Household Response to Time-Varying Electricity Prices

Matthew Harding[1] and Steven Sexton[2]

[1]Department of Economics, University of California, Irvine, California 92697; email: harding1@uci.edu

[2]Sanford School of Public Policy, Duke University, Durham, North Carolina 27708; email: steven.sexton@duke.edu

Annu. Rev. Resour. Econ. 2017. 9:19.1–19.23

The *Annual Review of Resource Economics* is online at resource.annualreviews.org

https://doi.org/10.1146/annurev-resource-100516-053437

JEL Codes: Q41, D03

Keywords

electricity, dynamic prices, time-of-use rate, demand response, peak load, automation

Abstract

The diffusion of smart metering technology and intermittent renewable electricity generation capacity makes the deployment of time-varying electricity rates increasingly feasible and important to the functioning of electricity grids. Such rates, which economists advocate to more efficiently match supply and demand, remain rare, though experiments assessing consumer responses are not. This review synthesizes evaluations of these experiments in the context of a theory of consumer inattention and adjustment costs that posits a role for automation technology to boost the short-run price elasticity of demand and affect demand-side reductions that can lower generation costs.

1. INTRODUCTION

In order to avert the power outages that became routine during cold winter mornings in postwar Britain, regulators implemented seasonal tariffs that raised electricity rates in winter, when electricity was scarce, and lowered rates the rest of the year, when generating capacity was less strained (Weightman 2011). The seasonal tariff, the first concerted effort by electricity suppliers to employ prices to lower peak demand, was abandoned after only one year because it had no appreciable effect on demand (Houthakker 1951, Weightman 2011). The British Electricity Authority resorted instead to public appeals for cooperation. Its campaign explained the peak-load problem as akin to rush hour on buses and trains, and it implored the public not to use increasingly popular electric fires that chiefly contributed to a ten-year trebling of demand:

> We must go easy with electricity during the Peak Hours. If too many people try to use too much electricity during Peaks, the power stations have to cut supplies, and that means discomfort and inconvenience. We can plan our day to use the electricity we want in *Off-Peak* hours (Weightman 2011).

The inability of the so-called Clow differential to ameliorate the peak demand problem in Britain did little to abate enthusiasm among economists for time-varying prices. A robust literature dating at least back to Clark (1911) documents the consistent prescription from economists to use dynamic prices to lower peak demand and avoid the excess capacity in off-peak periods that attends time-varying electricity demand and uneconomical storage. The inefficacy of the Clow differential is readily ascribed to inelastic demand and low substitutability of electricity services across seasons (Houthakker 1951). After all, one is unlikely to find home heating in summer a satisfactory substitute for home heating in winter. Nevertheless, Britain's early experience with time-varying prices provided an early indication of the potential limitations of prices in reallocating electricity demand across time.

Since then, dozens of robust trials and pilot programs in the United States and elsewhere have tested responses to pricing regimes that better approximate the economist ideal of retail rates adjusting instantaneously to real-time generation costs. These time-varying price regimes differ along several dimensions. First, some have incorporated dynamic rates, which, distinct from time-of-use (TOU) rates, respond to changes in generating costs. TOU rates include two or more fixed rates that vary across periods of the day and perhaps days of the week but are not dictated by real-time generating costs and do not vary in the short run. Second, the rates have varied in frequency of price changes, which Borenstein (2005b) termed granularity. Third, rates vary in timeliness—the lag between announcement of new rates and their implementation (Borenstein 2005b).

Few trials have exposed residential customers to real-time pricing (RTP) that varied according to contemporaneous generating costs (Allcott 2011b). More common are tariffs that expose residential customers to TOU rates that differ across peak and off-peak periods (Aigner & Hausman 1980, Braithwait 2000, Harding & Lamarche 2016, Mitchell & Acton 1980, Train & Mehrez 1994) and critical peak pricing (CPP) that introduces infrequent but often dramatic, unanticipated, and short-lived price variation (Bollinger & Hartmann 2016, Faruqui & George 2005, Faruqui et al. 2012, Herter 2007, Jessoe & Rapson 2014, Wolak 2010). Despite experimentation, much of it in randomized control settings, there remains little agreement as to how effective widespread adoption of time-varying prices is in reducing electricity costs.

Ambiguity in price responsiveness derives from at least two sources of heterogeneity. First, the experiments themselves vary in important ways. They test distinct price interventions. Some evaluate TOU pricing regimes; others test responses to CPP events, whereas still others introduce RTP. These distinct regimes are explicitly defined, and their characteristics are summarized in

Table 1 Electricity tariff types in the United States

Price regime	Definition	Granularity	Timeliness	Uncertainty	Reflection of generating costs
Flat-rate	Time-invariant rates	None	High	None	Low
Time-of-use (TOU)	Predetermined rates that vary by time of day, day of week, or week of year but do not vary in the short run according to generating costs	Low	High	None	Moderate
Critical peak pricing (CPP)	Flat rates that increase by predetermined amounts for specified lengths of time when generating costs exceed thresholds	Moderate	Moderate	Moderate	Moderate
Variable critical peak pricing (VPP)	Rates that vary during CPP events according to generating costs	Moderate	Moderate	Moderately high	Moderately high
Real-time pricing (RTP)	Rates that vary (typically) hourly to reflect contemporaneous generating costs	High	Low	High	High

Table 1. Given the differences in granularity, timeliness, and uncertainty across these regimes, behavioral responses are expected to vary. Experiments also differ in duration, and they impose price changes of varying magnitudes. Moreover, some interventions seek to boost the accessibility and salience of price and consumption information. Some equip customers with technologies to automate responses to price changes.

A second source of heterogeneity is derived from the customers themselves, and in particular, their energy consumption habits. Responses to temporary or persistent variation in electricity rates depend upon available mechanisms of response. Customers can respond to high prices, for instance, by adjusting home heating and cooling demands, which may be relatively elastic among the demands for electricity services. But if high prices coincide with temperate weather, then heating and cooling demands are low, and they afford consumers little opportunity to respond to price signals. Likewise, some customers will exhibit greater elasticity than others. Customers also vary in their stocks of energy-consuming durables and in their attentiveness to and costs of adjusting to energy prices. To the extent that these characteristics are not randomly distributed across space, then draws from distinct utility customer populations are likely to yield distinct experimental results.

Perhaps due to uncertainty over the consumer response to dynamic prices, such tariffs remain rare among residential households, even though engineers and economists recognized the inefficiency of flat-rate pricing more than a century ago (e.g., Clark 1911). TOU rates had, in fact, been advocated in industry circles since the earliest days of the industry, when virtually all electricity was consumed for lighting at night. But the favored price regime at the time was characterized by demand charges that imposed prices according to the magnitude of an individual customer's peak demand rather than the magnitude of his consumption during the system peak. A 1921 survey of US electric companies found only one instance of time-differentiated rates—for auxiliary and emergency service to industrial customers in Detroit, Michigan (Eisenmenger 1921).

Nearly a century later, dynamic pricing remained a novelty (FERC 2011). By one estimate, less than 1% of US households were enrolled in TOU rates in 2014 (Wald 2014).[1] In Texas, where

[1] Borenstein & Bushnell (2015) report that only a small percentage of utility customers face tariffs with any dynamic component.

retail competition provided a unique inducement for tariff innovation, less than 5% of households faced time-varying prices (Krauss & Cardwell 2015). Yet by 2016, rapid expansion and planned growth of variable renewable capacities created an ever-greater imperative for dynamic prices. The intermittency of wind and solar generation is accommodated only by building costly reserve-generating capacity and storage or by load control. Load control is accomplished by involuntary curtailments or by voluntary adjustments such as those induced by price signals.

Substantial investments in metering technology since 2009 contributed to an electric grid that by 2016 was poised to capitalize on price responses to resolve the perennial peak demand problem and the recent challenge of integrating intermittent renewable generation capacity. Sixty-five million smart meters that record electricity consumption at high temporal resolution were deployed to more than half of US households by the end of 2015. A mere eight years earlier, only seven million smart meters had been installed. The recent smart meter expansion was propelled by funding from the American Recovery and Reinvestment Act, which dedicated approximately US$5 billion in federal funds to smart meter deployment beginning in 2009. As much as $20 billion of additional utility investments were expected to produce a ten-year, tenfold increase in installed smart meters by 2017.[2]

Given such substantial investments in technologies that enable dynamic rates, and given the growing imperative for precise demand response imposed by the penetration of variable renewable energy, an understanding of the consistent patterns of consumer response to pricing interventions is exceedingly important. Similarly important is the ability to relate these patterns to theories of consumer behavior that can inform rate design. This review, therefore, endeavors to synthesize several decades of electricity price experimentation and to account for the dimensions of heterogeneity that may obscure—in predictable ways—the consistent patterns of electricity demand response. For instance, scarcity of attention, which only recently became a subject of major interest to economists, is shown in the most recent wave of empirical research to dramatically affect the price elasticity of electricity demand, with important implications for rate design and the scope of demand response.

Section 2 provides a brief review of the theory of efficient electricity pricing, which demands not just prices that vary temporally but also spatially to account for transmission and distribution constraints. A synthesis of the empirical literature on dynamic pricing response is undertaken in Section 3. Section 4 reviews the limited impacts of dynamic pricing on consumer and producer welfare, and Section 5 evaluates the evidence on environmental impacts of load shifting. A final section considers the implications of dynamic pricing for the modern electricity grid and enumerates ongoing research needs.

2. THE INEFFICIENCY OF TIME-INVARIANT RATES

Electricity generation costs exhibit persistent diurnal and seasonal patterns due to changing demand; they also show idiosyncratic and sometimes dramatic variation that bears on the optimal design of retail rates. Demand peaks in the summer across the United States during the late afternoon as households return home from work. This pattern is evident in **Figure 1**, which depicts the average hourly load (in megawatts) for the PJM Interconnection LLC (PJM) transmission organization that serves parts of the US Midwest, Northeast, and mid-Atlantic regions. Peak load is met by generating units that adjust their production to demand conditions. These "load following" generators are characterized by relatively low fixed costs suitable for plants that operate only

[2]Author calculations and based on Cooper (2016) and FERC (2015).

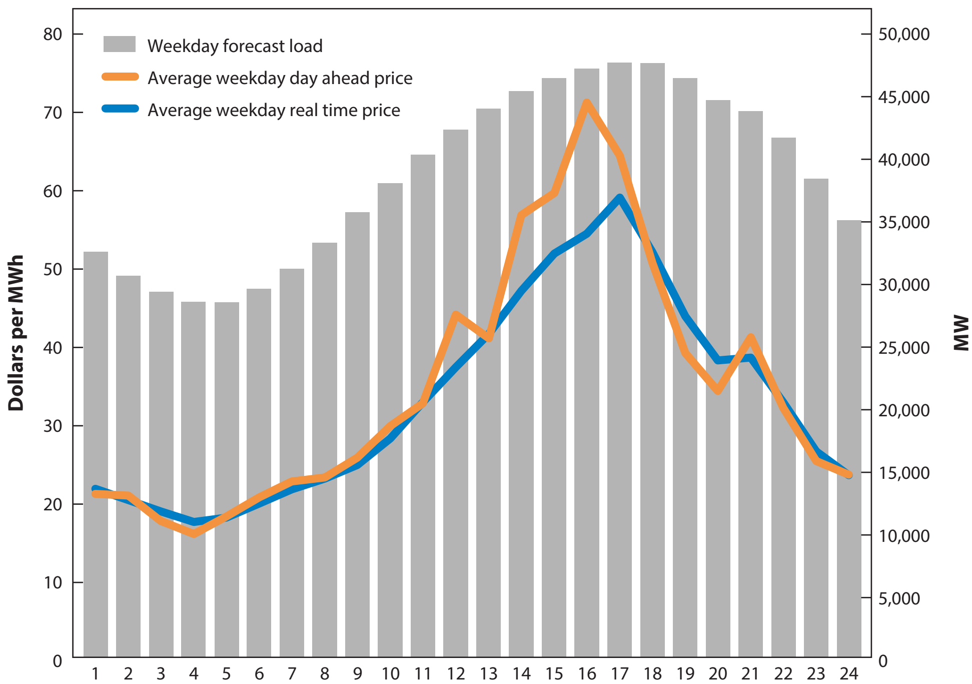

Figure 1

Average hourly load, day-ahead prices, and real-time prices for the utility PJM Interconnection LLC in August, 2016 in the US Midwest, Northeast, and mid-Atlantic regions.

at peak demand. Their marginal costs of production, however, are relatively high due to the costs of source fuel. Consequently, electricity prices must rise with demand to induce these producers to ramp up supply, as seen in **Figure 1**, which also reports average day-ahead and real-time electricity prices in the PJM. This persistent pattern of demand and the attendant evolution of prices motivate appeals for retail electricity rates that vary—at the least—by time of day.

Shocks to the electricity grid can also induce considerable variation in prices for the same hours across different days. Short-term wholesale electricity prices are prone to volatility because of imprecision in demand forecasts, insensitivity of demand to prices, binding constraints on supply capacity at peak periods, and costly storage (Borenstein 2002). Prices surge when weather shocks or unexpected generator failures stretch grid capacity. In the summer of 2016, for instance, hot weather and risk of transmission failures from lightning strikes propelled the spot price of electricity in New York to $1,042/MWh, from $94 an hour earlier, and $50 still earlier in the day (Malik 2016, Wattles 2016). In California and Texas, by contrast, electricity prices repeatedly turned negative in 2015 and 2016 to induce costly output reductions necessary to accommodate unexpectedly high renewable generation (Malik & Weber 2016). These shocks render even TOU rates suboptimal. Immune to the wholesale price volatility across days, customers facing TOU rates overconsume in periods of unusually high prices and underconsume in periods of atypically low prices. Economists, therefore, champion RTP that transmit both systematic and idiosyncratic price fluctuations to consumers, typically with an incremental margin to compensate utilities for fixed costs (e.g., Borenstein 2005a).

The inefficiency of fixed, flat-rate tariffs that provide customers constant prices irrespective of electricity generation costs was perhaps never more evident than during the California electricity crisis of 2000–2001. High costs, pressure from industrial customers, and excessive and costly capacity investments by the state's three vertically integrated investor-owned utilities spurred effort to deregulate the industry by introducing a competitive wholesale market and competitive retail customer choice (Joskow 2001). However, retail rates were fixed during a transitional period when high demand growth, high natural gas prices, and low hydroelectric generation caused wholesale prices to climb 500% between 1999 and 2000.

By early 2001, average wholesale spot prices were ten times greater than they were two and three years earlier, before the transition to competitive markets began in earnest. Unable to recover the costs of supplying electricity, California's largest utilities became insolvent, and the state was obligated to procure electricity in wholesale markets at a cost of more than $1 billion per month (Borenstein 2002, Joskow 2001). The state also entered into long-term contracts at high rates that continue to burden the state's ratepayers. These efforts still did not spare customers from involuntary curtailments as the new independent system operator endeavored to maintain grid stability. Had retail customers faced RTP, high prices during the crisis may have induced conservation that could have lowered generation costs and averted blackouts. They also would have allowed utilities to avoid daily losses in the millions of dollars that caused them to stop paying their bills (Borenstein 2002). The absence of a demand response by retail customers to high wholesale prices is considered a primary cause of the California crisis (Borenstein 2002, Borenstein et al. 2002).

Though dynamic retail prices have long been understood as a palliative for the peak-load problem of electricity generation, only relatively recently has attention turned to the problem of peak-load congestion in transmission networks (e.g., Wolak 2011). Just as generator capacity binds during peak periods, so too does transmission capacity. Marginal costs of electricity supply to load centers, therefore, vary not only across hours of the day, but also across regions of transmission networks. Thus, a marginal unit of production downstream from a transmission bottleneck, for instance, is more valuable than a marginal unit of production upstream because it avoids capital investment in new transmission capacity.

Just as fixed, uniform retail rates provide no incentive for shifting demand across time, neither do they provide incentives for shifting demand across space. Because capacity constraints bind to varying degrees and at varying times across the grid, the first-best retail electricity rates vary by both space and time. Though no such pricing has been introduced at the retail level, regional transmission operators in some regions of the United States have implemented locational marginal pricing (LMP), or nodal pricing, in wholesale markets to appropriately value generation capacity throughout the grid. On a summer day in the PJM, the highest LMP exceeds the lowest LMP during a peak hour by more than 300%, reflecting heterogeneity in transmission congestion and losses throughout the region. PJM estimated the total cost of congestion in the region in 2015 at $1.38 billion (PJM Interconnect. 2015). Wholesale LMPs could guide efficient deployment of distributed renewable energy capacity, in addition to central plant capacity, if those investing in the distributed capacity faced appropriate prices. However, virtually all adopters of rooftop solar photovoltaics face incentives based on retail rates that are undifferentiated according to their value to the grid. Unsurprisingly, then, there is virtually no evidence that installed rooftop solar capacity has avoided transmission or distribution investments (Borenstein 2012).

Conditional on capacity investments, efficient prices for retail electricity are equal to the marginal cost of supply at every moment in time and in every location on the grid. But marginal cost pricing generates revenue shortfalls for utilities because of scale economies in generation, transmission, and distribution. Fixed costs are not recovered. Retail rates have historically been set to allow considerable shares of fixed costs to be recovered from volumetric charges, as opposed to fixed access charges. Thus, not only were rates fixed, but they were fixed too high relative to efficient rates. Fixed cost recovery can instead be attained by a fixed charge per customer that would not distort consumption along the intensive margin. Moreover, because demand for grid connections, i.e., electricity service, is inelastic, such access charges do not impose substantial distortions along the extensive margin (Borenstein & Bushnell 2015).

Electricity demand is itself inelastic in the short run because of the importance of lighting, heating and cooling, appliances, and electronics equipment to modern homes and because of limited substitution possibilities in the short run (Allcott 2011a, Ito 2014, Jessoe & Rapson 2014, Reiss & White 2005). In the longer run, electricity demand exhibits greater elasticity due to opportunities for fuel switching and energy efficiency investments. The extent of efficiency losses from suboptimal rate design depends upon the degree to which price-inelastic consumers vary their consumption with prices. Were demand perfectly inelastic, then suboptimal rates would impose no distortions on the intensive margin. Though households are known to exhibit some price response in the short run, only the recent wave of experiments has proposed to resolve how short the short run can be to still elicit responses. That is, do consumers respond to very short-run intraday price variation? Do they respond to price changes that are anticipated versus unanticipated or large versus small? The following section endeavors to answer those questions by synthesizing the recent empirical literature in the context of behavioral theories of attention scarcity.

3. LESSONS FROM EMPIRICAL EVIDENCE ON HOUSEHOLD RESPONSE TO DYNAMIC PRICES

The early wave of residential, time-varying pricing evaluations included 15 experiments funded by the US Department of Energy (DOE) that implemented TOU prices in 12 states. The experiments were expressly intended to determine the impact of the rates on load patterns, as well as to evaluate customer acceptance of TOU rates and to demonstrate technical and administrative feasibility of the rates. However, the experiments were plagued by a variety of problems that limited the internal and external validity of their estimated impacts on electricity demand (Aigner 1985, Miedema & White 1980). Variously, they suffered from small and highly selected samples, and insufficient independent price variation from which to estimate demand parameters (Aigner & Ghali 1989, Train & Mehrez 1994). Aigner (1985) nevertheless concluded that the dynamic prices "worked" but that there remained "a hung jury" as to the question of magnitudes. The various experiments yielded no consensus as to how much peak conservation could be expected.

A more recent wave of experimentation and evaluation has been undertaken by state regulators and utilities. These studies are also subject to critique, which we turn to briefly at the end of this section. Still, they have yielded credible experimental results that, combined with earlier findings, begin to inform a theory of consumer response to dynamic electricity prices (Braithwait 2000; Faruqui & Sergici 2010, 2013; Faruqui et al. 2009; Taylor et al. 2005). Such a theory, in turn, can inform utilities, regulators, and other market participants who must consider rate design and technology and capacity investments in light of a substantial recent expansion of smart meters that make dynamic rates practical. Such a theory also helps to reconcile apparent differences in existing and future experimental results and to guide further experimentation that is needed to fully characterize residential customer responses to time-varying prices. Nonetheless, the existing body of empirical work suggests some lessons learned.

4. PEAK DEMAND ELASTICITIES ARE GENERALLY LOW AND SENSITIVE TO ADJUSTMENT OPPORTUNITIES

In prescribing solutions to the peak demand problem, economists have long asserted the importance of "getting the prices right" (e.g., Clark 1911; Boiteux 1960, 1964; Borenstein 2002, 2005a,b, 2009; Borenstein & Holland 2005; Hausman & Neufeld 1984; Hogan 1999; Houthakker 1951; Letzler 2007; Steiner 1957; Turvey 1968; Watkins 1915, 1916;). Indeed, Joskow (2012, p. 40) asserts that "using appropriate prices to provide consumers with an incentive to cut peak demand during a small number of hours can reduce generating costs significantly in the long run." Yet a first lesson corroborated by the body of empirical research is the one learned by regulators in postwar Britain whose seasonal rates yielded essentially no demand response. In the absence of technologies that enable demand response, the introduction of dynamic rates is not likely to solve or even considerably improve the peak-load problem as economists had claimed. A review by RTI International for the DOE found that the early wave of experiments all demonstrated peak demand reductions, though they were not statistically significant in all studies, and price elasticities were generally small (Miedema & White 1980).

In one of the first evaluations of the modern wave of dynamic pricing experiments, Allcott (2011b) estimated a demand elasticity of −0.06 to −0.08 among Chicago households recruited to a randomized trial of the first-ever hourly RTP tariff for residential customers. Though households exhibited statistically significant demand response to both intrahour and interhour price variation, the reductions in peak demand were insufficient to merit the considerable investment necessary to implement the more sophisticated pricing regimes. Compensating variation for the typical household was equal to 1–2% of annual electricity expenditures (or $10), but Allcott concluded that the costs of conservation and metering technology likely outweighed the benefits. The conclusion that dynamic prices had economically insignificant effects on demand, particularly peak demand, concurred with several postmortems of the first wave of US experiments in the 1970s and 1980s.

Studies among the recent wave of experimentation also find low responsiveness to dynamic prices in the absence of "enabling" technologies that either reveal price and consumption information or automate price responses. Bollinger & Hartmann (2016), for instance, evaluated a randomized control trial conducted by an electric utility in the southern United States in 2011. Volunteer households were randomly assigned to the control, a TOU tariff, or a variable peak pricing (VPP) tariff that imposed a price during peak periods that varied according to market conditions. Households in each arm of the experiment also faced seven CPP events on occasions when reserve capacity margins were nearly exhausted. Prices during the CPP events were five times greater than the flat-rate prices faced by households in the control group. Households were notified about CPP events 2 h in advance. In the baseline intervention, households could access a website to learn price and consumption information. Average peak period demand reductions reported by the authors imply demand elasticities of −0.16 and −0.13 among households facing the TOU and VPP tariffs, respectively. During CPP events, the implied elasticities are −0.17 and −0.11 for each treatment group, respectively. Thus, consumers are no more sensitive to CPP events than to TOU or VPP when adjustments are constrained to those that can be implemented within 2 h of a CPP event or during the event itself.

Likewise, in a 2011 randomized control trial in Connecticut, Jessoe & Rapson (2014) introduced six CPP events that exogenously increased prices 200–600% for a 4-h period. In one arm of their experiment, treated households were alerted to the price changes by phone, text message, or email one day in advance of the event. Demand responses to price changes with day-ahead notice imply a price elasticity of −0.10. When notification of CPP events is provided only 30 min in advance of the price changes, no statistically significant response is observed. Wolak (2010) evaluated a similar intervention in Washington, DC in 2008, estimating a 9.7% demand reduction in response to a six-times-greater price during CPP events. The implied elasticity is −0.12. Notably, the experiment also featured a treatment in which households faced similar marginal incentives for peak period conservation in the form of rebates for reductions in demand from a reference level. Households were only half as responsive to the rebates as they were to the CPP, which Wolak attributes to "an option to quit" conserving. Unlike households facing the CPP treatment, households enrolled in the rebate treatment did not face the CPP marginal cost for consumption beyond their reference levels. Lesser responsiveness to potential gains from consumption changes as opposed to potential losses may also be indicative of loss aversion (Kahneman et al. 1991, Tversky & Kahneman 1991).

A number of experiments evaluated by The Brattle Group, a consultancy, from 2003–2010 also imply low demand response to dynamic prices in the absence of enabling technologies. In Michigan, demand reductions from TOU pricing imply elasticities of −0.13 and −0.14 (Faruqui et al. 2013). Responses to CPP events that more than tripled the TOU peak price imply elasticities of −0.18 and −0.19. In California, implied elasticities for TOU pricing and CPP are −0.13 and −0.17, respectively (Faruqui & George 2005). In Connecticut, TOU peak rates 40–60% above prevailing flat rates induced demand reductions of 1.5–3%, implying elasticities of −0.06 to −0.07. An elasticity of −0.18 is implied by a 16% average demand reduction in response to nine-times-greater CPP with day-ahead notification (Faruqui et al. 2012).

Although nearly all evaluations document peak demand reductions due to elevated peak prices, these studies consistently demonstrate low residential price responsiveness to the mere introduction of TOU, RTP, or CPP tariffs. Among the recent experimental evaluations, implied elasticities are all less than 0.20 in absolute value, as summarized in **Table 2**, suggesting that substantial price changes are necessary to induce economically meaningful demand response. This result is perhaps unsurprising, given that an optimizing household only reduces demand at peak if it (*a*) perceives higher prices and (*b*) identifies channels of demand reduction for which the benefits of avoided electricity expenditures at peak exceed the costs of foregone electricity services at peak. The costs of reducing consumption during pricing events, such as CPP, presumably increase as the window of advanced notification shrinks; i.e., timeliness declines, because intertemporal substitution opportunities are constrained, and adjustment costs are high. For instance, if CPP events are called in the afternoon with only a few minutes or few hours of notice, members of a household may be at work and unable to adjust thermostat settings or other passive uses of electricity in response to CPP events without returning home at great inconvenience. Likewise, opportunities for intertemporal substitutions toward consumption in advance of the pricing events are limited.

Even if households correctly perceive dynamic prices and have opportunities to adjust consumption at a relatively low cost, they may not perceive the marginal costs of electricity-consuming activities because of ignorance about the electricity consumed in the production of electricity services. Consequently, they would be unable to determine the benefits in avoided electricity costs of deviating from normal consumption patterns. A household may not know the hourly electricity consumed by a television, for instance, let alone the cost of that consumption given flat or dynamic rates. Yet the efficiency benefits of marginal cost pricing (or dynamic pricing generally) depend upon precisely this kind of perfect optimization on the basis of perfect information. Price (2014) characterizes the consumer problem as an incredibly complicated dynamic programming problem the likes of which are typically difficult for consumers to solve (e.g., Brown et al. 2009, Cho & Rust 2010, Houser et al. 2004). A bias in favor of status quo consumption is consequently unsurprising.

5. INFORMATION ABOUT CONSUMPTION AND PRICES BOOSTS PEAK DEMAND ELASTICITIES

Households are likely to be ignorant of the electricity consumed by their marginal consumption of electricity services because monthly billing records afford limited feedback. It is nearly impossible for households to attribute changes in monthly electricity consumption to changes in consumption

Table 2 Implied price elasticities of electricity demand from dynamic pricing experiments in the United States[a]

Study	Location, date of study	Information feedback	Automation technology	TOU	CPP	CPP timeliness
Bollinger & Hartmann (2016)[b]	Oklahoma, June–Sept., 2011	Portal	None	−15.8%	−17.1%	2-h
		Portal, IHD	None	−25.2%	−25.7%	2-h
		Portal	PCT	−47.3%	−46.5%	2-h
		Portal, IHD	PCT	−42.5%	−42.8%	2-h
Jessoe & Rapson (2014)	Connecticut, July–Aug., 2011	None	None	None	−10.4%	day-ahead
		IHD	None	None	−30.4%	day-ahead
		None	None	None	0.0%	30-min
		IHD	None	None	0.0%	30-min
Faruqui et al. (2013)	Michigan, July–Sept., 2010	None	None	−12.9%	−18.1%	day-ahead
		None	PCT	−10.0%	−23.1%	day-ahead
Faruqui et al. (2012)	Connecticut, June–Aug., 2009	None	None	−7.5%	−18.1%	day-ahead
		IHD/color-changing globe	None	−7.5%	−18.1%	day-ahead
		None	PCT	−7.5%	−26.2%	day-ahead
Faruqui & Sergici (2011)	Baltimore, June–Sept., 2008	None	None	None	−22.7%	day-ahead
		Color-changing globe	(utility-controlled) AC switch	None	−36.7%	day-ahead
Wolak (2010)	District of Columbia, July 2008–Mar. 2009	None	None	None	−11.6%	day-ahead
		None	PCT	None	−27.9%	day-ahead
Herter et al. (2007)	California, July 2003–Sept., 2004	None	None	None	−16.3%	day-ahead
		None	PCT	None	−51.3%	4-h
Faruqui & George (2005)	California, July 2003–Sept., 2004	None	None	−13.4%	−16.8%	day-ahead
		None	PCT	−9.8%	−34.0%	4-h

[a]Results from Allcott (2011b) and Harding & Lamarche (2016) are not included in the table due to inconsistency in the reported format. Both articles focused on the hourly change in consumer responses instead of reporting the general treatment effects or elasticities.
[b]The Bollinger & Hartmann (2016) study also included treatment effects of VPP with CPP. With day-ahead notification, elasticity for CPP is −13% for households equipped with only access to a web portal. This elasticity drops to −11% if households receive 2-h ahead notifications.
Abbreviations: AC, air conditioning; CPP, critical peak pricing; IHD, in-home display; PCT, programmable communicating thermostat; TOU, time-of-use.

of particular energy services, e.g., lighting, electronics, and heating. Faruqui et al. (2010, p. 1598) characterize the information burden required for optimal dynamic pricing response thus:

> Imagine a world in which Joe Smith drives up to the gas pump in his large SUV, fills up his truck, and drives away without paying a dime. The gasoline is not free, but Smith won't know how much he has purchased or how much he owes until 3 months later because he has a quarterly account with the gas station. When his wife drives up to the pump in the family sedan, she goes through the same procedure, as does their high school senior, who drives up to the pump in her compact coupe. The Smiths get a combined bill and don't know how the charges accumulated. Was it Joe's driving, his wife's driving or their daughter's driving that accounted for the lion's share of the bill? What makes life even more interesting for the Smiths is that none of their cars have a speedometer or a gas gauge. They get no

feedback at all on how to manage their gas bill. Are the Smiths living in some type of parallel universe? No, if we were to change the gas station to an electric utility, the Smiths are living in the world as we know it today.

Consequently, there are at least two types of information problems. The first is information pertaining to dynamic electricity rates. Households may not know the price they face in any instant (Ito 2014, Shin 1985). The second information problem derives from the typical consumer's ignorance about the consumption of household appliances, electronics, and heating and cooling systems.

At least since Stigler (1961), economists have understood that buyers incur search costs to learn about sellers' prices at any given time and that these costs can affect market performance. In the context of electricity demand response, the costs of acquiring information about prices or one's own electricity consumption constitute costs of taking action, or costs of adjustment, that are weighed against the benefits, which may be quite small. Therefore, information burdens impose a hurdle to dynamic pricing response that explains, at least in part, the limited responsiveness to time-varying prices.

Perhaps the greatest information burden is imposed upon consumers enrolled in RTP tariffs who face prices that change hourly (or, theoretically, more frequently), i.e., with high granularity and low timeliness. To respond optimally, such consumers must monitor prices hourly. They also tend to face lesser rewards for their attention to prices if rate variation is constrained by variation in wholesale prices. In contrast, TOU rates do not impose any short-run uncertainty in prices and typically introduce only two or three rates for peak and off-peak periods and perhaps peak shoulders. Information about these rates can be obtained at low cost and used in subsequent decision-making indefinitely. Likewise, whereas CPP tariffs introduce considerable but infrequent volatility that may exceed occasional wholesale price fluctuations, all recent CPP experiments alerted customers to the pending price changes and their magnitudes shortly before each CPP period. This was typically accomplished via the customers' preferred means (phone, email, or text message), thereby considerably reducing the cost of acquiring price information. The timeliness of these alerts varied across experiments.

Cognizant of the potential information problems associated with time-varying prices, a number of the recent pricing experiments provided households with low-cost access to information about real-time electricity prices and their own consumption to lower the costs of taking action. In the Chicago pricing experiment evaluated by Allcott (2011b), some households were provided small plastic globes that changed color along a continuous spectrum to indicate how high or low contemporaneous hourly prices were. Alcott estimates that the information technology does not significantly change consumption at low RTP, but it induces average incremental conservation of 150 W/h at \$0.15/kWh and 200 W at the highest RTP in the experiment. At the highest prices, the information technology increases the average treatment effect by about two-thirds. The incremental conservation induced by the technology is equivalent to the energy saved by one in five households turning off a window air conditioning unit for the hour.

In their evaluation of a dynamic pricing pilot in Baltimore from 2008–2009, Faruqui & Sergici (2011) determined that CPP response was 25% greater on average among households equipped with the color-changing plastic globes. The magnitude of the price information effect on demand is smaller in this setting than in the Chicago experiment, as theory would predict. The CPP events in the Baltimore experiment were accompanied by day-ahead notifications that the prices would be elevated to the CPP determined at the outset of the experiment. Hence, the energy price globes did not serve to inform customers about CPP, assuming they received communications about impending CPP events from the utility. In contrast, the RTP customers in Chicago received price information only from the in-home information technology or from a website. The effect of price revelation technology on consumption decisions during CPP events in Baltimore suggests either that households did not receive or attend to CPP alerts from the utility or that they forgot about CPP events until the energy price globes reminded them about contemporaneous high prices. Even day-ahead price information may not be adequate to make prices salient at the point of consumption during CPP events, a point that garners further attention later in this section.

Another type of in-home technology was introduced in some experiments to overcome customer ignorance about the quantity of electricity consumed in production of electricity services, such as clothes washing, home heating, and computer usage. In the experiment evaluated by Bollinger & Hartmann (2016), the utility in the southern United States equipped some of the experimental households with an in-home display (IHD) that reported current electricity price, current consumption, daily cumulative consumption, and hourly electricity cost. Across the dynamic tariffs evaluated, the IHD served to increase peak-load reductions by at least 45% and as much as 76% relative to peak reductions in households without the information displays. Likewise, in their CPP experiment, Jessoe & Rapson (2014) estimate that IHDs tripled peak-load reductions during 4-h critical peak periods with day-ahead notifications, yielding an implied CPP elasticity of −0.30. This elasticity is similar in magnitude to the most comparable implied elasticity from Bollinger & Hartmann (2016) that characterizes the critical peak response of households enrolled in TOU pricing and equipped with IHDs. Their estimated demand reductions imply an elasticity of −0.25.

Harding & Lamarche (2016), in contrast, estimate hourly treatment effects from interventions that introduce IHDs to random households facing TOU rates. Households not randomly assigned IHDs had access to a website from which they could monitor prices and consumption. The authors find that the IHDs do not induce any hourly demand changes that are significant at the 1% level, though some reduction in peak demand occurs, as do modest increases in early morning consumption. Harding & Lamarche (2016, p. 917) conclude, however, that “there is no evidence that IHDs empower consumers to change their behavior any more than the web portal alone.” The absence of a significant IHD effect amid TOU pricing contrasts with significant effects in CPP experiments, suggesting that TOU rates do not vary sufficiently across peak and off-peak periods to command attention to IHDs among a large fraction of treated households.

6. HOUSEHOLDS EXHIBIT RATIONAL OR IRRATIONAL INATTENTION TO ELECTRICITY PRICE AND CONSUMPTION INFORMATION

In experimental settings such as that discussed by Harding & Lamarche (2016), IHDs do not convey unique price information because TOU rates, distinct from RTP, do not vary across days, only within days according to fixed schedules. Similarly, CPP events in these experimental settings are typically accompanied by day-ahead price alerts. Consequently, IHDs are not needed to provide price information in the bulk of the recent experiments. Interpretation of the incremental peak demand reductions due to IHDs, therefore, leads to the conclusion that households equipped with IHDs respond either to boosted price salience or to “learning about the electricity usage associated with the portfolio of household production alternatives” (Jessoe & Rapson 2014, p. 1432). Jessoe and Rapson, in fact, rule out salience explanations because they observe statistically greater responses among households equipped with IHDs relative to households without IHDs, conditional on receipt and acknowledgment of day-ahead CPP alerts. That is, even among those households that acknowledge CPP alerts, IHDs cause incremental usage reductions during pricing events. Thus, if one assumes that the receipt of day-ahead alerts makes prices fully salient at the point of consumption, then the greater demand reductions among households with IHDs must be attributable to a phenomenon other than price salience, e.g., due to learning about how to reduce consumption. It is possible, however, that in the absence of IHDs, day-ahead price alerts do not make prices fully salient when electricity is consumed 24 or more hours after receipt of alerts. Consumers may forget about the CPP events, or CPP alerts may not be conveyed to all household members.

Either the salience or learning explanations of the IHD impact on peak demand reductions implies consumer inattention to electricity consumption. Whether that inattention is rational or irrational depends upon interpretation. If one accepts Jessoe & Rapson's (2014) explanation that IHDs help consumers learn about their electricity usage, then it is conceivable that such consumers are rationally inattentive to their electricity consumption, perceiving the savings from avoided peak consumption to be dwarfed by the costs of attention and behavior change. Jessoe and Rapson note that the ever-decreasing cost of information technology can surmount the challenge to demand response posed by poorly informed consumers. But it seems likely that the learning they assert is afforded by IHDs can be achieved at an arbitrarily low cost independent of the IHDs. Specifically, a residential electricity consumer can learn quickly and easily via internet search or review of product manuals about the expected electricity consumption of electronic devices. That consumers do not undertake even low-cost searches to improve their decision making suggests either that the perceived benefits from more informed decision making must be very low, or that agents exhibit some irrationality, e.g., due to cognitive constraints or inattention (DellaVigna 2009, Kahneman 2003, Thaler & Sunstein 2003).

The benefits of gaining information about electricity consumption and taking action to avert high prices are typically quite small. The average household observed by Jessoe & Rapson (2014), for instance, could save only $0.60 per 4-h CPP event by reducing peak consumption 20%, which represents the magnitude of the estimated average demand reduction induced by the CPP event. Greater peak demand reductions would yield greater pecuniary savings but presumably at greater opportunity cost of foregone electricity services. Wolak (2010) notes that a dramatic 1-h price spike to $10/kWh would be necessary to induce a household to conserve 20% if it typically consumed 2.5 kW/h and faced a $5 cost to attend to price changes and make behavioral adjustments. Such a price increase is exceedingly rare, suggesting that the benefits of attention to price changes and electricity consumption may not warrant the cost. Importantly, the cost of attending to price changes and of adjusting consumption accordingly may greatly exceed the cost of learning how to reduce consumption. The learning costs that Jessoe and Rapson assert are lowered by IHDs are presumably incurred only once, whereas the costs of attending to price changes and adjusting behavior accordingly perpetuate. Sustained price increases, e.g., over 4 h or more, can lower the magnitude of the price increase necessary to induce demand response amid high attention and adjustment costs. But such sustained increases depart from the theoretical ideal of marginal cost pricing unless the sustained price increases are dictated by market conditions.

As Jessoe & Rapson (2014) explain, information interventions influence consumption decisions in a variety of other settings in which the information could be relatively cheaply obtained independent of the interventions. Simple information interventions are shown to alter behavior (in presumably welfare-improving ways) in the context of retirement plan investments (Duflo & Saez 2003), government benefit take-up among eligible populations (Bhargava & Manoli 2012), cell phone usage when overage rates apply (Grubb & Osborne 2015), and calorie intake (Bollinger et al. 2011). The benefits of information acquisition in some of these settings, however, are potentially considerably greater than they are in the context of demand response to time-varying electricity prices. The fact that households do not undertake low-cost high-reward learning suggests that some inattention may be irrational.

If cognitive ability and attention are constrained (e.g., Simon 1955, Tversky & Kahneman 1974), then consumers may be unable to weigh all of the various attributes of consumption choices. Thus, salient product attributes are expected to weigh more heavily in decision-making than nonsalient ones, and as price attributes become less salient, perceived prices fall (DellaVigna 2009). Motivated by such insights from psychology, economists have demonstrated that individuals are less responsive to (*a*) shrouded shipping fees than to auction prices on eBay (Brown et al. 2010, Hossain & Morgan 2006); (*b*) rebates for car purchases than to car purchase price (Busse et al. 2006); (*c*) taxes excluded from product prices than to taxes included in prices (Chetty & Saez 2005, Chetty et al. 2009); (*d*) income tax incentives than to sales tax incentives (Gallagher & Muehlegger 2011); and (*e*) earnings statements issued just before weekends than to statements issued earlier in weeks (DellaVigna & Pollet 2009).

Sexton (2015) shows that price salience influences electricity consumption. Observing that price salience is likely to decline with enrollment in automatic bill payment programs because the costs of inattention decline, Sexton demonstrates that electricity consumption among residential customers increases with autopay enrollment.[3] Likewise, Gilbert & Graf Zivin (2014) employ high-frequency billing data to infer that households reduce electricity consumption immediately following receipt of an electricity bill, suggesting that energy cost reminders can reduce consumption around system peaks. Relatedly, Cappers et al. (2015) evaluate responsiveness to time-varying prices among households that were randomly enrolled in CPP (by default) and those that were randomly permitted to opt into CPP. Households that defaulted into CPP exhibited less responsiveness to peak prices than did those who opted into it. The authors attribute the heterogeneous responses to inattention among the households exposed to CPP by default. Thus, to the extent that electricity costs are insalient to consumers, then energy price globes and IHDs may serve not only to convey information but also to boost the salience of electricity prices—static or dynamic—that are otherwise conveyed only in monthly bills (or website portals) that customers may ignore (Sexton 2015). Such inattention may be considered irrational, as it attends undeliberate downweighting of insalient prices.

7. HOUSEHOLD RESPONSE TO DYNAMIC PRICES EXHIBITS NONTRIVIAL COSTS OF ACTION THAT IMPEDE PEAK REDUCTIONS

Costs of attention to electricity prices constitute one component of the costs associated with household responses to dynamic prices. Though there is common acknowledgment in the literature that demand responses to dynamic prices may impose costs on residential customers (e.g., Allcott 2011b; Jessoe & Rapson 2014; Wolak 2010, 2011), the nature of these potential costs is not well defined. In their report on the 1970s DOE pilot programs, Miedema & White (1980) assessed that the financial incentive provided by a TOU rate may have to reach a threshold level to stimulate a significant response by most customers. Yet in his analysis of Washington, DC's dynamic pricing pilot, Wolak (2011) estimated that households exhibited similar price elasticities of demand whether responding to small or large price changes. He concludes, therefore, that there can be no economically significant cost of taking action. This conclusion, however, is conditional on customers being notified via phone, email, or text message 24-h in advance of high hourly prices. Such alerts obviated the need for customers to attend regularly to changing prices to adjust

[3]Sexton (2015) asserts that costs of inattention decline because charges would accrue for delinquent accounts to which households were insufficiently attentive. Enrollees in automatic payment programs can be inattentive and not accrue charges for account delinquency.

demand during these high-price periods. The increase in price responsiveness due to information technologies such as price lights and IHDs indicate, contrary to Wolak (2011), that information acquisition and attention costs are nontrivial.

In addition to information and attention costs, which can be lowered by information technologies, other costs of action include the costs of executing changes in consumption and the opportunity costs of foregone electricity consumption. Costs of taking action and of foregoing electricity consumption are expected to be lower when the timeliness of high price announcements (e.g., CPP events), is greater. More advanced warning allows a greater range of electricity consumption substitutions that lowers the opportunity cost of foregone consumption.

For instance, 24-h notice allows substitution of electricity consumption before high-price events for electricity consumption during high periods of high costs. With less than 24-h notice, forward substitution could be impeded by work schedules and daily routines. Likewise, with sufficient advanced warning about impending high prices, households can adjust noncommunicating thermostats before leaving home for the duration of the CPP event. But short notice could compel households to return to the home specifically to adjust the thermostat to reduce consumption during high-peak prices. The cost of adjustment would be considerably higher. Thus, it is not surprising that, although Jessoe & Rapson (2014) estimate demand reductions in response to CPP events with 24-h warnings, they find no response to CPP events issued with only 30-min warnings. With such short notice, it is likely that the costs of adjusting consumption were sufficiently high to reduce demand response observed with advanced warnings. More generally, given the narrow scope for benefits from taking action, it seems plausible that many households will choose not to incur the full suite of demand response costs necessary to adjust consumption to time-varying prices.

8. HOME AUTOMATION TECHNOLOGIES OVERCOME ADJUSTMENT COSTS TO CONSIDERABLY INCREASE PEAK DEMAND ELASTICITIES

If there are costs to taking action in response to dynamic prices, then technologies that automate such responses may increase demand elasticities by effectively taking consumer response out of demand response. That is the dramatic effect identified by Bollinger & Hartmann (2016) and Harding & Lamarche (2016) in their separate evaluations of the same experiment conducted by a utility in the southern United States. Programmable communicating thermostats (PCTs) were randomly introduced into some homes that were randomly assigned various time-varying pricing tariffs. These thermostats receive price information from utilities and can turn off air conditioning systems according to time of day, in-home temperature, or importantly, electricity price. Bollinger and Hartmann estimate that demand reductions in response to VPP, CPP, and TOU pricing at least doubled with the introduction of the automation technology. The addition of the PCTs to households equipped with IHDs and that face TOU rates causes peak demand reductions to increase from an average of 16% to an average of 27%, yielding an implied elasticity at peak demand of −0.43. Harding & Lamarche (2016) estimate that PCTs induce a 48% reduction in peak demand. Critical peak event elasticities with PCTs are of a similar magnitude to peak elasticities (Bollinger & Hartmann 2016).

The results also support other stylized facts about the importance of information problems and costs of action in electricity demand response. First, the fact that substantial gains in peak demand response are affected by automation, even conditional on ready access to information via IHDs, suggests that costs of action are a substantial deterrent to demand response. IHDs boost peak reductions approximately 50%, whereas automation boosts responsiveness an additional 100% or more (Bollinger & Hartmann 2016). Second, for homes facing the same tariffs but not equipped with the IHDs, the PCTs cause an even greater tripling of peak demand reductions, yielding responses that are comparable to the average responses of households equipped with IHDs. That is, automation essentially overcomes information problems. Third, information costs are expected to be higher for households facing VPP as opposed to TOU rates because of irregular price movements. Therefore, automation is expected to be more valuable amid dynamic rates because it absolves consumers of the burden of attentiveness to ever-changing prices.[4] Indeed, implied elasticities at peak increase by an even greater margin among households facing VPP rather than TOU rates to approximately −0.55 (Bollinger & Hartmann 2016). This further suggests that attentiveness to changing prices constitutes a real cost of demand response.

9. INATTENTION TO AUTOMATION TECHNOLOGIES INDICATES THE IMPORTANCE OF DEFAULT TECHNOLOGY SETTINGS

In contrast to Bollinger & Hartmann (2016) and Harding & Lamarche (2016), Faruqui & Sergici (2010) review a 2006 pilot study in Colorado showing that PCTs cause no incremental peak demand reductions relative to TOU interventions, though PCTs nearly double the demand reductions achieved without enabling technologies during CPP events. A similar pattern is reported in Faruqui & George (2005) for a California pricing pilot. In a Michigan experiment, PCTs were estimated to have no persistent discernable effect on demand in TOU peak and CPP periods (Faruqui et al. 2013). These seemingly contradictory results may cast doubt on the efficacy of automation technology, but they are readily reconciled by considering that PCTs must be programmed to respond to price changes. If the costs of consumer attention are high, then PCT technologies may never be optimally engaged to automate dynamic pricing response. Bollinger and Hartmann describe customer control over settings on the PCTs in the program they evaluated. Customers could select from several settings according to their preference for cost savings or comfort. PCT installers recommended to households a particular setting that may have functioned as a default setting. In other experiments, there may have been no such recommendation or default setting. In the Michigan and Colorado studies, PCTs may have been programmed to reduce consumption only during CPP events.

Considerable literature in behavioral economics and psychology documents the importance of defaults in determining consumer behavior across varied settings. Organ donation, for instance, is shown to dramatically increase when individuals must opt out of organ donation rather than opt into it (Johnson & Goldstein 2003). Choi et al. (2004) and Madrian & Shea (2001) document a similar phenomenon in company 401(k) (retirement) plan enrollment: Enrollment increases considerably when workers are automatically enrolled and must actively opt out of participation. Thaler & Sunstein (2003) attribute the importance of defaults to both inertia or status quo bias, which may be consequences of inattention, and to the normative information or legitimacy conveyed by defaults. Either explanation seems relevant to PCT utilization and suggests that the effective introduction of PCTs should employ default settings to maximize demand response. Such defaults will, of course, need to balance utility companies' interest in dramatic peak demand reductions and customer welfare losses from discomfort during peak periods. Defaults could be avoided if the thermostats require customers to program them before employing them for regular operations.

[4]Households may also be inattentive to the PCTs, suggesting that PCTs may be most effective if their default settings affect some price responsiveness or if they require households to program settings during installation.

10. THERE IS LIMITED EVIDENCE OF INTENTIONAL LOAD SHIFTING

Dynamic retail rates are intended to reshape load curves to avoid excess capital investment. The preceding section documents the varying degrees to which pricing and technology interventions yield reductions in peak demand. Given peak demand reductions, do households shift consumption to off-peak periods, perhaps avoiding any net reductions in consumption, or do they reduce overall consumption by conserving during peaks? The available evidence shows little intentional load shifting. Similar to Allcott (2011b) 30 years later, the Miedema & White (1980) review find no evidence of increases during off-peak periods, suggesting that the net effect of the dynamic tariffs was to induce conservation at high prices rather than to shift load to low-cost periods. Rather than observing increased consumption outside peak periods, as would be indicative of load shifting, Jessoe & Rapson (2014) identify conservation that persists outside CPP event windows. Herter & Wayland (2010) find some evidence of load shifting from the California Statewide Pricing Pilot 2003–2004. However, they point out that the pilot suffered from extensive selection and attrition.

Harding & Lamarche (2016) document load shifting in evening and night hours among households equipped with PCTs. **Figure 2** depicts the baseline intent to treat effects estimated by Harding and Lamarche for households equipped only with web-based price and consumption information, IHDs and web-based information, and PCTs and web-based information, respectively. Among households with PCTs, electricity consumption increases an estimated 22% at 7 PM when prices fall to off-peak levels. Consumption remains high relative to control groups into the subsequent morning hours. A qualitatively similar consumption pattern is observed among groups without PCTs, though estimated responses are not statistically different from zero. Therefore, evidence of load shifting among PCT households likely reflects, at least in part, the automated response of thermostats to increase home cooling when high peak-period prices fall in the off-peak period. They find no evidence of increased electricity consumption ahead of peak periods, which would be indicative of anticipatory efforts to cool homes before high prices were imposed. To the extent that the observed electricity consumption is attributable to automated PCT responses, then the result corroborates findings elsewhere in the literature that show no evidence of intentional conscious substitution of electricity consumption across hours of the day.

11. LIMITATIONS AND FURTHER RESEARCH NEEDS

Although the previous discussion identifies lessons learned from many evaluations of time-varying pricing experiments and pilot programs, some common limitations among these studies leave unanswered important questions about how effectively demand response can solve the peak-load problem. The first of these limitations concerns the external validity or generalizability of experimental results. Most of these studies relied upon volunteer households that were randomly assigned to treatments and control conditional on their recruitment. Most evaluations observe very limited characteristics of utility customers, typically only involving electricity consumption. This precludes an assessment of the comparability of households recruited into the experiments and those not recruited. Given that attention to electricity prices proves important for demand response, except in the presence of PCTs, it seems likely that recruited households exhibit greater interest in and attention to prices and utility information than other consumers. Demand response among recruited households is therefore likely to differ systematically from the demand response of the underlying population of interest. Treatment effects among the broader population may be smaller than those estimated in the experiments except where automation surmounts attention and information problems.

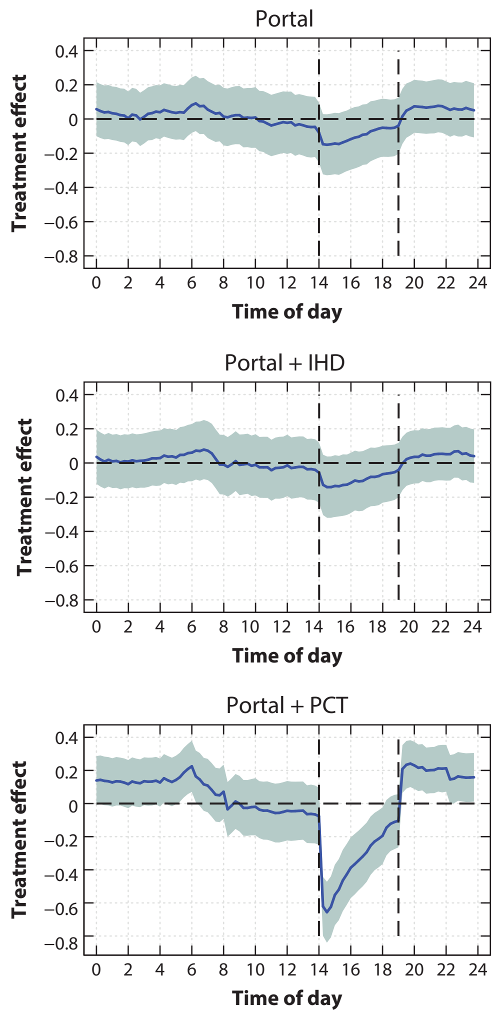

Figure 2

This figure is adapted from from Harding & Lamarche (2016, figure 1). It demonstrates the intention-to-treat effects of pricing events by technology computed at 15-min intervals. Shaded areas represent 99% point-wise confidence intervals.

A second limitation is that the experiments and pricing pilots are short-lived. Thus, they are not equipped to determine long-run responses to dynamic prices and enabling technologies. For instance, faced with dynamic prices in the long run, households may invest in a suite of automation devices designed to optimize discretionary electricity consumption. Product makers would also be expected to introduce new appliance and electronics features to enable automation. Households may also replace inefficient durable goods with energy-efficient capital over time. These long-run capital adjustments are likely to increase demand response relative to that estimated in the short-run experiments (Price 2014). At the same time, however, it is conceivable that the novelty of dynamic prices declines over time, and inattention to prices and enabling technology increases, diminishing demand response.

Finally, none of these studies address the welfare impacts of the various dynamic tariffs they evaluate. Bollinger & Hartmann (2016) estimate that the discounted present value of household welfare gains from introduction of a PCT is approximately \$275 when households face the experimental time-varying rates and discount future consumption at a 10% rate. But they do not estimate the welfare changes attributable to the underlying price variation. Further research should be designed to determine the welfare impacts of time-varying prices conditional on available technologies. Bollinger & Hartmann (2016) estimate that producer surplus is increased by introducing PCTs to customer households but that the producer gains are modest unless the technology can be selectively introduced to those households expected to exhibit greater responsiveness to the prices and technology. The surplus gained from the prices themselves is unexplored. It is also unknown how even persistent peak demand reductions on the order of those estimated in these studies would affect capital investments and retail rates.

12. CONCLUSION

Understanding about consumer response to dynamic electricity prices has improved markedly since British regulators first attempted to overcome peak demand with seasonally differentiated tariffs in the 1940s. A wave of experiments undertaken in the United States in the 1970s and the first decades of the twenty-first century demonstrate that consumers respond to prices that vary within and across days. Contrary to the common assertion of economists that "getting the prices right" would solve the peak-load problem, however, the evidence suggests very low price elasticities of demand during peaks unless enabling technologies are available to households. Technologies that inform consumers about prices and electricity consumption boost peak demand reductions by 50% or more. Their importance suggests that consumers are uninformed about their electricity consumption habits and unwilling to make nominal investments to learn, or that they are rationally or irrationally inattentive to their electricity consumption, which constitutes only a few percent of annual expenditures for a typical household. Attention to prices and contemporaneous electricity consumption constitutes costs associated with adjustment to varying prices that may dwarf the benefits of adjustment, which may constitute less than \$1 in savings for a typical CPP event.

Given these and other costs of taking action, prices either must rise considerably or for extended durations to provide necessary incentives for demand response. However, such tariffs are likely to deviate from the ideal of marginal cost pricing. Technologies that lower costs of adjustment, such as the PCTs employed in a number of studies, are shown to dramatically increase peak demand elasticities by essentially eliminating human response from demand response. The effect of automation technologies on electricity consumption suggests that information and attention problems can be surmounted to achieve peak demand reductions sufficient to address the peak-load problem. Nonetheless, as smart meters proliferate and increasing intermittent renewable generation warrants precise demand response, caution may be warranted. There may be a limit to how much regulators and utilities can rely upon automation to deliver sustained peak demand reductions because of limits on consumer acceptance of automation and conservation.

DISCLOSURE STATEMENT

For the past three years, M.H. has consulted for the Electric Power Research Institute (EPRI) and received funding from the Sloan Foundation for research related to the topics covered in this review.

ACKNOWLEDGMENTS

The authors gratefully acknowledge excellent research assistance by Qingran Li.

LITERATURE CITED

Aigner D. 1985. The residential electricity time-of-use pricing experiments: What have we learned? In *Social Experimentation*, ed. JA Hausman, DA Wise, pp. 11–54. Chicago: Univ. Chicago Press

Aigner DJ, Ghali K. 1989. Self-selection in the residential electricity time-of-use pricing experiments. *J. Appl. Econ.* 4(Suppl. 1):131–44

Aigner DJ, Hausman JA. 1980. Correcting for truncation bias in the analysis of experiments in time-of-day pricing of electricity. *Bell J. Econ.* 11(1):131–42

Allcott H. 2011a. Consumers' perceptions and misperceptions of energy costs. *Am. Econ. Rev.* 101(3):98–104

Allcott H. 2011b. Rethinking real-time electricity pricing. *Resour. Energy Econ.* 33(4):820–42

Bhargava S, Manoli D. 2012. Why are benefits left on the table? Assessing the role of information, complexity, and stigma on take-up with an IRS field experiment. *Adv. Consumer Res.* 40:298–302

Boiteux M. 1960. Peak-load pricing. *J. Bus.* 33(2):157–79

Boiteux M. 1964. Marginal cost pricing. In *Marginal Cost Pricing in Practice*, ed. JR Nelson, pp. 51–58. Englewood, NJ: Prentice Hall

Bollinger B, Hartmann WR. 2016. *Welfare effects of home automation technology with dynamic pricing*. Work. Pap., Fuqua Sch. Bus., Duke Univ., Durham, NC. **http://www.bryanbollinger.com/index_files/HomeAutomation.pdf**

Bollinger B, Leslie P, Sorensen A. 2011. Calorie posting in chain restaurants. *Am. Econ. J. Econ. Policy* 3(1):91–128

Borenstein S. 2002. The trouble with electricity markets: understanding California's restructuring disaster. *J. Econ. Perspect.* 16(1):191–211

Borenstein S. 2005a. The long-run efficiency of real-time electricity pricing. *Energy J.* 26(3):93–116

Borenstein S. 2005b. Time-varying retail electricity prices: theory and practice. In *Electricity Deregulation: Choices and Challenges*, ed. J Griffin, SL Puller, pp. 317–58. Chicago: Univ. Chicago Press

Borenstein S. 2009. Electricity pricing that reflects its real-time cost. *NBER Reporter* 1. **http://www.nber.org/reporter/2009number1/borenstein.html**

Borenstein S. 2012. The private and public economics of renewable electricity generation. *J. Econ. Perspect.* 26(1):67–92

Borenstein S, Bushnell J. 2015. The US electricity industry after 20 years of restructuring. *Annu. Rev. Econ.* 7:437–63

Borenstein S, Holland S. 2005. On the efficiency of competitive markets with time-invariant retail prices. *RAND J. Econ.* 36(3):469–93

Borenstein S, Jaske M, Rosenfeld A. 2002. *Dynamic pricing, advanced metering, and demand response in electricity markets*. Work. Pap. 105, Cent. Study Energy Mark., Univ. Calif., Berkeley

Braithwait S. 2000. Residential TOU price response in the presence of interactive communication equipment. In *Pricing in Competitive Electricity Markets*, ed. A. Faruqui, K Eakin, pp. 359–73. Berlin: Springer Sci. Bus. Media

Brown A, Chua ZE, Camerer CF. 2009. Learning and visceral temptation in dynamic savings experiments. *Q. J. Econ.* 124(1):197–231

Brown J, Hossain T, Morgan J. 2010. Shrouded attributes and information suppression: evidence from the field. *Q. J. Econ.* 125(2):859–76

Busse M, Silva-Risso J, Zettelmeyer F. 2006. $1,000 cash back: the pass-through of auto manufacturer promotions. *Am. Econ. Rev.* 96(4):1253–70

Cappers P, Fowlie M, Spurlock CA, Todd A, Wolfram C, Baylis P. 2015. *Default effects, follow-on behavior and welfare in residential electricity pricing programs*. Work. Pap., NBER Summer Inst., Cambridge, Mass. **http://conference.nber.org/confer/2015/SI2015/EEE/Cappers_Fowlie_Spurlock_Todd_Wolfram_Baylis.pdf**

Chetty R, Looney A, Kroft K. 2009. Salience and taxation: theory and evidence. *Am. Econ. Rev.* 99(4):1145–77

Chetty R, Saez E. 2005. Dividend taxes and corporate behavior: evidence from the 2003 dividend tax cut. *Q. J. Econ.* 120(3):791–833

Cho S, Rust J. 2010. The flat rental puzzle. *Rev. Econ. Stud.* 77(2):534–59

Choi JJ, Laibson D, Madrian BC, Metrick A. 2004. For better or for worse: default effects and 401 (k) savings behavior. In *Perspectives on the Economics of Aging*, ed. DA Wise, pp. 81–126. Chicago: Univ. Chicago Press

Clark JM. 1911. Rates for public utilities. *Am. Econ. Rev.* 1(3):473–87

Cooper A. 2016. *Electric company smart meter deployments: foundation for a smart grid*. Rep., Inst. Elect. Innov., Edison Found., Washington, DC. **http://www.edisonfoundation.net/iei/publications/Documents/Final%20Electric%20Company%20Smart%20Meter%20Deployments-%20Foundation%20for%20A%20Smart%20Energy%20Grid.pdf**

DellaVigna S. 2009. Psychology and economics: evidence from the field. *J. Econ. Lit.* 47(2):315–72

DellaVigna S, Pollet JM. 2009. Investor inattention and Friday earnings announcements. *J. Finance* 64(2):709–49

Duflo E, Saez E. 2003. The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment. *Q. J. Econ.* 118(3):815–42

Eisenmenger HE. 1921. *Central Station Rates in Theory and Practice*. Chicago: FJ Drake & Co.

Faruqui A, George S. 2005. Quantifying customer response to dynamic pricing. *Electr. J.* 18(4):53–63

Faruqui A, Hledik R, Tsoukalis J. 2009. The power of dynamic pricing. *Electr. J.* 22(3):42–56

Faruqui A, Sergici S. 2010. Household response to dynamic pricing of electricity: a survey of 15 experiments. *J. Regul. Econ.* 38(2):193–225

Faruqui A, Sergici S. 2011. Dynamic pricing of electricity in the mid-Atlantic region: econometric results from the Baltimore gas and electric company experiment. *J. Regul. Econ.* 40(1):82–109

Faruqui A, Sergici S. 2013. Arcturus: international evidence on dynamic pricing. *Electr. J.* 26(7):55–65

Faruqui A, Sergici S, Akaba L. 2012. *Dynamic pricing in a moderate climate: the evidence from Connecticut*. SSRN Work. Pap. 2028178, Rochester, NY

Faruqui A, Sergici S, Akaba L. 2013. Dynamic pricing of electricity for residential customers: the evidence from Michigan. *Energy Effic.* 6(3):571–84

Faruqui A, Sergici S, Sharif A. 2010. The impact of informational feedback on energy consumption—a survey of the experimental evidence. *Energy* 35(4):1598–608

FERC (US Fed. Energy Reg. Comm.). 2011. *2010 assessment of demand response and advanced metering*. Staff Rep., FERC, Washington, DC. **http://www.ferc.gov/legal/staff-reports/2010-dr-report.pdf**

FERC (US Fed. Energy Reg. Comm.). 2015. *2015 assessment of demand response and advanced metering*. Staff Rep., FERC, Washington, DC. **https://www.ferc.gov/legal/staff-reports/2015/demand-response.pdf**

Gallagher KS, Muehlegger E. 2011. Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology. *J. Environ. Econ. Manag.* 61(1):1–15

Gilbert B, Zivin JG. 2014. Dynamic salience with intermittent billing: evidence from smart electricity meters. *J. Econ. Behav. Organ.* 107:176–90

Grubb MD, Osborne M. 2015. Cellular service demand: biased beliefs, learning, and bill shock. *Am. Econ. Rev.* 105(1):234–71

Harding M, Lamarche C. 2016. Empowering consumers through data and smart technology: experimental evidence on the consequences of time-of-use electricity pricing policies. *J. Policy Anal. Manag.* 35(4):906–31

Hausman WJ, Neufeld JL. 1984. Time-of-day pricing in the U.S. electric power industry at the turn of the century. *RAND J. Econ.* 15(1):116–26

Herter K. 2007. Residential implementation of critical-peak pricing of electricity. *Energy Policy* 35(4):2121–30

Herter K, Wayland S. 2010. Residential response to critical-peak pricing of electricity: California evidence. *Energy* 35(4):1561–67

Hogan WW. 1999. *Getting prices right in PJM: analysis and summary: April 1998 through March 1999*. Work. Pap., Harvard Univ., Cambridge, Mass. **https://www.hks.harvard.edu/fs/whogan/pjm0399.pdf**

Hossain T, Morgan J. 2006. Plus shipping and handling. *Adv. Econ. Anal. Policy* 6:1–27

Houser D, Keane M, McCabe K. 2004. Behavior in a dynamic decision problem: an analysis of experimental bayesian type classification algorithm. *Econometrica* 72(3):781–822

Houthakker HS. 1951. Electricity tariffs in theory and practice. *Econ. J.* 61(241):1–25
Ito K. 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. *Am. Econ. Rev.* 104(2):537–63
Jessoe K, Rapson D. 2014. Knowledge is (less) power: experimental evidence from residential energy use. *Am. Econ. Rev.* 104(4):1417–38
Johnson EJ, Goldstein D. 2003. Do defaults save lives? *Science* 302(5649):1338–39
Joskow PL. 2001. California's electricity crisis. *Oxf. Rev. Econ. Policy* 17(3):365–88
Joskow PL. 2012. Creating a smarter US electricity grid. *J. Econ. Perspect.* 26(1):29–47
Kahneman D. 2003. Maps of bounded rationality: psychology for behavioral economics. *Am. Econ. Rev.* 93(5):1449–75
Kahneman D, Knetsch JL, Thaler RH. 1991. Anomalies: the endowment effect, loss aversion, and status quo bias. *J. Econ. Perspect.* 5(1):193–206
Krauss C, Cardwell D. 2015. A Texas utility offers a nighttime special: free electricity. *New York Times*, Nov. 8. **http://www.nytimes.com/2015/11/09/business/energy-environment/a-texas-utility-offers-a-nighttime-special-free-electricity.html**
Letzler RJ. 2007. *Implementing opt-in, residential, dynamic electricity pricing: insights from economics and psychology*. PhD Thesis, Univ. Calif., Berkeley
Madrian BC, Shea DF. 2001. The power of suggestion: inertia in 401(k) participation and savings behavior. *Q. J. Econ.* 116(4):1149–525
Malik N. 2016. A thunderstorm just drove New York power prices above $1,000. *Bloomberg*, July 5. **https://www.bloomberg.com/news/articles/2016-07-25/a-thunderstorm-just-drove-new-york-power-prices-above-1-000**
Malik N, Weber H. 2016. One thing California, Texas have in common is negative power. *Bloomberg*, Apr. 5. **https://www.bloomberg.com/news/articles/2016-04-05/one-thing-california-texas-have-in-common-is-negative-power**
Miedema AK, White SB. 1980. *Time-of-use electricity price effects: summary I*. Rep. DOE/RG/08684-T6. Res. Triangle Inst., Res. Triangle Park, NC
Mitchell B, Acton J. 1980. *The effects of time-of-use rates in the Los Angeles electricity study*. Rep. N-1533-DWP/HF, RAND, Santa Monica, Calif. **http://www.rand.org/content/dam/rand/pubs/notes/2007/N1533.pdf**
PJM Interconnect. 2015. *State of the market*. Rep., Monit. Anal., Eagleville, Pa. **http://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2015/2015-som-pjm-volume2-sec3.pdf**
Price MK. 2014. Using field experiments to address environmental externalities and resource scarcity: major lessons learned and new directions for future research. *Oxf. Rev. Econ. Policy* 30(4):621–38
Reiss PC, White MW. 2005. Household electricity demand, revisited. *Rev. Econ. Stud.* 72(3):853–83
Sexton S. 2015. Automatic bill payment and salience effects: evidence from electricity consumption. *Rev. Econ. Stat.* 97(2):229–41
Shin J-S. 1985. Perception of price when price information is costly: evidence from residential electricity demand. *Rev. Econ. Stat.* 67(4):591–98
Simon HA. 1955. A behavioral model of rational choice. *Q. J. Econ.* 69:99–118
Steiner PO. 1957. Peak loads and efficient pricing. *Q. J. Econ.* 71(4):585–610
Stigler GJ. 1961. The economics of information. *J. Polit. Econ.* 69(3):213–25
Taylor TN, Schwarz PM, Cochell JE. 2005. 24/7 hourly response to electricity real-time pricing with up to eight summers of experience. *J. Regul. Econ.* 27(3):235–62
Thaler RH, Sunstein CR. 2003. Libertarian paternalism. *Am. Econ. Rev.* 93(2):175–79
Train K, Mehrez G. 1994. Optional time-of-use prices for electricity: econometric analysis of surplus and Pareto impacts. *RAND J. Econ.* 25(2):263–83
Turvey R. 1968. Peak load pricing. *J. Pol. Econ.* 76(1):101–13
Tversky A, Kahneman D. 1974. Judgment under uncertainty: heuristics and biases. *Science* 185(4157):1124–31
Tversky A, Kahneman D. 1991. Loss aversion in riskless choice: a reference-dependent model. *Q. J. Econ.* 106(4):1039–61

Wald ML. 2014. Power savings of smart meters prove slow to materialize. *New York Times*, Dec. 6. **http://www.nytimes.com/2014/12/06/business/energy-environment/power-savings-of-smart-meters-prove-slow-to-materialize.html?_r=0**

Watkins GP. 1915. A third factor in the variation of productivity: the load factor. *Am. Econ. Rev.* 5(4):753–86

Watkins GP. 1916. The theory of differential rates. *Q. J. Econ.* 30(4):682–703

Wattles J. 2016. New York City electricity price spikes 1000%. *CNN.com*, July 25. **http://money.cnn.com/2016/07/25/news/companies/new-york-energy-prices-storm/**

Weightman G. 2011. *Children of Light: How Electricity Changed Britain Forever*. London: Atlantic

Wolak FA. 2010. *An experimental comparison of critical peak and hourly pricing: the PowerCentsDC Program*. Work. Pap., Stanford Univ., Stanford, Calif. **http://www.stanford.edu/group/fwolak/cgi-bin/sites/default/files/files/An%20Experimental%20Comparison%20of%20Critical%20Peak%20and%20Hourly%20Pricing_March%202010_Wolak.pdf**

Wolak FA. 2011. Measuring the benefits of greater spatial granularity in short-term pricing in wholesale electricity markets. *Am. Econ. Rev.* 101(3):247–52