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Utilization and Customer Behavior: Smart Choices for the Smart Grid

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Abstract

The smart grid offers a wide array of opportunities to improve efficiency of the electricity grid via load management policies. This chapter reviews the current state of knowledge in the economics literature as it relates to time-varying pricing and to behavioral interventions, which together comprise a large portion of regulators' policy choice set. The authors present evidence that consumers respond to financial incentives, but that these are not the only determinants of behavior. For example, consumers are often uninformed and inattentive, and exhibit a tendency to respond to non-monetary incentives as well as monetary. The authors conclude that time-varying pricing is an effective and essential policy instrument, while instruments designed to boost customer attentiveness and allow households to become better informed about their energy use play an important complementary role. Smart meters are crucial in making such a policy package feasible. The power of randomized experimental designs, which underlie much of the evidence that is presented, is also discussed. The authors highlight important areas for future research, and recommend that such future research efforts continue to leverage randomized designs.

Keywords: time-varying pricing, time of use pricing, critical peak pricing, social norms, smart grid, smart meters, randomized design.

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1 INTRODUCTION

When the price of a good does not reflect the marginal costs associated with its production and use, economists generally conclude that the quantity that is being produced and consumed is not optimal. This explains, at least in part, economists' continued fascination with the electricity industry. In the case of residential electricity, prices and costs are systemically and sometimes dramatically misaligned, for two reasons. First, in part because progress on pricing carbon remains meager, residential electricity rates – and energy prices more generally – do not reflect the associated pollution and other social costs. Second, since virtually all US residential electricity customers face flat tariffs that remain fixed for months at a time, retail rates rarely correspond to wholesale costs, which can fluctuate by the minute as different generation sources are brought online and taken offline in response to regional demand conditions. The proliferation of smart grid technology and smart meters provides a crucial base from which this misalignment can be addressed. However, recent economic research is establishing that additional conditions may need to be met to ensure that customers will adjust the timing and total quantity of their electricity usage as much as expected in response to changing rates, and therefore that the alignment of prices with costs will lead to actual improvements for utilities, customers, and society. The purpose of this chapter is to review economic research on the drivers of residential electricity choices, and to draw guidance on how smart grid technology and smart meters can be most effectively leveraged to achieve optimality in the electricity sector.

Economists have studied the welfare losses due to the disconnect between flat retail electricity rates and fluctuating marginal generation costs for over fifty years.[a] These welfare losses are driven by the fact that households facing a flat retail tariff will consume too much electricity at peak times and not enough electricity at off-peak times: when high-marginal-cost peaking generation capacity is brought online to meet large upswings in demand, retail rates will generally be far below wholesale prices, and vice versa when total demand can be covered by low-marginal-cost base load generation capacity. In the short run, this over-consumption at peak times and under-consumption at off-peak times implies that existing generation capacity is being utilized sub-optimally, while, in the long run, it can lead to excess investment in capacity. Borenstein and Holland (2005) estimate that these short-run and long-run losses amount to between 3% and 11% of electricity bills, on the order of billions of dollars annually at the national level.

To reduce or eliminate these welfare losses, economists are generally in favor of "time-varying pricing." Time-varying pricing policies refer broadly to any policy that attempts to align retail prices of electricity with wholesale prices more closely than standard flat retail rates do: time-varying pricing thus raises the retail price of electricity at peak times and lowers it at off-peak times. If households adjust their usage inversely with the price they face, time-varying pricing will therefore lower peak demand and raise off-peak demand towards optimal levels. The effectiveness of time-varying pricing in terms of reducing welfare losses hinges crucially on this question of whether and how much households will change their electricity consumption patterns in response to changes in rates.

Time-varying pricing policies have been implemented on a small scale in the United States since the 1970s, but penetration among residential customers remains negligible (Joskow and Wolfram, 2012). As discussed by Joskow (1985), one reason for early opposition to such policies was that some regulators doubted that consumers would actually respond to time-varying rates. Additionally, the costs of installing meters capable of monitoring usage by time of day and of adopting new billing systems were regarded as prohibitive. Advances in the functionality and affordability of smart meters have all but eliminated this second set of concerns (Joskow and Wolfram, 2012).

As for the question of customer responsiveness to prices, economists have amassed substantial evidence over the past four decades confirming that consumers do indeed decrease the amount of electricity they use at a given time in response to an increase in the price of electricity they face at that time – what economists refer to as exhibiting a negative own-price elasticity of electricity demand. The compelling nature of this body of evidence has been recognized by the Department of Energy (DOE) in a Report to Congress on implementing the US Energy Policy Act of 2005, which declared the expansion of time-varying pricing to be a matter of federal policy (U.S. Department of Energy, 2006). At the same time, however, economists have begun to identify a broader set of factors that also influence household electricity choices and in some cases may limit price sensitivity. This research has studied some drivers of choice that are very familiar to economists (e.g. future prices in addition to current prices), others that have only recently attracted economists' interest and may be more readily associated with behavioral psychology (e.g. social norms and rational inattention), and still others that are particularly relevant to the residential electricity setting (e.g. complex pricing schemes and intermittent price signals).

The conclusion that the authors draw from the economic research on residential electricity choices surveyed in this chapter is a slight variation on the basic conclusion that price elasticity is negative: When the price of electricity rises, *fully informed and attentive* consumers will use less electricity. This variation, however, does not alter the core policy implication that the authors draw: that time-varying pricing is an effective and essential policy instrument for load management and the reduction of short-run and long-run welfare losses in the electricity sector. This is not to say that the more recent literature lacks policy relevance. On the contrary, it has provided invaluable insights on how time-varying pricing can achieve the greatest impact. For example, one of the clearest messages that emerges is that customers generally exhibit strong inattention to electricity rates, so that the degree to which they adjust their usage in response to rate changes increases substantially when those rate changes are accompanied by reminders and information. It also suggests a potential role for so-called behavioral "nudges" that make the choice to conserve electricity more attractive to consumers, for example via messages that compare their usage to their neighbors' usage.

The authors argue that the additional levers brought to light by this recent research have a powerful role to play in support of and as complements to time-varying pricing policies, but that they are not adequate substitutes for price-based policies on their own. Smart meters are therefore important not only because they make time-varying pricing technically and administratively feasible, but also because they provide a platform for deploying a suite of supporting instruments to reinforce price incentives. Further, smart meters have been integral in capturing and making available much of the data that economists have relied on in building their understanding of residential electricity choices, both in terms of price response and behavioral factors. Thus, increasing penetration of smart grid technologies not only makes more effective policies possible, but also provides a means to obtain a more sophisticated understanding of how customers respond to those policies, thereby building in the opportunity to further improve those policies over time.

The focus of this chapter, as the preceding makes clear, will be on correcting the misalignment between retail electricity rates on the one hand and generation costs as reflected in wholesale electricity prices on the other. Nevertheless, the conclusions presented here hold insights for policies targeting the second type of misalignment mentioned at the outset – between electricity rates and environmental costs – as well. Customers' responsiveness to electricity prices is not limited to rate changes following from time-varying pricing policies only; rather, the empirical evidence is equally supportive of the conclusion that informed and attentive consumers will respond to an overall rate increase by conserving electricity more generally. In this sense, the implementation of time-varying pricing policies may offer a subsidiary benefit, in terms of acting as a bellwether and attuning regulators and consumers alike to price-based policies. Additional experience with time-varying pricing will also give policy makers and economists further opportunities to fine-tune their understanding of the precise ways in which consumers respond to rate changes and complementary instruments.

The chapter is organized as follows. Before empirical evidence on the drivers of residential electricity choices is reviewed, Section 2 explains the nature of empirical evidence in economics more generally. Section 3 then begins with an overview of different forms of time-varying electricity pricing, and proceeds to review empirical evidence on how households respond to changes in electricity prices induced by time-varying pricing policies and by rate changes more generally. Section 4 discusses various behavioral psychology concepts that economists have studied and introduced into their models of economic decision-making, in the context of reviewing empirical evidence on how some of these behavioral factors can influence household electricity choices. Finally, Section 5 discusses implications for policy and for future research. The authors conclude that time-varying pricing provides an essential foundation for electricity management policies; discuss specific characteristics and supporting instruments that economists' present understanding indicates will make such policies most effective; suggest the most promising avenues for future studies in terms of refining and extending that understanding; and highlight the crucial role of smart meters both in making such policy packages implementable and in enabling such future research.[b]

2 A METHODOLOGICAL PRIMER

An overarching objective of empirical research in energy economics is to isolate the causal effect of some action or policy – such as a change in the rate structure or the distribution of a framed message to customers – on behavior. The smart grid offers opportunities and challenges in this regard. The ability afforded by the smart grid to deploy interventions in real-time – including price changes and behavioral interventions – and measure their minute-by-minute effect on electricity use is far superior to that offered by previous technologies. On the other hand, the times during which such interventions may be most valuable (peak) are inherently different from other times; and households targeted for conservation treatments are likely to be systematically different from others (e.g. more energy-intensive). If an intervention is implemented in such a way that researchers cannot properly control for such differences when evaluating that intervention, it can be difficult or impossible to identify causal effects, and thus to draw meaningful conclusions about the effectiveness (or ineffectiveness) of that intervention.

In this section, randomized experimental research designs, which provide a powerful tool for overcoming this challenge of identifying causal effects, are discussed. Incorporating randomized design into policy deployments facilitates the credible estimation of clear and causal relations between those policies and observed outcomes. The motivations for explaining and emphasizing this point are twofold. First, many of the results reviewed in Sections 3 and 4 were estimated within randomized experimental research frameworks. The discussion of such frameworks is meant to provide confidence that these results capture true determinants of choices and outcomes rather than just correlations or spurious associations. Second, retrieving causal effects is of paramount importance when assessing whether an intervention achieved desired outcomes, and when drawing lessons from that intervention for future policies. It is hoped that the present primer will encourage regulators and industry, when designing future interventions, to consider the types of evaluation efforts that will be facilitated by the design and deployment of those interventions.

As a motivating example, consider how a researcher may go about determining which framing of environmental messages will encourage the most conservation. A famous contribution from the behavioral psychology literature, by Goldstein, Cialdini, and Griskevicius (2008), describes how hotels can effectively induce guests to reuse their towels, saving water, energy, and waste. The principles underlying these interventions are analogous to potential smart grid applications. Hotels wanted to know whether it was best to appeal to guests' prosocial tendencies by posting signs in the bathrooms that described the environmental benefits of conservation, or whether appealing to people's deep-seated instinct to conform to social norms would be more effective. For expedience, these interventions are labeled as "environmental" and "norms" respectively in what follows.

In an ideal and fictitious world, researchers would be able to simultaneously observe behavior for a given individual in the presence of each intervention and without any intervention at all.[c] But this is obviously impossible: either an individual is exposed to a given intervention at a certain point in time, or he is not. A reasonable alternative (and the basis for "good" and "bad" empirical research alike) is to compare conservation in groups of guests exposed to each message, both to each other and to guests who received no message at all. The difference between "good" and "bad" lies in the care with which these comparisons are made. Suppose that one hotel chooses to use the environmental treatment, a second hotel uses the social norms message, and a third uses no message at all. Comparing towel reuse across these hotels is almost certain to provide a misleading measure of how effective each intervention is, because presumably the hotels have selected the message that they believe will be most effective for their segment of the customer population. Guests in the "environmental" hotel may be systematically more responsive to the environmental message than the broader population; and the same for social norms. Furthermore, a before/after comparison of towel reuse within the hotels will likely be exposed to trends in overall interest in conservation, making it very difficult to pinpoint what fraction of the behavioral change is due to the intervention itself.

Randomization is an elegant way to overcome these challenges, which is why it has been the gold standard for important scientific research (e.g. biomedical treatments) for decades. In a randomized experiment, hotel rooms (and by extension, their inhabitants) are randomly assigned to receive either one of the two treatments or no treatment at all (the "control" group). By nature of the randomization, there is no systematic difference, on average, between the guests in each group. Furthermore, it is simple to test for statistical differences in observable characteristics across the groups to support this claim. The power and elegance of the randomized experiment is that, after the groups are exposed to their respective intervention, differences in the rate of towel reuse between the groups can be directly attributed to the interventions themselves. That is, there is a legitimate claim that the differences were *caused by* the interventions, and not some other spurious event.[d]

Goldstein, Cialdini, and Griskevicius (2008) randomly placed cards with an environmental message or a social norms message in different hotel rooms. On the basis of this experiment, they discovered that people have a strong desire to conform to social norms, and that this proclivity is far stronger than their desire to engage in environmentally-friendly conservation (at least with respect to reusing their hotel towels). Of the guests who were greeted with a bathroom sign asking them to "help save the environment," 35% reused their towels. By comparison, of the guests given a sign stating that "almost 75% of guests . . . participate in our resource savings program by using their towels more than once," 44% reused their towels. The authors discovered further that the power of the norms treatment was enhanced by delivering more precise information about others' behavior (e.g. 75% of guests who stayed *in this room* participate . . .).

It would be extremely difficult to generate credible estimates of the causal treatment effect of such nuanced interventions in the absence of randomization. This is the main reason why field experiments are increasingly being utilized to gain insights into customer choices in the electricity setting. They have been deployed with increasing frequency to test customer responsiveness to time-varying pricing and to understand the broader set of behavioral factors that influence decision making. In the next two sections, several contributions from this literature are reviewed.[e]

3 THE ROLE OF PRICE IN RESIDENTIAL ELECTRICITY CHOICES

3.1 Types of Time-Varying Pricing

Time-varying electricity rates can take a variety of forms, of which the three most common are the focus here. Following Borenstein (2005), these are classified according to two important characteristics: *granularity* – the frequency with which rates change; and *timeliness* – the lag between the time that a new rate is announced and the time that it is in effect. The more granular is a pricing scheme, the more rate changes will consumers potentially face within a month, day, or hour. The more timely is a pricing scheme, the less advance notice will consumers have regarding what the rate will be when it next changes. The greater the granularity and timeliness that a time-varying pricing scheme has, the greater will be the flexibilty for utilities and regulators to set retail rates appropriate for the regional demand and grid conditions (i.e. wholesale market) on a moment-by-moment basis.

The most well-known and widely-deployed form of time-varying electricity rates is known as Time of Use (TOU). Under TOU, electricity usage is divided into two or three blocks according to the time of day at which it was consumed. Higher rates are then applied to blocks corresponding to times of day that have historically been associated with high production costs. The same rate applies to a given block across all days.[f] TOU is only slightly more granular than a flat rate, with only two or three different rates rather than a single rate applied to a consumer's usage at different times in a given month. TOU also lacks timeliness, as the block-specific rates are set days to months before they first take effect, and stay in effect for weeks to months at a time. This poor granularity and timeliness imply that retail price variation under TOU will capture only a fraction – about 6-13% at most – of the variation in wholesale costs, thereby limiting TOU's potential to reduce the inefficiencies associated with flat rates (Borenstein, 2005; Jessoe and Rapson, 2014). On the other hand, TOU has the benefit of being fairly easy for consumers to understand, and familiar to those experienced with telephone services and other retail products with prices that usually change by time of day.

At the opposite extreme from TOU in terms of both granularity and timeliness is Real-time Pricing (RTP). Under RTP, the number of separate blocks per day is much larger – usually 24, or one per hour – and rates can differ both across blocks within a day and for a given block across days. RTP is thus very granular, with, in principle, hundreds of different rates applied to a customer's usage at different times in a given month. RTP is also very timely. Under day-ahead RTP, there is a daily announcement of rates that will apply in each hour on the following day. Regulators and utilities can thus set retail rates according to next-day forecasts of wholesale costs, which are much more precise than forecasts weeks or months in advance. Timeliness can be improved even further with what might be termed "true" RTP, under which the rate for a given hour is only set and announced sometime during the previous hour. While RTP is the form of dynamic pricing that can come closest to eliminating all welfare losses from retail rate misalignment, it is not popular, and when it has been implemented at all, it has only covered commercial and industrial customers for the most part. One barrier to wider implementation has been insufficient technology, both in terms of cost-effectively monitoring and billing usage by the hour, and in terms of enabling consumers to adjust their usage with the same frequency that rates change. The wider diffusion of smart meters and complementary technologies, however, is lowering this barrier. RTP is also not entirely outside of consumer experience, with prices for retail products such as gasoline and fresh seafood often changing frequently in response to market conditions.

Between the extremes of TOU and RTP lies Critical Peak Pricing (CPP). Under CPP, customers face the potential for one additional block to be occasionally added to their baseline pricing scheme. This additional block can be invoked at the discretion of utilities and regulators, but only for a fixed number of critical hours or days in a given year, and with some reasonable (but small) amount of advance notice to the consumer. This affords utilities the flexibility to charge an additional rate premium for the few hours per year when generation capacity is fully utilized and retail rates would otherwise be most drastically misaligned with wholesale costs. This one potential additional block increases granularity modestly relative to TOU, but the value of that added granularity is disproportionately high because of the ability to target the time that the additional block will be in effect. As with RTP, the timeliness of CPP can vary with the specific way in which the policy is implemented: The rate that applies to the additional block can be announced and set at the same time that the baseline rates are set (generally months in advance), at the same time that the critical event is announced and the additional block invoked (generally a day in advance), or within a few hours or even minutes of when the additional block actually comes into effect.

None of the specific forms of time-varying pricing described here necessarily leads to a given customer's electric bill increasing. To achieve revenue adequacy under flat retail rates, rate-of-return regulated utilities must set the tariff rate such that it is substantially lower than wholesale costs during the short periods that generation costs are highest, but somewhat higher than wholesale costs for the longer periods when generation capacity utilization and marginal costs are low.[g] For households that consume the majority of their electricity at off-peak times, retail rates that match wholesale costs more and more closely can therefore lead to larger and larger bill reductions, though the opposite will be true for residential customers that consume a lot of electricity at peak times and continue to do so after time-varying prices are implemented. In the longer run, time-varying pricing can also lead to lower overall rates for all customers, as generation capacity is utilized more efficiently and the pace of investment in new capacity moderates. However, in addition to the benefits of time-varying pricing in terms of lower bills for at least some customers and improved system efficiency and optimality in the electricity sector more generally, a lingering drawback is the increased customer exposure to risk and uncertainty from the potential increase in volatility of rates and bills. This issue and potential solutions are discussed by Borenstein (2005, 2013).

3.2 Evidence on the Effectiveness of Time-Varying Pricing

The earliest implementations of time-varying pricing in the United States focused on TOU. Aigner (1985) reviews a number of studies of pilot TOU experiments that were conducted in various states in the 1970s and 1980s. While highlighting a number of issues with the design of those experiments and with drawing lessons from them for broader implementations, he is careful to draw conclusions based only on those that he evaluates as having been well designed. His first overall conclusion is that the experiments demonstrated that TOU pricing "worked," in the sense that the rationale for TOU pricing was confirmed: treated households consumed less at peak times, when they faced a higher price, and more at non-peak times, when they faced a lower price, relative to control households. A second conclusion was that, at the same time, the studies revealed a wide range of sensitivities to price across the various pilot experiments. Caves, Christensen, and Herriges (1984) took up this question of heterogeneity of price response, again focusing on the subset of well-designed experiments from these early TOU pilot programs. They find that price sensitivity varied primarily according to region and appliance stock, and that, after controlling for differences in these household characteristics, the response to TOU was largely uniform across experiments.

Despite the positive results of these trials, residential TOU pricing was not subsequently deployed on a large scale in the United States. By the early 2000s, however, there was a resurgence of interest in time-varying pricing. Several new pilot experiments were conducted, some focusing on TOU but many also incorporating CPP. Faruqui and Sergici (2010) survey a number of studies assessing more recent pilot experiments and deployments, primarily in the United States. All of the programs provide an experimental design that underpins the empirical results.[h] The first conclusion they draw is that time-varying pricing in general worked in the sense that treated households in these programs lowered their peak usage relative to control households. The second conclusion they draw is that CPP was more effective at inducing peak usage reductions than TOU, likely due to the sharper price incentive faced during critical hours under CPP. Finally, they conclude that both TOU and CPP are more effective in terms of eliciting larger reductions in peak usage when "enabling technologies" are present, e.g. programmable thermostats connected to smart meters and devices permitting appliances to be controlled remotely. This last conclusion is also a key finding of Jessoe and Rapson (2014), which is discussed in more detail in Section 4.

The main conclusion drawn by Faruqui and Sergici (2010) – that time-varying pricing works – also extends to the single experiment they examine that involved RTP. This same program is examined in more detail by Allcott (2011a), who notes that, in addition to reducing usage at peak times, treated households did not increase usage at off-peak times, so that their overall usage fell. Unfortunately, further evidence on the effectiveness of RTP remains scarce, for the simple reason that experience with RTP pilots and deployments at the residential level is extremely limited.[i]

Economists have also estimated responsiveness to electricity rate changes outside of the context of time-varying pricing, relying instead on, for example, variation in overall rates across time or geographic region. Recent studies include Alberini, Gans, and Velez-Lopez (2011), Fell, Li, and Paul (2014), Reiss and White (2005), and Ito (2014). Each of these studies finds a negative elasticity of electricity demand, i.e. finds evidence that households respond to an increase in rates by decreasing electricity usage. However, there is a wide range across these studies in the magnitudes of the estimated elasticities, and Reiss and White (2005) also identify substantial heterogeneity in price elasticity across households. This diversity of estimates is likely largely attributable to the different empirical methods employed, including how well the different methods are able to control for unobserved drivers such as behavioral factors. The influence that such behavioral factors can have on customer decision making is discussed in the following section.

4 THE ROLE OF BEHAVIORAL FACTORS IN RESIDENTIAL ELECTRICITY CHOICES

In addition to facilitating the transmission of high-frequency price changes to consumers, the smart grid offers utilities and regulators a new way to communicate with customers. Should they wish, they could deliver information or framed messages intended to encourage customers to change behavior. This section briefly discusses selected economic research on "non-standard" decision making that sheds light on what behavioral messages might work, as well as when and why they might work. Developing such an understanding is particularly important because of the number of electricity industry players advocating for behavioral interventions.

The roots of economic research on non-standard decision making go back to Simon (1955), who coined the term "bounded rationality" to describe how consumers make decisions in the face of costly information acquisition or costly cognition. This framework leads directly to the concept of "rational inattention," i.e. the notion that limited consumer attention can be consistent with rational, optimizing behavior. The authors regard customer inattention as the primary challenge that electricity policy must face, and discuss this issue first. Social norms – and the role of the desire to conform to such norms in making individuals responsive to certain messages – are then discussed. Finally, the discussion turns to various questions that arise when behavioral interventions – whether designed to combat inattention, target desires to align with norms, or otherwise – are contemplated as alternatives or complements to price-based policies; the authors stress that there is still much to learn in this area.

4.1 Inattention as an Impediment to Customer Response

Consumers are remarkably inattentive to their electricity usage decisions, often with good reason. Suppose a family decides that it wants to cut its electricity use (and bills) by 10 percent. This is an enormous percentage decrease relative to most interventions in the energy realm. However, it may not add up to much savings. If the family initially pays $100/month, a 10 percent decrease amounts to a movie ticket, or a few cups of coffee. In order to understand which appliances are electricity guzzlers, and which household energy services the family is willing to live without, a significant investment of time and effort is required. When faced with the option of incurring these costs in order to save $10 per month, most people will simply not bother. This represents an extraordinary barrier to customer response: households would prefer, other things equal, to have lower bills while enjoying the highest possible level of services from their electrical appliances, not to mention having electricity usage in line with their neighbors' levels, contributing to environmental improvement, and so on; but when the cognitive effort required to balance all of these objectives is large while the financial consequences of failing to do so are small, policies targeting any of these considerations are at risk of being simply ignored.

With this observation in mind, researchers have tried to quantify the benefit of lowering information acquisition costs using smart technologies associated with the Home Area Network. Jessoe and Rapson (2014) designed a randomized experiment in which treatment households were exposed to – and given advance notice of – critical peak pricing events of two to four hours in length during which their prices increased by 250 to 600 percent. A subset of these households were also given an in-home display showing real-time electricity use in the home. Comparing the response to the CPP price increases by households with and without the display to a control group, the group with the display was 2-3 times as responsive to price as the group without the display. The explanation for this difference is that it was much easier for people with the display to become informed about which appliances have high energy requirements. As a result, when prices increased, these households knew which appliances to turn off. Similarly, Gans, Alberini, and Longo (2013) and Faruqui, Sergici, and Sharif (2010) provide evidence that the introduction of in-home displays can lead households to reduce their usage in general, even in the absence of a change in rates. Further, Gilbert and Graff Zivin (2014) find that households tend to reduce their usage shortly after receiving their monthly bill, but that this effect evaporates later in the month; while Sexton (2014) finds that households tend to increase their usage after signing up for automatic bill payments. All of these studies indicate a potential to substantially affect usage patterns simply by drawing customers' attention to – and enabling them to acquire better information on – their consumption and expenditure.

4.2 Customer Response to Social Comparisons

Another type of behavioral intervention appeals to people's inherent desire to conform to social norms. As discussed by Allcott (2011b), when households are sent a report informing them how much electricity they use relative to other, similar households, they reduce their usage by about two percent. This intervention has garnered a great deal of public attention, not least because a two percent reduction adds up to a lot of energy for utilities with a desire or mandate to stimulate conservation. Notice, however, that the impetus for behavioral change in this case is the desire not to deviate too far from the behavior of others, not necessarily to engage in pro-social behavior. As the results of Schultz et al. (2007) suggest, if the message is not carefully crafted to also include a component appealing to pro-social tendencies, or if it is not targeted only at high-consumption households, the net effect might be dampened because customers with usage below the norm may respond by increasing consumption.[j] Furthermore, as demonstrated by Allcott and Rogers (2014), the norms-driven conservation effect deteriorates over time in the absence of repeated interventions.

4.3 Comparing Behavioral Interventions and Price-Based Policies

This subsection discusses how behavioral interventions might compare to price-based policies in terms of both effectiveness and costs of implementation, as well as the possibility of eschewing the choice between the two and instead pursuing both types of policy in combination. The overarching message is that existing literature has only begun to address these questions, and that the area is thus ripe for future investigation.

Because the goals of electricity management do not encompass general conservation only, but also reductions at peak times, the relative effectiveness of different policies should also be assessed with respect to peak load reductions. However, while it is possible to deliver behavioral interventions that correspond to critical hours, there is little experience with such efforts. In particular, there have been no norms-based interventions like the ones studied by Allcott (2011b) and Allcott and Rogers (2014), to the authors' knowledge, that have targeted critical hours.

The only example of a time-targeted behavioral intervention of a similar nature in the residential electricity field of which the authors are aware is by Ito, Ida, and Tanaka (2015). This study finds that Japanese electricity customers reduced usage during critical events by 3.1 percent on average when asked to conserve during those hours. The effect is small relative to the 15.4 percent average reduction exhibited by a treatment cell that also faced a higher marginal price at those times. Further, the price response was about the same across several critical events, whereas the "moral suasion" effect was as high as 8 percent for the first events but decayed to zero for later events. The price treatment, unlike the moral suasion treatment, also caused usage reductions at times and on days when there was no price increase; supporting survey evidence suggests that this is explained by customers who received the price treatment developing habits related to more efficient electricity use as a result.

Similar to the findings of Ito, Ida, and Tanaka (2015) but with respect to general rather than peak usage, Reiss and White (2008) find that consumers in San Diego reduced usage more quickly and to a greater degree in response to higher prices than when they were exposed to a mass public conservation campaign. Despite the similar findings of these two studies, further work would be valuable in continuing to compare the effectiveness of these different types of interventions; the authors highlight this as a high-priority area for future research.

Behavioral interventions are generally regarded as having a cost advantage over other types of interventions. For example, Allcott and Mullainathan (2010) argue that the cost of a program that distributes norms-based messages relative to the reduction in usage achieved compares favorably to that of various energy efficiency programs. However, in terms of rate changes rather than energy efficiency policies, it would seem that the cost of distributing notification of an overall rate change would be identical to the cost of sending behavioral messages, as both would seem to primarily involve administrative costs associated with billing. In terms of targeting either a rate change or a behavioral message to a given time of day or critical event, conditional on the requisite metering and communication devices being installed, the costs would again seem to be identical.[k] Answering the cost question more broadly would thus require examining factors beyond notification costs, including, for example, costs associated with program design and approval.[l] The authors are not aware of any studies that make such a comprehensive measurement effort, and flag this as another potentially important question for future research.

Leaving aside the question of their *relative* merits, the studies reviewed thus far demonstrate that both price-based policies and behavioral interventions can be effective policy levers in an *absolute* sense. A question that naturally arises is whether policy makers need to choose between the types of interventions in the first place, or if they should instead simply pursue them in combination. Answering this question requires an examination of the types of motivation that each type of policy could act on. In general, people can have both "extrinsic" and "intrinsic" motivations (Benabou and Tirole, 2003). Extrinsic motivation is related to external rewards, such as financial payments. Intrinsic motivation is more subtle (but potentially powerful), and is related to internal factors such as matters of identity. Price-based policies can generally be expected to act primarily on extrinsic motivation, while behavioral interventions may be more likely to act on intrinsic motivation. While these need not be strict relations, policies that combine price and behavioral elements would seem to be more likely to act on both extrinsic and intrinsic motivations simultaneously. Whether price and behavioral interventions should be combined will thus depend to some degree on how extrinsic and intrinsic motivations might interact. A potential catch in this regard is that these different types of incentives can counteract each other in important ways.

Consider the following example from Gneezy and Rustichini (2000). A daycare notices that parents are arriving late to pick up their children at the end of the day. To create an incentive for more timely pickups, the daycare begins to charge parents for arriving late. However, to its surprise, after these fines come into effect, parents are even *more* late than they were initially. How is this possible? There were two factors at play. The extrinsic factor was financial: initially it was (monetarily) free to show up late. But, initially, there was also a hidden cost on the intrinsic margin: parents felt guilty when they were not on time. Thus, there was a dual effect of imposing a price on tardiness: the daycare triggered extrinsic motivations, in terms of increasing the monetary cost of arriving late; but simultaneously triggered intrinsic motivations in the opposite direction, in terms of implicitly sending parents the message that paying the late charges entitled them to the relatively inexpensive babysitting they effectively thus obtained. That is, the guilt that was constraining them from arriving even later initially was alleviated by the option to pay for extra time at the daycare.

These observations extend to electricity demand, and may help to inform policy design relating to the smart grid. Jessoe, Rapson, and Smith (2014) document an instance where consumers use *less* electricity when the price of electricity *falls* as a result of a policy intervention. On the surface, this seem perplexing. However, the result becomes more reasonable when the intrinsic incentives triggered by the policy are considered in addition to the extrinsic incentives. Prior to the rate structure change that led to a price reduction for some customers, the utility sent customers various communications. These communications made clear that the rate change was targeted at the highest-usage customers, thus potentially inducing a desire in these customers to align with the social norm and/or assuage guilt. The communications also would have made customers more attentive to their usage than normal for a time. Thus, it seems reasonable that the intrinsic motivations and the information effect triggered by the policy could have overcome the extrinsic incentive.

These examples suggest that the design of hybrid policies that could act on both intrinsic and extrinsic motivations should be approached with caution, along two dimensions. First, care must be taken to ensure that the particular incentives of each type to be targeted by a given intervention – accounting for interactions between them – operate in the same direction, so that the various components of the policy enhance rather than offset one another. Second, a policy may act on both motivations even without the knowledge or intent of its designers. Therefore, the possibility that an intervention designed to trigger one type of motivation might also trigger the other should be recognized and analyzed in advance. This is yet another important area in which future research would be desirable.

4.4 Summary

The primary conclusion to be drawn from this survey of behavioral factors in the residential electricity setting is that customer inattention is an enormous challenge that any policy must overcome in order to be effective. The silver lining of this finding, however, is that consumers are more responsive when more attentive and informed, and that smart grid technologies provide an effective means through which consumers can acquire information. A further conclusion is that interventions that appeal to people's desire to conform to social norms by providing social comparisons can be an effective lever for achieving conservation. However, among the many questions the authors have flagged as important areas for future work, perhaps the most important is whether such interventions can be designed such that they achieve meaningful reductions at targeted peak times.

The foregoing presents some of the best-understood evidence on the potential for behavioral factors to influence decision making in the domain of residential electricity usage. However, in a sense, this section has barely scratched the surface of ongoing work by economists in this area. DellaVigna (2009) provides a comprehensive review of empirical evidence on many other specific behavioral drivers in contexts and industries other than energy; it seems likely that several of the insights from this literature will soon be examined within the residential electricity context as well. For example, DellaVigna (2009) discusses evidence that participation in employee savings programs increases when participation is the default and opting out is free, relative to when non-participation is the default and opting in is free; very recently, Faruqui, Hledik, and Lessem (2014) have provided the first evidence of which the authors are aware that the same finding may hold regarding customer adoption of time-varying electricity pricing.

5 CONCLUSION

When the price of electricity rises, fully informed and attentive consumers will use less electricity. This chapter has reviewed substantial evidence from the economics literature that supports this conclusion. Much of this evidence is based on randomized experimental research designs, providing confidence in the causal link from prices to usage. The authors conclude that time-varying pricing is an effective and essential policy instrument for load management and the reduction of short-run and long-run welfare losses in the electricity sector.

Interventions designed to boost customer attentiveness form an important complement to time-varying pricing. Consumer inattention is an enormous challenge that any residential electricity policy faces. Rather than incurring high costs in terms of time and effort to balance consumption and other objectives with electricity costs, households will often prefer to ignore their electricity expenditure and usage. This can substantially dampen and delay consumer response to any intervention. Fortunately, smart grid technologies provide a comprehensive vehicle for improving customer attention. In-home displays connected to smart meters serve as a low-cost means for households to monitor their usage at high frequency and to learn which of the household services they obtain from their electrical appliances are the most costly and energy-intensive. The communications capabilities afforded by these technologies also allow utilities to provide timely notifications regarding upcoming interventions to their customers, and allow households to choose how and when to receive such notifications and reminders.

Behavioral interventions may be able to play an important supporting role as well, but the authors do not recommend that they be pursued at the expense of price-based policies. While interventions that provide social comparisons in order to appeal to consumers' desires to conform to social norms have received much attention and have been effective at inducing general conservation, the extent to which they can achieve peak load reductions is still an open question. In terms of the numerous areas flagged in Section 4 for future study, the most important involve whether such norms-based interventions can be modified to target peak times, and if so, how peak reductions thus achieved compare to those achieved by price-based interventions. A related open question is how price-based and behavioral interventions – and the psychological motivations they act on – might interact when deployed in combination. The authors believe that the ideal way to investigate these and other open questions is in the field, and encourage regulators and industry to work with researchers to learn how deployments and pilot projects can be designed in ways that facilitate the highest quality evaluations.

While several questions await fuller understanding, existing evidence provides strong support, at least from the effectiveness standpoint, for a full-scale roll-out of time-varying pricing. The authors' specific recommendation is to move beyond TOU in favor of a CPP design. The CPP framework allows a sharp price incentive to be delivered at a few precisely targeted times per year, thereby stimulating households to reduce usage when such reductions are most important. The occasional nature of CPP price changes also limits the burden on households in terms of the attention and cognitive effort they are induced to devote to their electricity decision making relative to their existing baseline. This burden could be reduced further – and the potential for yet stronger customer response thereby increased – through the provision of in-home displays, the careful design of notification systems, and the development of programs to train households on the capabilities of the displays and customizability of notifications. Once in place, such a policy package could be easily modified to include the delivery of social comparisons or other behavioral interventions that are found to be desirable in terms of enhancing peak load reductions.

The economic research establishing the effectiveness of such a policy package has been accumulating over many years, and has depended on the communication and monitoring capabilities afforded by smart grid investments. Future research on the outstanding questions that have been highlighted and others will likewise rely heavily on smart meters and other smart grid technologies. Thus, as the penetration of smart grid technologies continues to expand, so too will the ability to understand residential electricity choices in finer detail. However, the true returns on smart grid investments will only be realized when research findings are mobilized in practice. The deployment of a policy such as the one outlined here to a substantial portion of the population is presently feasible, and represents a considerable opportunity to realize these returns.

NOTES

[a]Early contributions include Steiner (1957), Williamson (1966), Kahn (1970), and Panzar (1976), and more recent contributions include Borenstein (2005), Joskow and Wolfram (2012), and many others.

[b]The focus of this chapter is on the effectiveness of time-varying pricing and behavioral policies in meeting objectives related to electricity usage patterns. The purpose is not to compare such policies to alternatives, such as automated demand response. Neither is the purpose to assess the costs of implementing such policies in relation to the benefits of meeting a given objective.

[c]This ideal serves as the starting point for the "potential outcomes framework," also known as the "Rubin Causal Model." For readers interested in a more technical exposition, Rubin (1974) and Holland (1986) are seminal references.

[d]Readers who would like a more technical discussion of this point may refer to Duflo, Glennerster, and Kremer (2007), who also discuss considerations associated with introducing randomization into policy implementation in the field.

[e]List and Price (2013) discuss the distinction between field experiments and laboratory experiments, and also review a number of field experiments from the broader environmental economics literature. Researchers also have at their disposal a suite of alternative empirical methods when randomized experimental designs are infeasible. There is a long history of evaluating behavior in the residential electricity setting using quasi-experimental and structural methods. A discussion of these econometric techniques is beyond the scope of this chapter, but interested readers may refer to Angrist and Pischke (2009), who provide a relatively non-technical exposition of the most commonly-used methods. The majority of the studies reviewed in the next sections derive their results from field experiments, but the discussion is also supplemented with some results based on alternative research designs for completeness.

[f]The three blocks in a TOU pricing scheme are called the peak, off-peak, and – if there is a third – shoulder blocks. The rates associated with each block are usually set bi-annually. The hours covered by a given block are generally fixed or may change at most seasonally. The off-peak rate typically applies for all hours on weekends and holidays.

[g]For simplicity, this discussion neglects fixed costs, which are commonly reimbursed to utilities via (variable) price, thus further muddying the relationship between optimal wholesale and retail prices.

[h]One of the programs discussed by Faruqui and Sergici (2010) featured voluntary recruitment into treatment, weakening the experimental design. For this reason, they do not include this study in their meta-analysis of empirical results or the overall conclusions discussed here.

[i]In addition to programs involving the three forms of time-varying pricing described above, Faruqui and Sergici (2010) also examine a few instances of programs that offered peak-time rebates. Such programs are similar to CPP, except that, instead of facing a higher rate during critical hours, households receive payments for electricity they do *not* use at these times. Faruqui and Sergici (2010) find that these programs also led to reductions in peak usage, but note that difficulties arise with measuring the appropriate household-specific baseline usage level for calculating rebate levels. See also Wolak (2006).

[j]Note that Allcott (2011b) finds no evidence of such a "boomerang effect" in the setting he studies, which he attributes to an additional pro-social or "injunctive norms" aspect of the information contained in the household comparison reports.

[k]The primary purpose of time-varying rate structures is to induce load shifting rather than general conservation. In terms of comparing costs associated with effecting a given usage reduction at given times of day, the costs of expanding the penetration of smart grid technologies must therefore be considered for *both* price and behavioral interventions, as both would need to rely on the time-specific monitoring and communication capabilities of such technologies.

[l]Another category of costs that may be relevant is psychological costs. As Ito, Ida, and Tanaka (2015) discuss, when customers reduce usage in response to moral suasion, one interpretation is that they receive a "warm glow" from behaving as they are asked to; but moral suasion could just as plausibly lead to psychological costs related to, for example, social pressure, which customers then attempt to alleviate by reducing usage. An important component of answering the cost question would thus be a careful determination of what types of psychological costs would and would not be induced in a given setting by either type of intervention.

REFERENCES

Aigner, D. The residential time-of-use pricing experiments: What have we learned? In Hausman, J. A. and Wise, D. A., editors, *Social Experimentation*, pages 11–41. University of Chicago Press, Chicago, 1985.

Alberini, A., Gans, W., and Velez-Lopez, D. 2011. Residential consumption of gas and electricity in the U.S.: The role of prices and income. *Energy Economics*, 33(5):870–881.

Allcott, H. 2011a. Rethinking real-time electricity pricing. *Resource and Energy Economics*, 33(4):820–842.

Allcott, H. 2011b. Social norms and energy conservation. *Journal of Public Economics*, 95 (9-10):1082–1095.

Allcott, H. and Mullainathan, S. 2010. Behavior and energy policy. *Science*, 327(5970): 1204–1205.

Allcott, H. and Rogers, T. 2014. The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review*, 104 (10):3003–3037.

Angrist, J. D. and Pischke, J.-S. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, Princeton, 2009.

Benabou, R. and Tirole, J. 2003. Intrinsic and extrinsic motivation. *Review of Economic Studies*, 70(3):489–520.

Borenstein, S. Time-varying retail electricity prices: Theory and practice. In Griffin, J. and Puller, S. L., editors, *Electricity Deregulation: Choices and Challenges*, pages 317–358. University of Chicago Press, Chicago, 2005.

Borenstein, S. 2013. Effective and equitable adoption of opt-in residential dynamic electricity pricing. *Review of Industrial Organization*, 42(2):127–160.

Borenstein, S. and Holland, S. 2005. On the effiency of competitive electricity markets with time-invariant retail prices. *RAND Journal of Economics*, 36(3):469–493.

Caves, D. W., Christensen, L. R., and Herriges, J. A. 1984. Consistency of residential customer response in time-of-use electricity pricing experiments. *Journal of Econometrics*, 26:179–203.

DellaVigna, S. 2009. Psychology and economics: Evidence from the field. *Journal of Economic Literature*, 47(2):315–372.

Duflo, E., Glennerster, R., and Kremer, M. Using randomization in development economics research: A toolkit. In Schultz, T. P. and Strauss, J. A., editors, *Handbook of Development Economics, Volume 4*, pages 3895–3962. Elsevier, Amsterdam, 2007.

Faruqui, A. and Sergici, S. 2010. Household response to dynamic pricing of electricity: A survey of 15 experiments. *Journal of Regulatory Economics*, 38(2):193–225.

Faruqui, A., Sergici, S., and Sharif, A. 2010. The impact of informational feedback on energy consumption—a survey of the experimental evidence. *Energy*, 35(4):1598–1608.

Faruqui, A., Hledik, R., and Lessem, N. August 2014. Smart by default: Time-varying rates from the get-go – not just by opt-in. *Public Utilities Fortnightly*.

Fell, H., Li, S., and Paul, A. 2014. A new look at residential electricity demand using household expenditure data. *International Journal of Industrial Organization*, 33:37–47.

Gans, W., Alberini, A., and Longo, A. 2013. Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in northern ireland. *Energy Economics*, 36:729–743.

Gilbert, B. and Graff Zivin, J. 2014. Dynamic salience with intermittent billing: Evidence from smart electricity meters. *Journal of Economic Behavior & Organization*, 107, Part A: 176–190.

Gneezy, U. and Rustichini, A. 2000. Pay enough or don't pay at all. *Quarterly Journal of Economics*, 115(3):791–810.

Goldstein, N. J., Cialdini, R., and Griskevicius, V. 2008. A room with a viewpoint: Using social norms to motivate environmental conservation in hotels. *Journal of Consumer Research*, 35(3):472–482.

Holland, P. W. 1986. Statistics and causal inference. *Journal of the American Statistical Association*, 81(396):945–960.

Ito, K. 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. *American Economic Review*, 104(2):537–563.

Ito, K., Ida, T., and Tanaka, M. The persistence of moral suasion and economic incentives: Field experimental evidence from energy demand. National Bureau of Economic Research Working Paper No. 20910, January 2015.

Jessoe, K. and Rapson, D. 2014. Knowledge is (less) power: Experimental evidence from residential energy use. *American Economic Review*, 104(4):1417–1438.

Jessoe, K., Rapson, D., and Smith, J. B. 2014. Towards understanding the role of price in residential electricity choices: Evidence from a natural experiment. *Journal of Economic Behavior & Organization*, 107, Part A:191–208.

Joskow, P. Comment on the residential time-of-use pricing experiments: What have we learned? In Hausman, J. A. and Wise, D. A., editors, *Social Experimentation*, pages 42–48. University of Chicago Press, Chicago, 1985.

Joskow, P. and Wolfram, C. 2012. Dynamic pricing of electricity. *American Economic Review*, 102(3):381–385.

Kahn, A. E. *The Economics of Regulation: Principles and Institutions, Volume 1.* John Wiley & Sons, New York, 1970.

List, J. A. and Price, M. K. Using field experiments in environmental and resource economics. National Bureau of Economic Research Working Paper No. 19289, August 2013.

Panzar, J. C. 1976. A neoclassical approach to peak load pricing. *Bell Journal of Economics*, 7(2):521–530.

Reiss, P. C. and White, M. W. 2005. Household electricity demand, revisited. *Review of Economic Studies*, 72(3):853–883.

Reiss, P. C. and White, M. W. 2008. What changes energy consumption? Prices and public pressures. *RAND Journal of Economics*, 39(3):636–663.

Rubin, D. B. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66(5):688–701.

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., and Griskevicius, V. 2007. The constructive, destructive, and reconstructive power of social norms. *Psychological Science*, 18(5):429–434.

Sexton, S. 2014. Automatic bill payment and salience effects: Evidence from electricity consumption. *Review of Economics and Statistics*. DOI: 10.1162/REST_a_00465.

Simon, H. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics*, 69 (1):99–118.

Steiner, P. 1957. Peak loads and efficient pricing. *Quarterly Journal of Economics*, 71(4): 585–610.

U.S. Department of Energy. *Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them: A Report to the United States Congress Pursuant to Section 1252 of the Energy Policy Act of 2005.* 2006.

Williamson, O. 1966. Peak-load pricing and optimal capacity under indivisibility constraints. *American Economic Review*, 56(4):810–827.

Wolak, F. Residential customer response to real-time pricing: The Anaheim critical-peak pricing experiment. Working Paper, 2006.