a more cost-reflective tariff and the potential benefits from a tariff or from program details due to the reduction of consumption biases. The next section provides a theoretical example, in this vein, that counters the traditional narrative in support of the efficiency of real-time prices.

4.2 Simplified Efficiency Analysis

Here, we present a theoretical economic analysis to show how behavioral biases, information costs, and decision costs can affect the efficiency of the market-clearing quantity of electricity consumed. In particular, the example highlights how important it is for any time-varying price tariff to reduce potential consumption biases of consumers. In this example, the benefits of bias reductions in one example outweigh the benefits of a more cost-reflective tariff. This provides interesting insights about the best methods for dealing with behavioral biases in electricity purchases.

Figure 4 presents the demand curves for consumers under imagined fixed price or real-time tariffs. The optimal quantity demanded q_{Eff} is determined by the intersection of the 'experienced' demand curve QD_V with the RTP, P_{RTP}. However, consumers display some bias in their electricity consumption decisions. For instance, they might display present bias, valuing present consumption more than a bill to be paid weeks in the future. They might also be biased by inattention, such that they leave on electricity consuming devices that provide no utility to them. Therefore, the actual quantity consumed under the fixed price, q_D is given by the intersection of the customers 'decisional' demand curve $QD_{D,FP}$ with the fixed price P_{FP}. This is a peak period, where $P_{RTP} > P_{FP}$, so given the price-mismatch and the behavioral biases, $q_D > q_{Eff}$.

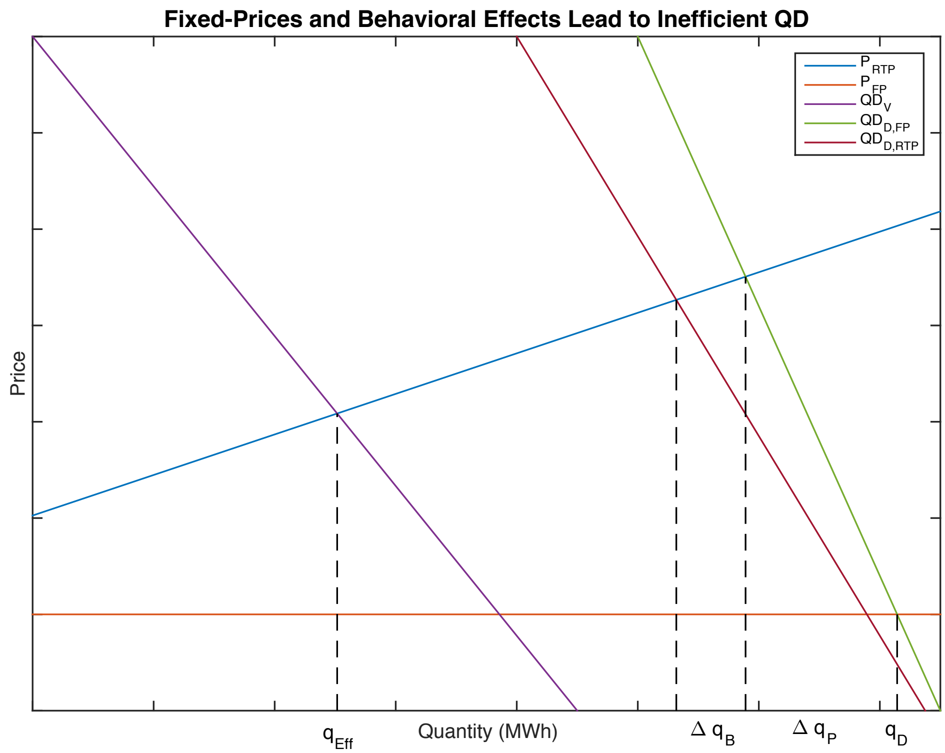

Figure 4: Benefits from a RTP: Price alignment and decisional bias reduction

In this example, there are two separate benefits of moving to the real-time price, as shown in Figure 4. The first is due to the change in price. When the price is increased to the wholesale, real-time price, quantity demanded decreases accordingly, by Δq_P. The second benefit is due to a reduction in the behavioral bias exhibited by consumers, as evidenced by the fact that the demand curve under real-time prices $QD_{D,RTP}$ has moved closer to the demand curve derived from experienced utility. Behavioral benefits reduce the market-clearing quantity by Δq_D. This could happen if, for instance, an RTP increases attention towards the costs of electricity and provides a framing effect that increases the response to perceived high prices.

Next, consider a critical-peak pricing mechanism, as shown in Figure 5. Imagine that under the CPP tariff, the utility sends out a text message a day in advance of estimated high price periods. This text message reduces consumer inattention, and it reduces present bias and hidden cost because it directly reminds customers of the price they will pay for electricity consumed. For that reason, the consumption bias for many customers is reduced, and customers become more sensitive to a higher price, like the one they will face during the critical peak period, P_{CPP}. The demand curve drawn from the decisional utility during the peak period is given by QD_{CPP}.

In this example as well, there are two separate benefits of moving to the time-varying price, in this case modeled as a critical-peak price. The first is due to the change in price. When the price is increased to be more reflective of the higher wholesale price, quantity demanded decreases accordingly, by Δq_P. The second benefit is due to a reduction in the behavioral bias exhibited by consumers, as evidenced by the fact that the demand curve under real-time prices $QD_{D,CPP}$ has moved closer to the demand curve derived from experienced utility. Behavioral benefits reduce the market-clearing quantity by Δq_B.

Compared to the RTP, the price benefits of the CPP are lower in this period, because the wholesale price exceeds the critical-peak price. However, compared to RTP, the benefits of the CPP rule from reducing behavioral biases are much higher. As a result, as shown in Figure 6, the resulting market-clearing quantity under the CPP is actually closer to the efficient quantity, $q_{Eff} < q_{CPP} < q_{RTP}$. In this example of a peak period with biased consumers, the critical peak price is an improvement over the real-time price, even though it is less cost-reflective, because it is associated with greater benefits from a reduction in behavioral biases.

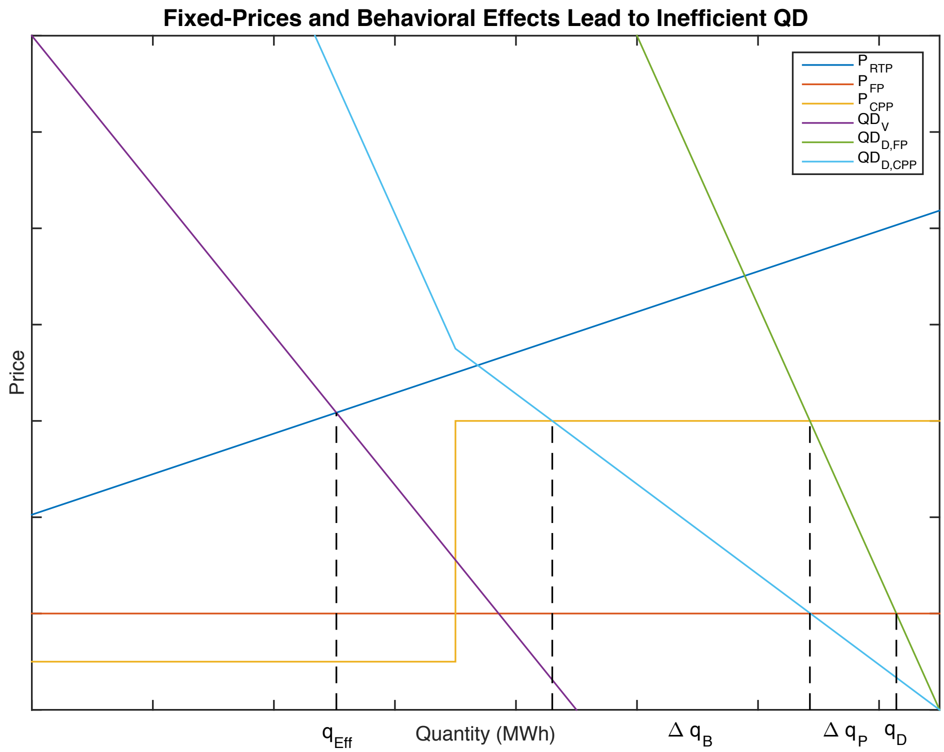

Figure 5: Benefits from a CPP: Some price alignment and behavioral bias reduction

To ground this example, consider an imagined but practical situation that illustrates the above scenario, where the average bias under a RTP is greater than that under a CPP tariff. Imagine that RTP and CPP options are introduced to consumers in January, when demand, which is dominated by air-conditioning load, is not particularly high. On the RTP rate, consumers are exposed to the real-time price, and at the end of each month they receive the month's price history and a rate-explainer as part of their bill. Automatic notifications for high price periods are offered for free to consumers, but few customers enroll because of the default effect and poor advertising. On the CPP price, customers are alerted by default to 10-15 high price events throughout the year.

Because the tariffs are introduced in the winter, when demand is not particularly high, there are no significant price spikes in the first few months; the price follows the typical pattern of demand, with peaks in the afternoons, but with no significant spikes. For that reason, many RTP customers notice and internalize a certain pattern in prices–the afternoons are more expensive. As the months go on, they reduce demand not in relation to the real-time price, which would require high information gathering costs, but rather in relation to the time-of-day, based on an approximate average price observed in each period.

Consequently, when the electricity price spikes, the learned bias prevents consumers from responding efficiently to the cost-reflective RTP. On the contrary, CPP customers simply reduce consumption during the hours in which they receive a notification, reflecting the simplicity of the tariff and the associated reduction in information costs. On a critical-peak day, like the one described above, the CPP consumers might actually respond in a more optimal way, even though their price does not reflect the true wholesale cost. (Note that behavioral biases can lead to under-consumption of energy as well, not just over-consumption.)

As shown in Section 4.1, the RTP is optimal for unbiased consumers with non-reducible transaction costs, i.e. customers for whom $b_{it} = 0$. However, if the tariff design imposes superfluous transaction costs on individuals, for instance through ineffective defaults, the RTP rate may no longer be optimal. For example, if the cost of receiving a price notification is less than the cost of gathering information about real-time prices, then costs are reduced when individuals receive notifications automatically during periods when the price is high enough to affect their optimal consumption. The RTP, as it is typically described, does not

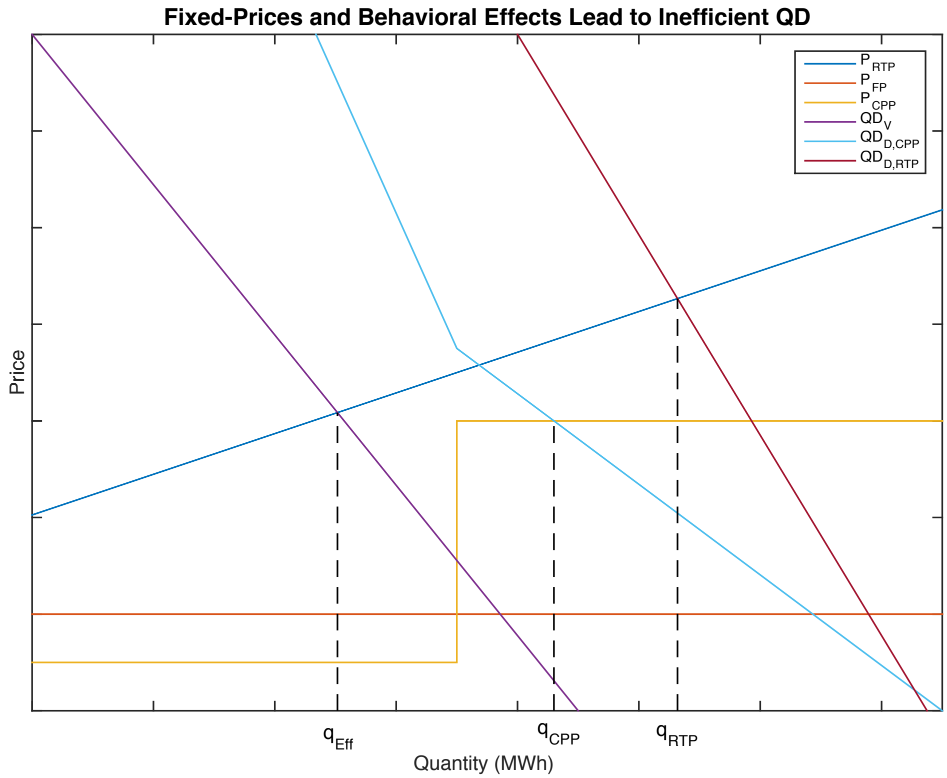

Figure 6: The consumption quantity demanded from a CPP can be more efficient than from a RTP if the CPP is more effective at reducing behavioral biases

include automatic high-price notifications, and they are not an intrinsic part of the rate design (as they are with CPP). Thus, if customers would benefit from price notifications, but do not sign up for them because of sign-up costs, default bias, or inattention, the RTP price could be suboptimal unless it appropriately employs notifications, for instance by default. Research should seek to measure the benefits of automatic notifications and quantify the optimal default notification frequency in order to inform electricity rate design.

If transaction costs have much larger effects than behavioral biases on energy demand, then an RTP rate, with the appropriate price notification policy, is likely to be optimal. But when considering a broader range of biases that consumers may exhibit in the purchase of a low-cost, sometimes relatively inconspicuous product such as energy, it is not clear that a price-reflective rate is the optimal solution to the regulators tariff decision–at least if it is not accompanied by interventions designed to counteract those biases.

5 Welfare Benefits of Time-Varying Prices

5.1 Biases and Targeting

As shown in the example above, a less cost-reflective tariff can be more efficient than the RTP if it provides extra benefits from a greater reduction of consumption bias. However, as shown in Section 4.1, the RTP is theoretically optimal, under certain standard system assumptions, for unbiased customers. It follows that efficiency can be improved if regulators or utilities are able to target customers, in a similar sense to subsidy targeting as described in existing work [32] [34], in order to offer the most appropriate rate to each set of customers.

Moreover, it is important to consider the different biases a consumer exhibits while consuming electricity through different devices, including automated devices. While the consumer might be subject to some behavioral bias such as inattention with respect to use of household lighting, an automatic A/C would respond algorithmically to the price, house temperature, and to its constructed distribution of future prices; it is fundamentally unbiased. The device through which electricity is consumed offers a natural way to target rate-defaults in order to increase the overall efficiency of a package of electricity tariffs. Some utilities have offered separate rates for individual devices: as noted in Appendix Section 8.2, Virginia Electric & Power Co offers controllable water-heater options, and several utilities offer separate metering and tariffs for electric car chargers.

The device used to consume electricity, and specifically the feature of whether or not that device is automated, can be used as a way to target consumer-device pairs for the appropriate tariff rule and possible subsidy or tax. As shown in existing theoretical work, targeting can increase the efficiency of a subsidy program [33] [34]. Any rate besides the real-time price has an efficiency cost, because it is not fully reflective of the real-time price. Thus, the appropriate tariff rule could target automated devices, and offer the RTP rate by default to those devices, while suggesting (through defaults, for instance) the bias-correcting rule to consumers for the non-automated devices they use.

Since every other rate besides a real-time price is less cost reflective than the real-time price, any non-RTP rate carries some opportunity cost compared to the RTP in terms of an efficiency loss from price substitution. As noted, the disadvantages of RTP might be reduced or eliminated if it is possible to provide effective reminders or information to the relevant consumers, overcoming present bias or inattention. But if such an approach proves ineffective or too costly, some other rate can be superior because of its benefits for reducing consumer bias. However, if an alternative rate is used it should be well targeted; that is, it should be marketed and focused at consumers without automatic control. Devices with automatic control should be served at the real-time price, whenever possible, in order to maximize efficiency.

However, the costs of targeting different rates at automated and non-automated devices may themselves be significant, both in terms of program design and especially due to additional costs for metering. It may therefore become important to think about trade-offs in rate design, because the rates that best engage human consumers are not most efficient for automated devices, and vice versa.

5.2 Automated Devices: Potential Benefits and Concerns

In theory, automated devices can offer significant cost-savings to consumers and to the electricity grid, because of their ability to shift demand based on real-time prices [35]. However, there are several questions to be addressed with respect to automated devices and their long-term benefits for reducing average costs for electricity consumption. These questions matter because they affect the extent to which regulations should push for increased usage of such devices and because they affect the terms of trade-off between tariffs that best engage human consumers and tariffs that best engage automated devices.

First, the benefits of automated devices may be overstated. The energy-saving benefits of these devices have typically been measured only through engineering analyses, as in the Rocky Mountain Institute's study [35]. But in energy efficiency research more broadly, it has become increasingly clear that engineering analysis can overstate the benefits of efficiency upgrades. Furthermore, it is understood that opt-in consumers are not generally representative in terms of their response to time-varying prices or use of efficiency devices. The most effective work researching consumer responses to time-varying prices uses empirical measurements in randomized control trials; similar research needs to be conducted to measure the effects of automated devices on consumer response to time-varying prices. Existing research on automated devices represents a promising start [27], but ultimately these studies should randomly assign automated technologies to customers defaulted into time-varying rates as well, in order to ascertain more general effects. It is also not yet clear how behavioral psychology affects the set-point decisions consumers make for automated devices. For instance, loss aversion may limit the flexibility consumers grant to such devices, even when the set-point is welfare dominated in expectation. The tendency for engineering estimates to overstate the energy-saving value of automated devices, as well as the potential for human behavior to limit their range, suggests that the benefits of automated devices may be exaggerated with respect to electricity price response.

Second, snapback effects might be much higher for automated devices [28], as opposed to general consumption by individuals. A snapback effect occurs when pricing outside of a peak period increases above the control group, as customers in the treatment group shift electricity away from the peak period into adjacent periods. Depending on the shape of prices throughout the day, snapback can greatly reduce the benefits associated with time-varying prices. However, no significant snapback effects have been measured for residential customers manually responding to time-varying electricity prices, and Allcott estimates that customers respond to peak prices only through conservation, not through energy shifting [36]. Snapback effects are expected to be much higher for automated devices, like A/Cs or car chargers, because of the fundamental requirements that affect their consumption patterns, given fixed set-points. Even though the overall response of manual consumers is lower than what could be expected with automated devices, the snapback effect should remind policy makers not to neglect the benefits of manual reductions in electricity usage when they are considering different rate options for time-varying prices. Because manual reductions are less likely to result in time-shifting of energy use, they have greater per unit benefits than peak reductions for automated devices.

Future empirical work should focus on automated devices and the benefits they could have in reducing peak consumption (for customers on TVP) and improving social welfare. While these devices undoubtedly aid customer response to TVP, they also increase snapback effects, and engineering estimates of their overall benefits might be overstated. Moreover, welfare calculations could help determine if targeting different rates at consumer and automated devices could be effective, given additional costs for metering or program design.

6 Policy Recommendations

Three major policy recommendations emerge naturally from the analysis thus far. *First*, opt-out default rules should be used much more widely to promote use of TVP. For residential consumers, opt-in remains the usual practice; opt-out is the preferable default. Commercial and industrial customers are still not widely exposed to time-varying prices, despite well-documented welfare benefits and higher average short-run elasticity of demand than residential consumers. Utilities should work with researchers to see if the default effect also influences commercial and industrial customers, especially if framed in the appropriate context.

Second, RTP may well turn out to be inferior to time-of-use or critical-peak prices because the former can result in less peak conservation of manually controlled devices than the latter. For that reason, RTP is not necessarily the most efficient rate option when behavioral biases are considered, though it remains the best rate option for unbiased customers. Notifications could reduce information costs associated with an RTP, so regulators should make sure the appropriate notification scheme and default settings are included as an integral part of rate design.

Third, since automated devices are essentially unbiased customers, a targeting process could be used to place automated devices on RTP rates while placing other consumers on rates more appropriate for their behavioral biases. Below are two practical examples for how this could occur.

In one scenario, residential customers are charged a TOU + CPP rate for all of their consumption. This rate takes into account the likely behavioral biases of customers and offers them a rate with low associated information costs. However, new EnergyStar appliances and electric vehicle chargers would automatically be fitted with a separate monitor that would communicate results to the central smart meter device. By default, these devices would be enrolled in a Contract for Differences with the utility, under which they would collect the difference between the wholesale RTP and the TOU + CPP rate for which they were originally charged. Under this scheme, the automatic device would respond directly to wholesale prices, and the customer would see an extra settlement line on their bill for each automated device. To avoid potential political objections, this settlement could be constrained so that it is only implemented when the customer saves money, which is expected to be the typical result because of the increased information received and flexibility afforded by the automated device. For this policy design to be useful, the cost of monitoring extra devices would need to be smaller than the extra benefits from enrolling the device on the RTP versus metering it at the TOU + CPP rate.

In a second scenario, all customers are charged a RTP, but the price is implemented in such a way that it provides many of the behavioral benefits of alternative price-designs. For instance, by default, an RTP should notify consumers automatically of impending high-prices, as if they were on a CPP. This type of notification procedure was used in the ComEd pilot study in order to increase consumer participation [27]. Furthermore, the frequency or price-point for notifications could be empirically tested, to determine the optimal notification strategy for reducing consumption bias; because of heterogeneity in consumer bias, the appropriate messaging procedure might be different across customers. This style of rate would not require additional metering costs, and automated devices would be encouraged to respond in the efficient way to the cost-reflective tariff.

Generally, utilities should also work to identify the specific program details that can maximize results. The high heterogeneity in measured values of peak reduction and demand elasticity suggest that program details have a major effect on how consumers respond to TVP. If a utility is considering implementing a TVP as a default, there may be a trade-off between increased notifications and defection; making the program more prominent can improve the customer response, but it could also lower reported customer welfare (if notifications are perceived as an annoyance) or increase drop-outs. If policymakers ultimately see clear welfare benefits in increased electricity conservation during peak hours, they should consider paying regulated utilities in part based on their success implementing these programs and engendering customer response, as is frequently done in energy efficiency programs. While outside the scope of this work, lessons from those programs can be used to help design policy that provides natural incentives to utilities to develop successful TVP programs, so they incorporate the best behavior research and knowledge to maximize their own returns.

7 Conclusion

Time-varying prices for electricity can help reduce cross-subsidies and significantly increase the efficiency of electricity consumption. While utilities increasingly offer forms of time-varying rates on an opt-in basis, overall consumer participation in time-varying rates is low, signaling the weakness of the opt-in design. In response, there is considerable current interest in default time-varying prices for consumers, which would undoubtedly increase participation. New research by Cappers et al. in SMUD suggests that an important set of customers–those who would not have opted-in to TOU prices but who do not opt-out from default TOU rates–respond to varying prices when defaulted into a TOU tariff. While the default rate argument is usually framed in terms of residential customers, it could also have benefits for commercial and industrial customers, especially if paired with subsidies reflecting the system benefits or when carefully framed to emphasize additional hidden costs incurred under the fixed-price rate.

In discussions about new default rates for time-varying prices, there is a continuing disagreement over the preferred rate-type: the real-time price or a less cost-reflective tariff like time-of-use or a critical-peak-price. In part, this argument centers on politics, because TOU and CPP prices are deemed to be less variable and thus more palatable to consumers. The real-time price is generally considered to be the most economically efficient policy. However, the real-time price is not necessarily the optimal policy when the behavioral biases of consumers are taken into account.

The best alternative option is the one that maximizes the sum of price and bias-reduction benefits from moving to a more cost-reflective tariff and from reducing behavioral inefficiencies and informational costs for consumers. This can be the real-time price, but only if price notifications are effectively designed and offered, for instance by default, with behavioral considerations in mind. Notifications for high-priced periods should be considered a potentially important part of any real-time price that is marketed to residential customers. Targeting should be used, if cost-effective, so that unbiased automated devices are exposed to the real-time price, even while human consumers pay an alternative tariff that reduces the cost of their biases.

Utilities should take into account the targeting of automated/non-automated devices, in order to maximize future welfare gains from time-varying prices, and they should consider the confluence of program details and behavioral factors in order to develop effective time-varying price programs that maximize customer response. Regulators should, in turn, continue to improve rewards-based compensation for utilities to ensure that they receive the proper incentive to develop and promote effective programs for time-varying prices that reduce costs for electricity consumers.

8 Appendix

8.1 Electricity Rate Details - Default Rates

Utility Name	State	Default Rate Types		
		Residential	Small C&I	Large C&I
Pacific Gas & Electric Co	CA	FP	TOU + CPP	TOU + CPP
Southern California Edison	CA	FP	TOU	TOU
Florida Power & Light	FL	FP	FP	FP
Consolidated Edison Co	NY	FP	FP	TOU
Georgia Power Co	GA	FP	FP	FP
Virginia Electric & Power Co	VA	FP	FP	TOU
DTE Electric Company	MI	FP	FP	FP
Public Service Elec & Gas	NJ	FP	FP	RTP (>500 kW)
Duke Energy Carolinas	NC	FP	FP	FP
Consumers Energy Co	MI	FP	FP	FP

Note: A few utilities do not have a true 'default' for large customers, forcing them to choose a rate structure upon signing up for service; for these utilities, we made the best possible determination as to which rate was presented or advertised as most standard or typical for consumers in that class.

8.2 Electricity Rate Details - Alternative Rates

Utility Name	State	Alternative Rate Options		
		Residential	Small C&I	Large C&I
Pacific Gas & Electric Co	CA	Opt-in TOU	TOU mandatory, plus customers w demand >200kW default to TOU + CPP (called Peak Day Pricing)	Opt-in Demand Bidding, Optional Binding Mandatory Curtailment Program (OBMC)
Southern California Edison	CA	Opt-in TOU	Opt-in RTP, Summer Discount Plan (DR), or CPP	Opt-in TOU
Florida Power & Light	FL	Opt-in TOU	Opt-in TOU	Opt-in TOU
Consolidated Edison Co	NY	Opt-in TOU	Opt-in TOU	Opt-in TOU or FP with Demand Charges
Georgia Power Co	GA	Two TOU Options, Demand Charge Option	Opt-in TOU, Demand Charge Plans	Required Demand Charges, but no options based on Coincident Peak
Virginia Electric & Power Co	VA	Opt-in TOU w/ or w/out Demand Charges, Controllable Water Heater Options	Opt-in TOU options. Tiered TOU pilot program with three sets of # of annual days w/ declining peak/off-peak ratios	FP Option now closed
DTE Electric Company	MI	Opt-in TOU, CPP, interruptible AC		
Public Service Elec & Gas	NJ	Opt-in TOU (called RLM)	Opt-in TOU, RTP	Opt-in TOU (may be standard for some customers)
Duke Energy Carolinas	NC	A/C Interruptibility Rider	Opt-in TOU (pilot)	Opt-in TOU (pilot)
Consumers Energy Co	MI	Opt-in TOU, CPP, Peak Rebate Programs	Opt-in CPP	Opt-in CPP

8.3 Electricity Rate Sources

Utility Name	State	Sources
Pacific Gas & Electric Co	CA	http://www.pge.com/tariffs/ERS.SHTML#ERS
Southern California Edison	CA	https://www.sce.com/wps/portal/home/business/electric-cars/electric-car-business-rates/
Florida Power & Light	FL	https://www.fpl.com/rates/pdf/new-customer-overview.pdf https://www.fpl.com/rates/time-of-use.html
Consolidated Edison Co	NY	http://en.openei.org/apps/USURDB/rate/view/5554c4655457a33b558b456d#3__Energy
Georgia Power Co	GA	https://www.georgiapower.com/business/prices-rates/home.cshtml https://www.georgiapower.com/residential/rate-plans/residential-tariffs.cshtml
Virginia Electric & Power Co	VA	https://www.dom.com/residential/dominion-virginia-power/customer-service/rates-and-regulation/residential-rate-schedules https://www.dom.com/business/dominion-virginia-power/rates/business-rates-schedules
DTE Electric Company	MI	https://www2.dteenergy.com/wps/wcm/connect/5b16c546-0484-401f-97b2-367cae9ee2cc/ResidentialElectricRates.pdf?MOD=AJPERES
Public Service Elec & Gas	NJ	https://pseg.com/family/pseandg/tariffs/electric/pdf/electric_tariff.pdf
Duke Energy Carolinas	NC	https://www.duke-energy.com/rates/north-carolina.asp
Consumers Energy Co	MI	https://www.consumersenergy.com/uploadedFiles/CEWEB/SHARED/Rates_and_Rules/electric-rate-book.pdf

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