Delivering Affordable Clean Energy to Consumers

Praveen K. Kopalle Dartmouth College

Jesse Burkhardt Colorado State University

Kenneth Gillingham Yale University

Lauren S. Grewal Dartmouth College

Nailya Ordabayeva Dartmouth College

Praveen Kopalle is the Signal Companies' Professor of Management and Professor of Marketing, Tuck School of Business, Dartmouth College, Hanover, NH 03755, phone: 603-646-3612, email: kopalle@dartmouth.edu. Jesse Burkhardt is an Associate Professor of Energy Economics, Colorado State University, 1200 Center Avenue Mall, Fort Collins, CO 80523, phone: 970-491-6951, email: jesse.burkhardt@colostate.edu. Kenneth Gillingham is a Professor of Economics, Yale University, 195 Prospect Street, New Haven, CT 06511, phone: 203-436-5465, e-mail: kenneth.gillingham@yale.edu. Lauren Grewal is an Associate Professor of Business Administration, Tuck School of Business, Dartmouth College, Hanover, NH 03755, phone: 603-646-0107, e-mail: lauren.s.grewal@tuck.dartmouth.edu. Nailya Ordabayeva is an Associate Professor of Business Administration, Tuck School of Business, Dartmouth College, Hanover, NH 03755, phone: 603-646-1773, e-mail: nailya.ordabayeva@tuck.dartmouth.edu. All authors contributed equally. The authors thank the editors, guest editors, and three anonymous reviewers for their helpful comments on an earlier draft of the manuscript.

Delivering Affordable Clean Energy to Consumers

ABSTRACT

In this work, we develop a marketing-centric framework for delivering affordable clean energy to consumers leveraging the 4 Ps and bi-directional flow of information between firms and consumers. Using a multimethod approach that covers a consumer survey, field experiment, and a decarbonization simulation to test the various aspects of the framework, our findings point to the need for a "system-wide" solution. Specifically, we examine consumer responsiveness to multiple levers within the 4 Ps, showcase the real effects of a combination of an automated solution and dynamic electricity pricing on behavior, and examine the role of dynamic prices and automation in transitioning to 100% clean electricity. We argue that there are ways to achieve affordable, 100% clean energy that many consumers will adopt. We conclude with a set of research questions examining additional aspects of the 4 Ps that can be leveraged to facilitate the wide-spread adoption of clean energy solutions.

Achieving widespread diffusion of clean, sustainable energy options is a critical tool in efforts to address climate change. Not only that, it is a key priority highlighted in the United Nations' Sustainable Development Goals (#7: Ensure access to affordable, reliable, sustainable and modern energy for all; #13: Take urgent action to combat climate change and its impacts; #9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation). Thus, understanding the various levers and strategies that could make such diffusion possible is an essential topic for researchers to study and address.

However, despite its importance, understanding how to truly achieve the diffusion of clean energy is a difficult task—both from a research point of view and in practice. This difficulty stems in part from the necessity for there to be a coordinated effort between policy makers and industry to economically produce and efficiently deliver and market affordable clean energy solutions. As well, a greater understanding of when and why consumers are willing to "buy-in" to these solutions is essential. Therefore, any research or advice towards ways to increase clean energy diffusion needs to be able to tackle not only one "level" in the system—but instead, needs to consider the complicated nature of a multi-stakeholder system that underlies clean energy adoption and diffusion.

Despite the need for research that examines all stakeholders, prior research in marketing has generally focused on the role of consumers when it comes to sustainable behaviors. For example, research has shown that affordability is a key barrier to the adoption of sustainable behaviors. Indeed, consumers believe that sustainable resources and goods, including clean energy, are costlier than their conventional counterparts (Gleim et al., 2013; Griskevicius, Tybur, and Van den Bergh, 2010; Hughner et al., 2007).

We posit that to achieve widespread adoption of clean energy solutions and to effectively combat climate change, a more comprehensive approach is needed to deliver clean energy to consumers and to facilitate consumer buy-in. This approach calls on firms to leverage a more comprehensive set of tools beyond those that influence affordability. To this end, we propose a framework that leverages the marketing mix variables, i.e., 4 Ps: Price to manage affordability and energy consumption patterns; Product focusing on the adoption of products such as smart appliances to facilitate monitoring of energy consumption and the transition to a decarbonized power grid; Place focusing on the automated mediation of energy supply and demand with the help of smart technology to smooth the demand-supply gap; and Promotion focusing on information provision, feedback, and social influence techniques to increase the appeal of clean energy solutions. In order to enhance the effectiveness of the marketing mix variables, we include segment characteristics in the analysis.

We argue that the deployment of the 4 Ps solution requires a two-way flow of information between firms and consumers. At one end, consumer response to the 4 Ps relies on the firm's accurate, personalized, and timely provision of information to consumers about key aspects of the 4 Ps (e.g., price changes, feedback about energy use). At the other end, firms' ability to effectively implement and adjust the 4 Ps (e.g., energy supply and use during critical peak periods) relies on the accurate, real-time flow of information from consumers to firms. Owing to the utilization of all aspects of the marketing plan (4 Ps) and an information loop connecting firms and consumers, we view this comprehensive framework as offering a "system-wide" solution to facilitate clean energy adoption and fight climate change. This is akin to a smart grid that is able to store, communicate and make decisions (Tuballa and Abundo 2016).

To examine the various aspects of this comprehensive framework and begin a conversation about strategies and policies that may be effective both from a policy or firm as well as a consumer perspective, we conducted a multi-method examination across different types of populations, clean energy types, and systems. We begin with a consumer survey that examines how consumer interest in clean energy adoption is influenced by the various components of the 4 Ps. It examines consumers' baseline interest in product offerings that leverage clean energy Ps. The survey also elicits consumers' willingness-to-pay for these solutions.

We proceed with a field experiment that zooms in on arguably the most instrumental components of the 4 Ps for dissemination of affordable clean energy (Price), as well as the role of smart technology such as NEST (Product). During this one-year experiment conducted in Austin, Texas, we observe minute-level electricity consumption, attributed to distinct appliances, such that we can establish a causal channel for the effects of dynamic electricity pricing on consumption patterns. The overall field experiment examined energy conservation during critical peak event days using three types of treatments: (i) informational messaging, (ii) pricing, and (iii) installing a NEST thermostat. In this paper, we focus on comparing the effect of pricing to installing a NEST thermostat. Burkhardt et al. (2023) provides more details on the overall experiment but performs an entirely different analysis and does not explore the NEST thermostat treatment arm.¹

The effect of pricing is examined by deploying a dynamic pricing strategy called Critical Peak Pricing (CPP). Under CPP the utility identifies a limited number of hours of the year when the grid is the most stressed and designates these hours as "critical peak periods." An example

¹ Burkhardt, Gillingham and Kopalle (2023) use some of the data from the same experiment run by Pecan Street and do not evaluate the NEST group, include the survey, or run the decarbonization simulation and focus on estimating the impact of information and pricing treatments.

would be the 20 hottest days in the summer from 4pm-7pm when the air conditioning load is extremely high and dirty peaking generators that spew harmful emissions are turned on to meet the high electricity demand. The utility notifies consumers in advance about the periods (usually 24 hours in advance) and charges them substantially more during these periods than the standard retail electricity rate. In our study, for example, CPP prices were \$0.64/kWh, which is substantially more than the usual retail electricity rates of about \$0.12/kWh. CPP is a subset of the broader category of dynamic pricing strategies, which allow prices to change over time rather than remain fixed. CPP is intended to encourage customers to reduce consumption or shift their consumption away from peak load periods.

Our field experiment results suggest a 16% decrease in greenhouse gas emissions during critical peak event days due to critical peak pricing (CPP) (Burkhardt et al., 2023). Interestingly, the field experiment does not yield a significant effect of a NEST thermostat, which could suggest that the mode of technology implementation (e.g., manual, automatic) matters. Given that the NEST thermostat does not work in isolation to conserve energy, we combine the two results and propose a technological, automated solution (akin to what consumers seem to want based on our survey). Specifically, our proposal is for the electric utility company to automatically link CPP event days with the NEST thermostat, raising the thermostat by only a few degrees during critical peak periods (with the possibility of manual override), so the inconvenience of a manual intervention is eliminated but real energy savings remain. This can be extended to a system-wide solution concept, where a smart grid is synchronized with a smart home, a NEST thermostat, plus a smart meter, to allow for modest automatic electricity conservation (so it does not noticeably affect well-being) at the times of the greatest grid stress. This solution will work during peak periods as well as when wind and solar intermittently shut

down, alleviating the need to keep excess dirty fossil fuel generation capacity online. This approach has the potential to provide a win-win-win situation for utility companies, consumers, and the environment.

In the final component of our study, we conduct a simulation in which we examine how energy savings produced by dynamic pricing can pave the way to a decarbonized energy grid with varying combinations of renewable clean energy sources. Specifically, we simulate the Texas grid leveraging the findings of our field experiment to explore how a system-wide solution could aid in the transition to 100% renewable energy. A key challenge of this transition is that renewable energy is inherently intermittent. Fossil fuels, on the other hand, are dispatchable and allow generators to respond to demand in real time. The current grid does not incentivize customers to respond to unexpected changes in renewable generation because retail prices are fixed for a given period of the day. Grid scale battery storage is a potential solution to the intermittency challenge, but it is currently prohibitively expensive. Applying a "system-wide solution" that emerged from our field experiment and survey, we show in our simulation that the daily need for battery storage could decrease by 53% on average, yielding a beneficial outcome for municipalities and consumers (who are willing to pay for the "system-wide solution" per our consumer survey findings). Ultimately, we propose that a path to transitioning to renewable energy in order to fight climate change can involve a holistic solution predicated on the integration of all 4 Ps and facilitated by a two-way information flow between firms and consumers. Next, we outline the conceptual foundations of this research.

Conceptual background

An extensive literature in multiple fields (marketing, economics, and psychology, among others) has explored various factors that may contribute to individuals' adoption of sustainable

and clean energy consumption practices and solutions. In Table 1, we overview common factors studied in prior research, as they relate to the 4 Ps, along with corresponding illustrative citations and findings. While this does not constitute an exhaustive review of all relevant papers and findings, it offers an insight into how different factors as they relate to the 4 Ps may work to influence the adoption and popularization of sustainable energy consumption behaviors.

| Theme | Examples of cites | Examples of findings |
|---------------------------------------|-----------------------------|---------------------------------------------------------------------------------|
| Affordability (Price) | Caves et al. (1984) | Time-of-use electricity pricing can work. |
| · · · · · · · · · · · · · · · · · · · | Faruqui and Sergici (2010) | Households respond to higher prices by lowering usage. |
| | Gleim et al. (2013) | Price is the most important factor that drives consumers' self-reported |
| | | purchases of sustainable goods. |
| | Heberlein and Wariner | Highlighting higher differential between peak-hour and off-peak-hour pricing |
| | (1983) | shifted energy consumption to off-peak hours. |
| | Ito (2015) | Discount on monthly energy bill in California reduced energy use in inland |
| | | regions, but not in coastal regions. |
| | Jessoe and Rapson (2014) | Price increases plus in-home devices can be effective in energy conservation. |
| | Klöckner et al. (2013) | Financial incentives in Norway increased overall purchases of electric |
| | | vehicles but mainly as a secondary vehicle in the household. |
| | Pitts and Wittenbach (1981) | Financial incentives had no influence on household decision to insulate their |
| | | homes. |
| | Reiss and White (2008) | Capping prices after a market shock precludes reduction in energy usage. |
| | Wolak (2011) | Dynamic pricing impacts electricity usage in the expected direction. |
| Information | Andor et al. (2022) | Marginal impact of informational treatments in electricity conservation. |
| provision and | Camilleri and Larrick | Highlighting energy (gas) costs rather than consumption (gallons) of vehicles |
| framing (Promotion) | (2014) | increased consumers' preferences for fuel-efficient vehicles. |
| | Kallbekken, Sælen, and | Presenting energy cost information at the aggregate (vs. granular) level (e.g., |
| | Hermansen (2013) | over a product's lifetime) more effectively encourages purchase of energy |
| | | efficient product options. |
| | Van Houwelingen and Van | Continuous (e.g., monthly vs. discrete) personalized energy consumption |
| | Raaij (1989) | reports more effectively reduced households' energy consumption. |
| | Wilhite and Ling (1995) | Offering households tips about how to improve energy efficiency encouraged |
| | | sustainable energy consumption. |
| Social influence | Ayres et al. (2013) | Peer comparison feedback can reduce electricity usage. |
| (Promotion) | Bollinger and Gillingham | Households' installation of solar panels increased the likelihood that their |
| | (2012) | neighbors would do the same. |
| | Ferraro and Price (2013) | Social comparison messages more effective than prosocial messages in |
| | | reducing water usage. |
| | Ito et al. (2018) | Relative impact of moral suasion and pricing on electricity conservation. |
| | Kraft-Todd et al. (2018) | Peer effects in adoption of clean energy solutions are stronger when |
| | | community leads exhibit (vs. just talk about) the consumption practice. |
| | Schulz et al. (2007) | Peer information creates a social norm and thus lowers carbon emissions |
| | | among households that consume more energy than others, but increases |
| | <u>C 1 ((-1, 2012</u> | consumption among households that consume less energy than others. |
| | Schwartz et al., 2013 | An ad that combined an environmental with a monetary appeal more |
| | | energy consumption than an ad that only |
| | | used a monetary appeal. |

 Table 1: Relevant Literature with Illustrative Cites and Findings on Common Drivers of

 Sustainable and Clean Energy Adoption

| Technology and automation (Product and Place) | Bollinger and Hartman (2020) | Critical peak pricing has been shown to be effective at inducing energy conservation and automation may have potential to respond to price signals for utility companies. |
|-----------------------------------------------------|------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| | Lee and Zhang (2022) | The utilization of smart thermostats lower overall energy demand, but can increase peak energy demand during times of low renewable energy production (e.g., winter). |
| Individual | Aspara, Luo, and Dhar | Incorporating carbon emissions in a car ownership tax reduced carbon |
| differences | (2017) | emissions of male drivers, particularly those with high intelligence. |
| (Segment | Hardisty, Johnson, and | Republicans respond to a carbon penalty only if it is framed as a tax, |
| characteristics) | Weber (2010) | Democrats respond regardless of whether it is framed as a tax or an offset. |

The table highlights the literature's predominant focus on the role of certain individual components of the 4 Ps – namely, Price and Promotion – in facilitating clean energy adoption. In doing so, the literature overlooks the potential role of other factors, such as Product, identifying the role of new technologies and energy source combinations to reduce carbon emissions, as well as Place, identifying the critical role of economic and sustainable delivery of clean energy to households. Thus, there is a need to develop a more holistic framework that recognizes the importance of integrating across all the Ps to facilitate firm innovation and consumer buy-in for clean energy solutions. First, we overview the main takeaways from prior research about the effectiveness of commonly studied factors as they pertain to the 4 Ps. We then delineate a "system-wide" approach requiring the integration and coordination across the 4 Ps, facilitated by a two-way information flow between firms and consumers.

Price

Prior research on affordability examines how various forms of financial rewards, incentives, and penalties impact clean energy consumption.

Financial rewards and incentives. Financial incentives are a common approach to increase the affordability and adoption rates of clean energy consumption. For example, consumers who purchase electric vehicles might receive tax deductions, rebates, or subsidies. Even if these tactics might increase immediate demand for electric vehicles, their overall implications for sustainable energy consumption are less evident. For example, Klöckner,

Nayum, and Mehmetoglu (2013) found that when the Norwegian government offered incentives for the purchase of electric vehicles, most households purchased electric cars as additional (rather than primary) vehicles, and such households also took more frequent trips and expressed a weaker desire or sense of responsibility to reduce car use, resulting in higher overall mileage. Thus, even if making electric vehicles more affordable increased EV demand, the incentives could have unintended negative consequences for overall energy use, i.e., the rebound effect (Gillingham and Palmer 2014). Similar findings emerge from other examples of financial rewards for buying sustainable energy goods, such as home insulation, for which tax credits seemingly had no effect on home insulation decisions (Pitts and Wittenbach, 1981).

Other forms of financial incentives employ techniques such as reducing the price per unit of use (or variable cost per use). Studies of households' sensitivity to price differences between peak versus off-peak hours yield mixed results. Highlighting the price differential might shift energy consumption to off-peak hours (Heberlein and Warriner, 1983), but such shifts do not seem to reduce households' overall energy use (Sexton et al.1987). More recent studies also propose that price discounts can be effective. For instance, according to Burkhardt, Gillingham, and Kopalle (2023), lowering energy prices during off-peak, night hours shifted energy consumption to these hours, mostly by encouraging rescheduled electric vehicle charging, which can be automated ahead of time. Uses of home appliances, such as air conditioners, that are not based on automated scheduling, but that account for the majority of households' energy use, did not change. Arguably then, automated scheduling of energy uses might shift households' energy consumption in financially and environmentally sustainable ways.

Financial penalties. On the other side of the equation, financial penalties such as taxes or price hikes can be levied on energy consumption using conventional sources. Economists have

argued that making conventional energy less affordable, in the form of a carbon tax, is vital for lowering CO₂ emissions and encouraging the development of alternative energy sources (Hansen et al., 2008; Hardisty, Johnson, and Weber, 2010). However, it is important to consider the potential backfiring effect of financial penalties due to the licensing effects resulting from the quantification and normalization of penalized behavior (Gneezy and Rustichini, 2000).

Structuring affordability policies to create continuous financial incentives or tying them to variable energy use (rather than discrete or temporary) can help promote sustainable energy production and consumption. However, as we review next, financial incentives (i.e., a pricing focus) alone may not be sufficient to ensure clean energy policies' lasting success. Therefore, we propose that the knowledge research has gained about the effects of pricing strategies to increase affordability perceptions need to be combined with additional tools that invoke the other 4 Ps may be necessary to achieve long-term sustainable outcomes.

Promotion

A growing number of studies in marketing examine the role of framing, feedback, and social norms in persuading consumers to adopt sustainable consumption habits.

Information provision and framing. Providing consumers with information about the benefits and consequences of clean energy consumption and their own energy consumption habits is commonly advised to achieve desired behavioral change. This is based on work in other domains showing that information provision can be effective. For instance, consumers reduce their mobile phone usage when they receive alerts that they are reaching the next pricing tier (Grubb and Osborne, 2015), and information about calorie content can reduce caloric intake (Bollinger et al., 2011). In the domain of energy use, information provision can be effective, but how the information is framed is important. Specifically, the gain versus loss framing has been

found to yield differential effects. For instance, using energy-efficient appliances might be described in terms of energy costs versus energy savings linked to different appliances in a certain time period, or it could be described in aspirational terms, according to the energy savings attained by a neighbor. Studies show that consumers weight environmental losses (e.g., deterioration in air quality) more heavily than environmental gains (e.g., improvement in air quality) (Hardisty and Weber, 2009). As a result, they are more likely to choose energy-efficient products (vehicles, appliances etc.) in response to prompts that highlight energy costs rather than energy consumption or savings (Bull, 2012; Camilleri and Larrick, 2014; Min et al., 2014). For example, consumers prefer fuel-efficient vehicles when they consider a comparison of different vehicles based on the cost of fuel rather than the gallons of gas they required (Camilleri and Larrick, 2014). Energy cost information may be even more effective if presented at aggregate rather than more granular levels, such as the cost of gas per 100,000 (vs. 100) driven miles or the cost of the energy required over a product's lifetime rather than just a year (Camilleri and Larrick, 2014; Kallbekken, Sælen, and Hermansen, 2013).

Importantly, providing personalizing information can yield desirable outcomes. In particular, providing households with personalized reports about their energy use and costs, then offering tailored tips about how to improve energy efficiency, can enhance sustainable energy consumption (Abrahamse et al., 2005; Wilhite and Ling, 1995; Winnett, Love, and Kidd, 1983). Such personalized reports could be even more impactful if they are continuous rather than discrete (e.g., monthly; Van Houwelingen and Van Raaij, 1989). Interestingly, combining personalized feedback with social comparison can be particularly effective, as it leverages the power of social competition and norms to yield desirable outcomes, as we discuss next. **Social influence.** A growing literature examines how social influence may be deployed to fight climate change. Studies show that information provision and feedback can leverage comparisons with relevant references such as households in a neighborhood and social norms (Allcott, 2011; Allcott and Rogers, 2014; Brandon et al. 2018). Such feedback can effectively motivate consumers to conserve in order to achieve favorable comparisons. For example, one utility company reported a 2–4% energy savings and significant reduction in CO₂ emissions after it provided information about how households' energy consumption compared with their peers' (Cuddy, Doherty, and Bos, 2010; Laskey and Kavazovic, 2010). Positive peer effects also appear in relation to the adoption of clean energy sources (solar panels; Bollinger and Gillingham, 2012; for a review see Wolske et al. 2020), especially if community leaders exhibit (not just talk about) clean energy consumption (i.e., install solar panels; Kraft-Todd et al., 2018).

Still, the effectiveness of peer information about sustainable energy use may vary with the target audience. Peer information has the intended effect among households that use more energy than others, but it can backfire and inadvertently increase energy consumption among households that use less energy, suggesting that peer information creates an implicit social norm about acceptable levels of energy consumption in the neighborhood (Schulz et al., 2007). Thus, properly targeting such information or tailoring it based on household energy use patterns, along with communicating peers' expected or approved (rather than just current) energy consumption behaviors, may help ensure the effectiveness of peer information for encouraging sustainable energy consumption practices (Beale and Bonsall, 2007; Jachimowicz et al., 2018).

Product and Place

Compared to affordability, information provision, and social dynamics, pertaining to the Price and Promotion levers of marketers, relatively limited work in marketing has explored the role of Product and Place – namely, new technologies and energy delivery methods – in facilitating the wide-spread diffusion of clean energy. However, recent work highlights the potential value of these factors. In a field experiment tracking electricity consumption across over 2,000 households, Bollinger and Hartmann (2020) found that, while information provision strategies implemented via an online portal and in-home display both sensitize demand to dynamic electricity pricing, programmable thermostats that automatically adjust to dynamic pricing are the most effective. The authors attribute this result to the benefits of automation in terms of reducing behavioral friction and enabling real-time response.

Other work points to the potential nuanced effects of smart thermostats. In an analysis of cross-country data of electricity consumption in hundreds of thousands of homes, Lee and Zhang (2022) show that smart thermostat use can reduce overall energy consumption but boost peak heating demand when renewable energy production is low (winter, morning). Thus, the role of technological solutions (such as smart thermostats and automation) in driving clean energy consumption merits further investigation. This is a gap we aim to address with our comprehensive 4 Ps framework.

Segment Characteristics

In addition to examining the main effects of individual tools on clean energy adoption, it is also important to consider how segment characteristics may modulate these effects. Extant work points to the value of accounting for consumers' baseline levels of engagement in conservation behaviors and bringing low-engagement consumers on board. Techniques such as social influence can be effective for these individuals. However, it is important to acknowledge the potential backfiring effects of such techniques for individuals with high initial baselines. For instance, providing personalized feedback about how consumers' energy consumption compares to the neighborhood average bolstered energy conservation among relatively unsustainable energy users, but lowered it among relatively sustainable users (Schulz et al., 2007).

Consumers' demographic characteristics such as income and geographic location may also dictate their energy needs and influence compliance with energy conservation appeals. For example, a 20% discount on monthly electricity bills in California, lowered overall energy consumption by 4% in inland regions, which are characterized by higher summer temperatures, lower household incomes, and relatively low energy consumption already (Ito, 2015). In coastal regions—with lower summer temperatures, higher household incomes, and excessive energy consumption—the incentive had no effect. The differences in consumers' information processing tendencies are also relevant. Among male drivers in Finland, incorporating carbon emissions data in determining annual car ownership taxes (Aspara, Luo, and Dhar, 2017) could be linked to lower carbon emissions among drivers with higher levels of intelligence and income. In absolute terms, a 3% drop in carbon emissions occurred among high (vs. low) intelligence groups.

Lastly, consumers' political ideology is also relevant for the success or clean energy solutions (Hardisty, Johnson, and Weber, 2010): Liberal consumers favor the carbon emission penalty, regardless of how it is framed, whereas politically conservative consumers only support the policy if it is framed as a carbon offset, and a tax framing sparks their significant opposition. In sum, it is critical to fine-tune financial penalties to match relevant segment characteristics.

This Research: System-wide Approach Integrating the 4 Ps

Taken together, the research on clean energy has addressed several individual tactics that may increase clean energy consumption. What the literature overview highlights, however, is that while affordability is clearly important, focusing on affordability alone may not be sufficient to encourage long-term adoption of clean energy options and consumption practices. Equally important, currently in the residential electricity usage sector, there is (in most cases) only a one-way flow of information to consumers. For example, a utility company transmits power from the electricity generation source to residential customers in the form of real-time supply because the generated electricity cannot be stored. However, there is no information flow to the consumers, such as price changes or automated changes to the use of appliances. For the most part, retail electricity prices for residential consumers are fixed with few exceptions such as peak period pricing. The key issue with this structure is that wholesale prices are constantly fluctuating while retail prices are not. So, residential consumers have no incentive to adjust consumption when wholesale prices increase. The reason wholesale prices increase during peak hours is because as demand shifts outward, more expensive generators turn on. These expensive and oftentimes dirtier generators only exist to supply peak period demand and keeping around expensive and dirty generators is inefficient.

Therefore, in this research, we explore how integrating affordability such as critical peak pricing with other solutions such as technology (i.e., utilizing a smart thermostat), can influence the adoption of clean energy consumption behaviors. We argue that a combination of energy storage and enabled consumer responsiveness such as smart homes with NEST thermostats that could be controlled by the utility or an aggregator holds promise to address the issue in the long run, allowing expensive and dirty peaking generators to be retired.

Specifically, we propose a comprehensive framework that emphasizes the integration and coordination among tools across the clean energy 4 Ps as well as consumer segment characteristics. This framework leverages Price and Promotion tools studied in prior research, as well as the role of Product and Place, in particular, technological solutions and automation of energy supply and use, which have been overlooked in prior research. Technological solutions

may play a critical role in large-scale implementation of clean energy solutions and tracking of consumer compliance with and retention of sustainable energy consumption practices over time.

- **Product**: Adoption of products such as smart thermometers (e.g., NEST) that facilitate consumer understanding and monitoring of their energy consumption habits; Delivery and consumption of energy from a combination of renewable clean sources (wind, solar), optimized based on the market's energy demand and battery storage capacity, to decarbonize the power grid.
- **Place**: Energy delivery mediated by technology that automatically adjusts households' energy use through smart tools such as NEST (allowing for manual override) to smooth energy supply over, for example, critical peak periods (4PM-7PM).
- **Price**: Deployment of pricing strategies such as critical peak pricing to encourage clean energy adoption and smooth the demand-supply gap during critical peak periods (4PM-7PM).
- **Promotion**: Education and feedback about households' energy use and clean energy options, as well as deployment of social influence and norms (e.g., word-of-mouth, opinion leaders) to facilitate clean energy adoption and use.
- Segment characteristics: We also examine the role of individual differences identified as relevant in prior research (demographics, cognitive processing, political ideology).

We posit that the deployment of the 4 Ps solution and consumer segment characteristics requires a two-way flow of information within the system between firms and consumers. At one end, consumer response to the 4 Ps relies on the firm's accurate, personalized, and timely provision of information about the crucial aspects of the 4 Ps (e.g., price changes, feedback about energy use and consumption norms) to consumers. At the other end, firms' ability to effectively implement and adjust the 4 Ps (e.g., energy supply and use during critical peak periods) relies on the accurate, real-time flow of information from consumers to firms. Owing to the utilization of all aspects of the marketing plan (4 Ps) and an information loop connecting firms and consumers, we view this comprehensive framework as offering a "system-wide" solution to facilitate clean energy adoption and fight climate change.

We conduct three studies to examine this comprehensive framework, and Figure 1 highlights the operationalizations of our framework components in the studies. We open with a consumer survey that examines consumer interest in clean energy adoption in response to various solutions within the 4 Ps (Product: utility plans that rely on renewable clean energy sources, electric/hybrid vehicles; Price: Critical Peak Pricing; Place: automated adjustment of energy supply and use during critical peak periods; and Promotion: personalized feedback and information about clean energy use). The survey also elicits consumers' willingness-to-pay for each solution to check if consumers would be willing to pay a premium for a system-wide solution. We proceed with a field experiment that zooms in on arguably the most instrumental of the 4 Ps for dissemination of affordable clean energy (Price), as well as the role of smart technology such as NEST (Product). The results of a one-year field experiment indicate that the critical peak pricing strategy reduces households' energy use by an average of 14%. The field study also shows the limited effectiveness of smart tools (NEST) alone in mediating energy consumption in the absence of an automation piece (managed by firms, but with an override available to consumers). In the final study, we describe the results of a simulation, in which we examine how energy savings produced by critical peak pricing can pave the way to a decarbonized energy grid with varying combinations of renewable clean energy sources.

Figure 1: Facilitating Adoption of Affordable Clean Energy

Physical Transmission of Energy



Virtual Transmission of Information

Consumer survey: Thoughts and intentions towards clean energy solutions

To begin to understand why consumers choose to adopt, or not to adopt, clean energy solutions, we conducted a survey with a broad sample of U.S. consumers to examine the relative appeal of various clean energy solutions. In particular, we aimed to determine relative "pain points" that keep consumers from engaging in a variety of clean energy solutions, including aspects such as pricing and perceived effort to use; tapping into a couple of the features that stood out during the field experiment. To effectively examine the role of affordability, we sought equal representation of participants from low-, mid-, and high-income tiers using features from Prolific for recruitment such that 33% of participants reported an annual household income of below \$40,000; 33% reported an income of \$40,000 to \$89,999; and 34% reported an income of above \$90,000. We also accounted for affordability and pricing metrics from a relative perspective (i.e., paying X% of a monthly bill on a clean energy solution), to determine affordability across incomes.

Method

We recruited 600 U.S ($M_{age} = 39, 36.5\%$ female) participants on Prolific Academic in exchange for monetary compensation across a wide range of household incomes. Participants first reported whether they engaged in consumption behaviors that promote sustainable energy use (i.e., whether they study their monthly electricity bill to understand their energy consumption habits, use a smart thermostat such as NEST, subscribe to a clean energy option offered by their utility provider, drive an elective vehicle, or drive a hybrid vehicle: "yes" vs. "no").

Afterwards, depending on whether the respondents indicated they did, or did not engage in the behavior, they reported the extent to which various factors influenced their behavior (i.e., the pain points or rationale behind their actions): 1) monetary cost/savings associated with the behavior, 2) effort associated with the behavior, 3) the behavior's perceived effectiveness, 4) belief in the environmental impact, and 5) personal belief regarding the importance of sustainable energy consumption; all from 1 = "not at all" to 7 = "very much so").

Subsequently, to gather how much additional cost consumers would be willing to absorb for cleaner energy solutions, participants indicated how much they would be willing to pay on a monthly basis (as an additional percentage on top of their current monthly bill, 0% - 150%) to engage in a number of clean energy features: 1) use a smart thermostat such as NEST, 2) subscribe to a clean energy option with their utility provider, 3) receive a personalized report about reducing energy costs, and 4) adopt an automated solution that adjusts energy consumption so as to lower carbon emissions and costs. Participants also indicated their willingness to pay a one-time upfront fee for each solution (1 = "not at all likely" to 7 = "extremely likely"). Next, participants answered how interested and willing they would be to manually adjust their energy consumption on a regular basis to lower emissions and costs, and interest and willingness to study their patterns to learn strategies to lower emissions and costs (both 1 = "not at all" to 7 = "very much"). Finally, participants indicated whether they would be willing to adopt each solution if it kept their current monthly energy bill as is and if it increased their bill by 10%, 20%, 30%, 40%, and 50% ("yes" vs. "no").

To examine potential variation in the appeal of various solutions across segments, we also measured relevant individual difference characteristics (need for cognition, 6-item version from Coelho, Hanel, and Wolf, 2018, adapted from Cacioppo, Petty, and Kao, 1984; green consumption values, 6 items from Haws, Winterich, and Naylor, 2013; and political ideology, single item from Jost, 2006) and demographics (education, annual household income, state, type of residence, type of area, home ownership, and household size).

Results

Current behaviors. Participants reported not currently engaging in most of the listed clean energy solutions: whereas 57.0% of participants reported studying their energy bill, only 25.4% own a smart thermostat such as NEST, 13.9% subscribe to a clean energy option with their utility provider, 11.5% drive a hybrid vehicle, and 4.5% drive an electric vehicle. This reflects the challenge of popularizing clean energy solutions in the mass market. None of the demographic characteristics influenced participants' propensity to study their energy bill (*p*'s > .10). However, the adoption of smart thermostats and clean energy options were positively linked to participants' income (*p*'s < .05), education (*p*'s < .05), and home ownership (*p*'s < .005); smart thermostats were additionally more prevalent in larger households (*p* = .021). Electric vehicles were more prevalent among homeowners (*p* = .020) and in larger households (*p* = .027), and hybrid vehicles were prevalent among more educated consumers (*p* = .007). In terms of the psychographic characteristics, need for cognition predicted participants' propensity to study their energy bill (*p* < .001), but not any other behavior (*p*'s > .1), and green values predicted all behaviors (*p*'s < .001), except electric vehicle use (*p* = .119).

Importantly, for those who avoided any given clean energy solution, monetary cost ranked as a significantly stronger culprit (averaged across solutions: $M_{\text{cost}} = 5.03$) than any other factor ($M_{\text{effort}} = 3.88$, $M_{\text{effectiveness}} = 2.95$, $M_{\text{environmental impact}} = 2.66$, $M_{\text{sustainability importance}} = 1.96$; all p's < .001). Similarly, among those who adopted any given solution, cost savings ranked as a significantly stronger motivator ($M_{\text{cost}} = 5.69$) than any other factor ($M_{\text{effort}} = 3.71$, $M_{\text{effectiveness}} = 5.22$, $M_{\text{environmental impact}} = 4.36$, $M_{\text{sustainability importance}} = 4.89$; all p's < .001). These findings underscore the primary role that affordability plays in the adoption of sustainable energy solutions.

Interest in the automated solution. Participants' average propensity to opt in for the automated solution (M = 25.01%) did not significantly differ from their propensity to opt in for a smart thermostat (M = 22.97%), a clean energy option offered by their energy provider (M = 27.36%), or personalized reports (M = 22.74%, p's > .1). However, participants reported a higher willingness-to-pay on a monthly basis for the automated solution (M = 17.50% on top of the current monthly bill) compared to a smart thermostat (M = 11.02%), personalized reports (M = 13.85%), and a clean energy option from their utility provider (M = 14.55%; p's < .05). This monthly willingness-to-pay was even higher among more environmentally conscious participants (p < .001), who hold conservative (vs. liberal) political views (p = .030)² and reside in metropolitan (vs. rural) areas (p = .004) and larger households (p = .006).

Participants were also more willing to incur a one-time cost for an automated solution (M = 4.01) than for personalized reports (M = 3.71, p = .01), and they were as willing to pay a onetime fee for an automated solution as for a smart thermostat (M = 4.12) and a clean energy option from an energy provider (M = 4.09; p's > .1). This willingness to pay a one-time fee for an automated solution was higher among more environmentally conscious (p < .001), educated (p =.005), and affluent (p < .001) participants who hold liberal (vs. conservative) political views (p <.001) and reside in metropolitan (vs. rural) areas (p = .049) and larger households (p = .026). The

² The consumer survey results revealed a positive coefficient of conservative (vs. liberal) ideology for WTP, which contrasts with prior political ideology findings. Two factors could help with the interpretation of these results. First, conservatives more strongly endorse the free market (Jost et al. 2003) that encourages and values providers' initiative, entrepreneurship, and market orientation. Since the development of smart technologies such as NEST, personalized customer feedback, and automation can be tied to firms' customer orientation and initiative in consumers' minds, conservatives' higher WTP for these offerings could reflect their perception and appreciation of firms that create these offerings. It may not necessarily reflect their greater interest in actually procuring and consuming these offerings themselves, as evidenced by the lack of a similar positive effect of conservative ideology on willingness to opt in to these offerings (the coefficient of ideology was negative for NEST and automated solution and it was non-significant for personalized feedback). It will be interesting to delve deeper into the role of segment characteristics such as political ideology in determining the effectiveness of various 4 P components in driving clean energy adoption.

variation observed in consumers' interest to adopt an automated solution when it is associated with a monthly vs. one-time fee suggests that the nature and structure of economic costs and savings associated with automated solutions may matter, and implementing the costs/savings on a variable (e.g., monthly) basis may increase the appeal of these solutions to the broad population. Furthermore, developing more targeted appeals for these solutions (leveraging relevant segment characteristics) may be beneficial (see Tables 2 and 3 for effect sizes across all variables for these WTP and opt-in outcomes and Table 4 for means across some segments).

When asked how interested and willing consumers would be to manually adjust their energy consumption, the only thing to significantly increase this was their green values (p < .001). Older individuals were marginally more willing and interested (p = .05), and no other demographics influenced this interest (all p's > .287). When asked how interested and willing consumers would be to study their energy consumption, consumers' green values significantly increased this behavior (p < .001) and their need for cognition did so only marginally (p = .05). No demographics influenced this interest (all p's > .335).

| | Outcome Variable | | | | | | | | |
|----------------------------------------------------------------------|-----------------------------|---------------------------------------------|-----------------------------------------------|----------------------------|--|--|--|--|--|
| Independent Variable | WTP for smart thermostat | WTP to Subscribe to clean energy options | WTP to receive personalized energy reports | WTP for Automated solution | | | | | |
| Constant | -6.29(10.87) | -4.698 (8.36) | -6.286 (10.87) | -3.101 (10.45) | | | | | |
| Need for Cognition | -2.409 (1.33)* | 658 (1.04) | -2.409 (1.33)* | -2.534 (1.28)** | | | | | |
| Green Values | 6.124 (1.42)*** | 4.996 (1.14)*** | 6.124 (1.42)*** | 7.586 (1.36)*** | | | | | |
| Political Ideology (Low = more liberal, High = more conservative) | 2.863 (.543)*** | .072 (.441) | 2.863 (.543)*** | 2.137 (.522)*** | | | | | |
| Age | 153 (.092)* | 159 (.073)** | 153 (.092)* | 274 (.088)** | | | | | |
| Gender | -1.756 (1.90) | 654 (1.52) | -1.756 (1.90) | -2.706(1.82) | | | | | |
| Education Level | .809 (.99) | 423 (.783) | .809 (.991) | .774(.953) | | | | | |
| Income Level | 136 (.355) | .371 (.279) | 136(.355) | 012(.341) | | | | | |
| Housing Situation (Area) | -1.488 (.947) | .192 (.781) | -1.488 (.974) | -1.598(.937) | | | | | |
| Housing Situation (Building) | 227 (1.04) | .284 (.821) | 227(1.04) | .308(.995) | | | | | |
| Own/Rent | 2.167 (1.62) | 2.944 (1.27)** | 2.167(1.62) | 1.916(1.56) | | | | | |
| Household Size | .692 (.863) | .702 (.672) | .692 (.863) | 1.916(.830) | | | | | |
| F-Value (df) | 4.39 (11, 430)*** | 3.54 (11, 499)*** | 4.29 (11,583)*** | 5.96 (11, 583)*** | | | | | |
| Adjusted R Square | .057 | 0.052 | 0.057 | 0.084 | | | | | |

 Table 2: WTP Table

The results of multiple regression analyses are presented in this table – unstandardized coefficient (standard error)

* p < .10, ** p < .05, *** p < .01

| | Outcome Variable | | | | | | | |
|----------------------------------------------------------------------|--------------------------------|---------------------------------------------|-----------------------------------------------------|-------------------------------|--|--|--|--|
| Independent Variable | Opt-in for smart thermostat | Opt-in to Subscribe to clean energy options | Opt-in to receive personalized energy reports | Opt-in for Automated solution | | | | |
| Constant | 2.903(.834)*** | 1.042(.727) | .692(.776) | 2.055(.730)** | | | | |
| Need for Cognition | 084(.102) | 124(.090) | 200(.095)** | 257(.089)** | | | | |
| Green Values | .549(.113)*** | .878(.099)*** | .681(.101)*** | .870(.095)*** | | | | |
| Political Ideology (Low = more liberal, High = more conservative) | 085(.044)* | 128(.038)*** | .035(.039) | 063(.036)* | | | | |
| Age | 009(.007) | 016(.006)** | 003(.007) | 021(.006)*** | | | | |
| Gender | 238(.149) | .187(1.32) | 137(.135) | 139(.127) | | | | |
| Education Level | 173(.077)** | 061(.068) | .091(.071) | .072(.067) | | | | |
| Income Level | .141(.029)*** | .079(.024)*** | .031(.025) | .045(.024)* | | | | |
| Housing Situation (Area) | 045(.077) | .000(.068) | 012(.070) | 010(.065) | | | | |
| Housing Situation (Building) | 008(.079)** | .046(.071) | .044(.074) | 021(.069) | | | | |
| Own/Rent | .283(.125) | .310(.110)** | .247(.116)** | .086(.109) | | | | |
| Household Size | 049(.069) | .045(.058) | .077(.062) | .120(.058) | | | | |
| F-Value (df) | 7.27 (11,430)*** | 16.48 (11,499)*** | 5.95 (11, 583)*** | 13.29 (11, 583)*** | | | | |
| Adjusted R Square | 0.135 | 0.250 | 0.084 | 0.185 | | | | |

Table 3: Willingness to Opt-In

The results of multiple regression analyses are presented in this table – unstandardized coefficient (standard error) * p < .10, ** p < .05, *** p < .01 _____

| Table 4: Means | Across | Samples for | Outcome | Variables |
|----------------|--------|-------------|---------|-----------|
| | | | | |

~

~

| | Outcome Variables: Means (SD) | | | | | | | |
|-------------------------|--------------------------------|---------------------------------------------------|--------------------------------------------------|----------------------------------|-----------------------------------|------------------------------------------------------|--------------------------------------------------------|-------------------------------------|
| Independent Variable | WTP for smart thermostat | WTP to Subscribe to clean energy options | WTP to receive personalized energy reports | WTP for Automated solution | Opt-in for smart thermostat | Opt-in to Subscribe to clean energy options | Opt-in to receive personalized energy reports | Opt-in for Automated solution |
| Liberal | 10.98(15.92) | 15.44(21.48) | 8.21 (19.85) | 12.73(21.17) | 4.47(2.03) | 4.57(1.99) | 3.72(2.11) | 4.18(2.08) |
| Conservative | 10.35(19.79) | 11.69(19.82) | 13.23(29.97) | 12.18(21.38) | 3.72(1.97) | 3.28(1.94) | 3.23(2.02) | 3.20(1.93) |
| Low Income | 10.09(18.69) | 13.63(20.84) | 11.41(27.14) | 13.25(24.47) | 3.63(2.03) | 3.73(2.13) | 3.26(2.18) | 3.41(2.13) |
| Middle Income | 11.90(18.28) | 13.43(21.54) | 10.57(24.57) | 12.29(20.50) | 4.43(2.07) | 3.99(2.00) | 3.65(1.96) | 4.03(1.94) |
| High Income | 10.09(16.68) | 14.02(20.07) | 10.22(24.85) | 11.82(17.05) | 4.44(1.85) | 4.17(2.02) | 3.67(2.06) | 3.73(2.07) |

Discussion

In sum, the consumer survey corroborated the low popularity and challenge of adoption of sustainable energy consumption behaviors in the broader population of U.S. consumers, and it underscored the critical importance of affordability in preventing consumers from adopting sustainable energy solutions and in facilitating these solutions' diffusion in the mass market. Importantly, the survey highlighted the potential appeal of automated solutions (e.g., automatic moderation of households' energy consumption to anticipate fluctuations in energy prices and

supply) in addressing this challenge. Next, we test different financial affordability framing tactics and an automated solution to determine what, in practice, changes behavior.

Field Experiment

In our field experiment, we simulate an increase the electricity rate during CPP periods (i.e., a financial penalty for using electricity during that time) indirectly by having the consumers receive the amount of the difference between the dollar amount of their actual bill, minus the experimental bill, if the experimental bill is less. Otherwise, they earn no savings. This approach is used because it was impossible to actually change the electricity rate for consumers without a very arduous electric utility rate case.

In addition to testing the impact of the higher price, operationalized as an experimental price increase between 4PM-7PM on 12 of the hottest days in Austin, TX in 2013 (critical peak event days), we consider the influence of a NEST thermostat installation by having a treatment arm that provides the NEST thermostat to the treated households. These technologically advanced thermostats automatically learn a household's electricity usage behavior and adjust the thermostat to suit a particular household's preferences; they have gained notable popularity, possibly due to their similarity to other personalized tools that develop recommendations based on people's normal behaviors, such as exercise and fitness trackers.

Considering the growing prevalence of such smart products, a question of both academic and practical interest pertains to how firms, and utility companies in particular, can leverage those tools to help consumers enhance their well-being, such as by enabling households to reduce their electricity consumption during peak load periods, in ways that are both cost effective and supportive of clean electricity efforts. "Cost" effective in terms of the utilities not having to resort to expensive solutions to match electricity supply and demand, when demand outstrips supply during critical peak periods, and "clean" with respect to reducing greenhouse gas emissions via conserving residential electricity usage.

By examining both impacts simultaneously, we seek to help policy makers establish effective information-based approaches; these politically palatable tactics promise to reduce residential electricity consumption during peak times. From a consumer perspective, a simple information-based tool may be advantageous; adopting a NEST thermostat does not entail changing prices, and their adjustment costs likely are lower than they would be with dynamic pricing (Spector et al. 1995). However, dynamic pricing approaches, such as CPP or real-time pricing, more directly align retail prices with wholesale prices. Therefore, both the thermostat and the pricing tactic offer potential to help consumers adjust their demand, depending on when the generation cost of electricity provision is highest.

Method

The field experiment was conducted by Pecan Street, a company that partners with utilities, in 2013-2014 in Austin, Texas, however we only observe 2013 for the NEST users and so we only use 2013 data. Households received \$200 in return for signing up for the experiment, the invitation promised that they could save money on their electric bills by reducing their electricity consumption during critical peak periods but also reassured them they would not lose money. All the 163 households that enrolled had appliance-level and circuit-level electricity measurement using smart meters. In the control condition, 57 homes did not receive any treatment during the one-year period; 44 households had a NEST thermostat installed in their homes; and the 62 households in the pricing condition received a text message a day prior to each CPP event, reading "Tomorrow is a Critical Peak Pricing event. Your experimental electric rate will be \$0.64 per kilowatt hour from 4 P.M. to 7 P.M. Pecan Street Inc. Pricing." (Pecan

Street, an Austin-based nonprofit organization, enrolled all households in this study and was our partner for this experiment.) The NEST group did not receive any such text messages because the NEST thermostat learns if consumers are changing their thermostat setting during hot summer afternoons, for example, and automatically adjusts the thermostat going forward.

Even though the households were randomly assigned to the control and the treatment conditions, the number of households across the three conditions varied somewhat due to a combination of dropout as well as Pecan Street's preference to include more households in the pricing treatment condition. Table 5 lists the electricity usage, kilowatt hour per minute (kWh/minute), for the control and two treatment conditions during the pre-treatment month of March. The unit of observation is the household-minute.³

| | Table 5. Electricity Use, 11e-11ea | unit in Su | iiiiiiai y 🕅 | Statistics | |
|---------|------------------------------------|------------|--------------|------------|-----------|
| | Mean (kWh/minute) | SD | min | max | N |
| Control | 0.791 | 0.981 | 0 | 9.999 | 1,985,171 |
| Pricing | 0.742 | 1.078 | 0 | 9.999 | 2,327,999 |
| NEST | 0.841 | 1.004 | 0 | 9.998 | 1,319,368 |

Table 5: Electricity Use, Pre-Treatment Summary Statistics

Test of Random Assignment

To test for random assignment into the treatment groups, we regress the pre-treatment period (March) use on dummies for each treatment group (the left out dummy variable is the control group), using the following equation:

$$use_{itg} = \alpha + \beta^g D^g + \epsilon_{itg}$$

where use_{itg} is electricity usage by household *I* in treatment group *g* at time *t*, and D^g is a vector of dummy variables for the treatments ($g \in \{pricing, nest\}$). Standard errors are clustered at the household level. Applying this method to test for random assignment is common in the literature; for example Busse, Silva-Risso et al. (2006) adopt a similar test to compare treatment and

³ We drop negative electricity use and use above 10 kWh/minute.

control series one month before treatment occurs. Our results (see Table 6) show that there is no significant difference at a 5% significance level in electricity usage during the pre-treatment period between each of the two treatments and the control condition. This suggests that the two treatment groups are not significantly different from the control group in terms of their electricity usage during the pre-treatment period and thus the randomization appears to have worked.

Table 6: Electricity Usage (kWh/minute) in Pre-Treatment Period Conditions Relative to Control

| | Electricity Use |
|---------|-----------------|
| Pricing | 0.079 |
| | (0.089) |
| NEST | 0.189 |
| | (0.109) |
| N | 5,721,017 |

Notes: Standard Errors Clustered at the Household Level. * p < .05, ** p < .01, *** p < .001. The NEST group has higher average pre-treatment use. We can only attribute this to randomization and attrition due to data limitations.

Results

In Tables 7 and 8, we present the main results in terms of the overall use exhibited by each of the treatment groups. We estimate the following regression equation to test our results:

$$Y_{it} = \sum_{i} \beta^{j} T_{ijt} + X \gamma + \rho_{i} + \phi_{t} + \epsilon_{it}$$
⁽¹⁾

where Y_{it} is total electricity or air conditioning electricity usage by household *i* in minute t, T_{ijt} is a dummy variable indicating that household *i* is in the treatment group $j \in \{Pricing, NEST\}$ and receives the treatment in time *t* i.e., 4:00–7:00 pm on critical peak days. The terms ρ_i and ϕ_t are household and quarter hour of the sample fixed effects. We use household fixed effects to control for unobserved heterogeneity at the consumer level, and quarter-hour of the sample fixed effect (i.e., fixed effects for each fifteen-minute interval of the sample) to control for timespecific demand shocks. The term $X\gamma$ contains all other triple difference interaction terms not absorbed by the fixed effects.⁴ In Table 7, the coefficient of interest is the triple difference coefficient, β^{j} . That is, the regression coefficient for the triple difference variable shows how different electricity usage was in a treatment condition relative to the control on a critical peak pricing day and during the critical peak time of 4pm to 7 pm.

| Table 7: Overall Regression Results | | | | | |
|--------------------------------------------|--------------------|--|--|--|--|
| | Overall Use | | | | |
| Triple Difference Coefficient, Pricing | -0.625**** (0.194) | | | | |
| Triple Difference Coefficient, Nest | 0.163 (0.177) | | | | |
| Household Fixed Effects | Yes | | | | |
| Quarter of hour Fixed Effects | Yes | | | | |
| R-squared | 0.324 | | | | |
| N | 58,733,445 | | | | |

Notes: Standard errors clustered by household. Standard Errors Clustered at the Household Level. * p < .05, ** p < .01, *** p < .001.

Table 8: Appliance-Level (Air-Conditioning) Regression Results for Pricing Group

| | Air Conditioning |
|----------------------------------------|-------------------|
| Triple Difference Coefficient, Pricing | -0.479*** (0.170) |
| Triple Difference Coefficient, Nest | -0.008 (0.179) |
| Household Fixed Effects | Yes |
| Quarter of hour Fixed Effects | Yes |
| R-squared | 0.309 |
| N | 43,090,826 |

Notes: Standard errors clustered by household. Standard Errors Clustered at the Household Level. p < .05, ** p < .01, *** p < .001.

Because the NEST thermostat is designed to learn a household's behavior but not to react

to peak load times, homeowners must manually adjust their thermostats in response to the CPP

treatment. We find no evidence that they did so, as indicated by the insignificant and near zero

coefficients in Table 7. We conjecture that the insignificant result of the NEST thermostat

treatment could be due to at least three reasons. First, and likely the most important, is a lack of a

"nudge", for example, a text message 24 hours prior to a critical peak pricing event to adjust

⁴ Our triple differences include the critical peak days relative to non-critical peak days, the critical peaks hours during the treatment period (4-7PM on critical peak days) relative to non-critical peak hours, and the treatment groups relative to the control group.

their thermostat and the NEST group did not receive such a message. Second is the inconvenience of manually changing the NEST thermostat during late afternoons when it is hot so NEST can "learn" the residential customer's behavior. Third, without an experimental price change, there was not a major incentive to change behavior. In contrast, in the pricing treatment households were notified of the experimental price hike of electricity during CPP and manually had to change their electricity usage (e.g., by changing their air conditioning). Given that the NEST thermostat does not work in isolation in terms of energy conservation, we combine the above two results and propose a technological, automated "system-wide" solution.

It is possible for utilities to program NEST thermostats remotely to reduce energy usage during peak times. The absence of responsive behaviors among the NEST thermostat treatment group implies that, while it may represent a useful technology, the NEST thermostat would still need to be programmed to respond (either manually or automatically) during CPP to achieve any actual reductions in energy use. Thus, we propose that this rapidly-diffusing new NEST technology needs to be complemented with a pricing policy and/or an automatic, remotely controlled system, to affect electricity use during peak times of high stress to the grid.

The pricing treatment indicates a significant (p < .05) reduction in electricity usage during CPP, relative to households in the control condition. We also observe household electricity use at the appliance and minute levels, so we can decompose the treatment by specific appliance. In our field experiment, we find that approximately 63% of the pricing treatment reduction can be attributed to diminished use of air conditioning (see Burkhardt et al. 2023). Furthermore, the decrease in usage across both years of the experiment translated to a 14% decrease in electricity usage during CPP and accordingly, a 16% reduction in greenhouse gas emissions. That is, an automated solution that combines CPP with NEST thermostat could achieve a 16% cleaner energy distribution relative to status-quo for peak periods.

Discussion

The results of the field experiment thus indicate that a pricing intervention, which provides information about energy costs during critical pricing periods lowers energy consumption more effectively than a NEST intervention which learns about households' energy use and automatically adjusts the thermostat accordingly. Notably, both interventions require manual moderation of energy use to lower costs and emissions, which is effortful for consumers, and hence an automated approach that would respond to critical pricing periods and energy supply fluctuations without requiring effort, may prove more effective at lowering carbon emissions and costs.

Decarbonization Simulation

We complement our consumer survey and field experiment with a decarbonization simulation, designed to explore what the field experiment results imply as we progress toward higher market shares of wind and solar energy sources.

Many municipalities and states in the U.S. have voted to go carbon free by some date, sometimes as early 2030. Further, companies such as Mercedes-Benz recently announced that they are going all-electric by the end of this decade (Sebastian 2021). Electrifying transportation and other aspects of the economy will dramatically increase electricity demand. Combined, this implies a large increase in renewable generation capacity over the next several decades. As the fraction of renewables on the grid increases, the challenge of balancing supply and demand increases because solar and wind energy are both intermittent generation technologies. Two of the major strategies available are 1) battery storage and 2) demand response in the form of

utilities or private companies controlling in home energy use, which could be done through a system-wide solution through automation by combining CPP and NEST thermostat, for example.

We first consider what would happen if all fossil fuel capacity in 2020 had been replaced with wind and solar. Without load conservation or load shifting, grid operators rely on fossil fuel backup generation, more intermittent renewable generation capacities from different locations, or energy storage (e.g., batteries) to ensure that the lights stay on. Then, by exploring cases with varying fractions of wind and solar, relative to their actual uses in 2020, we learn which combinations of wind and solar capacity would minimize the production deficit resulting from a loss of fossil fuel capacity, on average. This allows us to calculate the average production deficit during each hour of the day due to the intermittent and low-capacity utilization of renewables and to show how load conservation (CPP) or load shifting could help make up for this shortfall. Our analysis reveals the potential cost savings achieved through demand response and automation as the grid transitions away from fossil fuels.

For the simulation that we detail hereafter, we gather data from ERCOT (Electric Reliability Council of Texas): monthly generator-level coal and natural gas expenditures, total energy input in millions of BTUs (MMBtu), and total electricity produced in MWh for 2013–2020. We also obtain generator-level hourly emissions from the Environmental Protection Agency's Continuous Emissions Monitoring System (CEMS).⁵ We estimate each generator's variable cost (\$/MWh) by multiplying each generator's heat rate (i.e., total energy input (MMBtu)/total electricity output (MWh) by fuel expenditures. By combining these data with each generator's nameplate capacity, from Energy Information Administration (EIA) Form 860, we can construct simulated monthly supply curves for ERCOT. The mean variable cost is

⁵ https://www.eia.gov/electricity/data/emissions/

\$38.32/MWh, with a minimum of \$15.21/MWh and a maximum of \$239.07/MWh. The supply curve from March 2013 in Figure 3 is an example simulated supply curve. This construction assumes perfect competition. We drop variable cost values above the 99th percentile and below the 1st percentile of all variable costs, to avoid those that are unrealistically high (e.g., \$5,000/MWh) or unrealistically low (e.g., \$0.43/MWh).⁶

Figure 3: Variable Costs by Fossil Fuel Generator, ERCOT, March 2013

Next, we consider decarbonizing the Texas grid. To do so, we imagine that we shut down all coal and natural gas production. Figure 4 displays the hourly fossil fuel generation on average over and above the renewables in 2020 in ERCOT. Another way to think of this is the additional renewable capacity needed to keep the lights on in ERCOT (on average) if fossil fuels shut down, assuming renewables are fully dispatchable and can generate electricity whenever we want them to.

⁶ Note, the supply curve represents fossil fuel supply and does not include wind or solar.



However, in reality, renewables are not fully dispatchable. Figure 5 displays the average wind and solar capacity utilization rates (i.e., the fraction of the full rated capacity of the wind or solar farm that is producing electricity) by hour in 2020. These capacity utilization rates are useful for telling us when the wind is blowing and when the sun is shining. These are calculated by dividing the total wind and solar generation for each hour in 2020 by the wind and solar capacity in ERCOT. These capacity utilization rates will be used in our simulation.

Figure 5: Average Capacity Utilization Rate Over the 24-Hour Day



As a next step, we are interested in understanding what would happen if we actually tried to replace the fossil generation in the Texas grid with renewables. Of course, different amounts of solar and wind are possible—one could imagine a grid with a lot of solar and a little wind producing just as much total electricity over a day as a grid with a lot of wind and a little solar. However, the timing of the generation would be different between the different mixes and would depend on the utilization rates displayed in Figure 5. We examine different mixes of wind and solar and determine the mix that minimizes the average production deficit if fossil fuel generation were completely replaced by renewable energy.

To make this calculation, we scale up renewable capacity, divide it into fractions of wind and solar, multiply by the actual wind and solar hourly utilization rates (Figure 4), and subtract the result from the hourly fossil fuel generation.⁷ The result provides the generation surplus or deficit for each hour in 2020, according to our alternative grid. The results for different renewable mixes are displayed in Figure 6, which reveals that some hours would experience surplus generation, but others (i.e., peak hours) indicate shortages of up to nearly 20,000 MWh on average.



The surplus and shortages depend on the mix of wind and solar. In general, higher fractions of wind power appear to minimize generation deficits. In general, we observe a surplus in the middle of the day (higher with more solar on the grid) and a deficit at night. Wind tends to

⁷ ERCOT fossil fuel capacity was 96,730 MW in 2020.

flatten the curve over the day—ideally, we would have no deficits and minimal excess renewable electricity, which might just be wasted (i.e., curtailed).

Once we have the information in Figure 6, we can explore the need for energy storage in this high-renewables grid. We collapse the hourly surpluses and deficits to generate estimates of the total surplus or deficit over each day, which provides an estimate of the average daily need for battery storage. The results for each wind/solar generation mix are in row 1 of Table 9. This table shows that there is a massive surplus of electricity with high fractions of wind (negative values), but a major deficit with low fractions of wind (positive values). To keep the lights on, energy storage (such as battery storage) would be needed to cover the deficits unless we were willing to keep around the expensive and dirty peaking plants.

| v | | 1 | | (| , |
|-------|------------------------------|---------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 40% | 50% | 60% | 750/ Wind | | 000/ Wind |
| Wind | Wind | Wind | 7576 W INA | | 90% wind |
| 53431 | 21644 | -10143 | -57824 | | -105505 |
| 8315 | -23471 | -55259 | -102940 | | -150621 |
| | 40% Wind 53431 8315 | 40% 50% Wind Wind i3431 21644 8315 -23471 | 40% 50% 60% Wind Wind Wind i3431 21644 -10143 8315 -23471 -55259 | 40% 50% 60% 75% Wind Wind Wind Wind 53431 21644 -10143 -57824 8315 -23471 -55259 -102940 -102940 | 40% 50% 60% 75% Wind Wind Wind Wind 3431 21644 -10143 -57824 8315 -23471 -55259 -102940 -102940 |

Table 9: Daily Generation Surpluses and Deficits (MWh)

Notes: This table presents the daily sum of the generation in Figure 4. Surpluses are negative, and deficits are positive, so a negative value is good for the grid.

Next, we consider how much the CPP treatment effect would reduce the shortages. We multiply the total load for each hour by the average fraction of electricity demand that is residential (43%) and by the CPP treatment effect in percentage terms, and then subtract it from the total load. This analysis assumes that the CPP is a constant percentage across all hours and all households. The results can be seen in row 2 of Table 9. The results highlight how powerful CPP is for reducing the deficit at lower levels of wind. It also suggests that 100% renewables could be achieved with less investment in renewables. In a futuristic sense, our analysis in Table 9 gives a sense of the benefits we might expect from applying the CPP more broadly.

We next explicitly calculate how much battery storage capacity would be required to meet each of the renewable mix scenarios, in terms of MWh/day. By taking the average of the hourly deficits (see Figure 5) for all hours in 2020, as well as the maximum over all hours, we can find a maximum of the mean, which represents an estimate of the average daily load that is not immediately met by the additional counterfactual renewable generation—that is, an estimate of the need for battery storage in MWh (Table 10). We also find the maximum need for battery storage over all hours in 2020 by taking the maximum of the hourly deficits for all hours in 2020, as depicted in Table 10.

| 8 | | v | 0. | 8 (| , | | | |
|-------------------------------------------------|--------------|----------|----------|----------|----------|--|--|--|
| | 40% Wind | 50% Wind | 60% Wind | 75% Wind | 90% Wind | | | |
| Panel A: Average Daily Need for Battery Storage | | | | | | | | |
| Maximum Average Hourly Deficit | 16,144 | 12,746 | 9,349 | 5,449 | 4,437 | | | |
| Maximum Average Deficit Under CPP | 13,975 | 10,577 | 7,180 | 3,185 | 2,089 | | | |
| Savings from CPP | 2,169 | 2,169 | 2,169 | 2,264 | 2,348 | | | |
| Panel B: Maximum Daily Need for Batt | tery Storage | | | | | | | |
| Maximum Hourly Deficit | 46369 | 46403 | 46453 | 46428 | 46453 | | | |
| Maximum Deficit Under CPP | 42828 | 42862 | 42912 | 42887 | 42912 | | | |
| Savings from CPP | 3541 | 3541 | 3541 | 3541 | 3541 | | | |

Table 10: Average and Maximum Daily Need for Energy Storage (MWh)

Notes: Panel A of this table takes the average of the hourly deficits and surpluses in Figure 4 for 2020 and then takes the maximum over all hours. These numbers represent the average battery storage capacity required to meet the generation deficit on the maximum day. The battery would have to be used for more than one hour, but this is the capacity required to meet the hourly deficit. Panel B of this table takes the maximum of the hourly deficits and surpluses in Figure 4 for 2020 and then takes the maximum over all hours. These numbers represent the maximum battery storage capacity required to meet the generation deficit on the maximum day.

Consistent with Table 9, our analysis shows that the 90% wind–10% solar mix with CPP minimizes the need for battery storage on average. In addition, CPP reduces the need for energy storage by about 2,348 MWh on average, assuming there is a CPP reduction in every hour of the day and energy can only be stored and used within a 24-hour period. However, the average does not tell the entire story. To avoid blackouts, the grid would need storage capacity to meet the highest demand, net of renewable generation, which is equivalent to the maximum deficit. To meet this load, ERCOT would need approximately 43GWh of energy storage in our calculations.

To calculate how much CPP would save in generation costs if ERCOT maintained several natural gas generators rather than energy storage, we use the supply curve in Figure 3 and derive

the average savings in generation costs from the different wind/solar mix scenarios. Figure 7 presents the average generation cost saved; Figure 8 presents the maximum cost saved.



Figure 7: Average Savings in Generation Costs



A key result of our simulation is that some hours would have a surplus, but others, such as peak evening demand, would experience large shortfalls (up to nearly 20,000 MWh) from a switch to 100% renewables. This variation underscores the value of CPP during peak hours for ensuring sufficient energy provision under a decarbonized electricity system. An important caveat to this analysis is that these results do not account for occasional longer periods with low renewable

generation (e.g., a week of cloudy, calm weather). Dynamic pricing, where prices are elevated in response to the low renewable output may be very useful to reduce electricity loads during these periods. Moreover, dynamic pricing could greatly help to address the mismatch between the afternoons to evening peak demand that coincides with a significant decline in solar generation as the sun goes down, otherwise known as the "duck curve."

Other options include plentiful energy storage, building additional renewables, or keeping fossil fuel plants around as backup. All three are expensive propositions; the latter prevents efforts for deeper decarbonization. Our analysis shows that residential CPP can be very valuable in enabling high levels of renewables while keeping the lights on even without energy storage. Further, if energy storage is used to help cover the deficit periods from renewables not generating, CPP reduces the need for massive amounts of energy storage. Indeed, with 100% clean energy, our simulation shows that there would be a 53% decrease in the need for energy storage with CPP relative to without CPP, on average. Using a simulated supply curve for 2020, the average and maximum generation costs saved by CPP could be as high as \$1,000 per hour and \$15,000 per hour, respectively.

In summary, combining the result of our simulation with that of our field experiment and consumer survey, it becomes clearer that there is potential for pricing and automation to enable a system-wide solution to bring about 100% clean energy at a cost that consumers may just be willing to bear.

General Discussion

The results of our consumer survey, field experiment, and decarbonization simulation offer promising insights for the future of energy conservation. Our proposed approach would

integrate and combine the various components of the 4 Ps with a two-way flow of information between firms and consumers to facilitate the wide-spread adoption of clean energy solutions.

Our combined findings indicate that pricing can significantly reduce fossil fuel usage and greater reductions could be enabled through automation. Further, our survey shows that consumers are willing to absorb a small price differential for such an automated solution. If fossil fuels were to be replaced with clean energy from solar and wind, such a system-wide solution can substantially reduce the need for energy storage capacity. That is, responsive demand induced through CPP and implemented through a systems approach, if applied broadly, could reduce the need for energy capacity by an average of 53%. This could reduce costs sufficiently that the cost of energy storage capacity might be able to be absorbed by local municipalities and states that are moving to a 100% carbon free environment.

We thus propose that a solution for delivering affordable clean electricity to residential customers lies in jointly leveraging multiple components of the 4 Ps, which could be coordinated by the local utility or a third-party. This has three main advantages. One, it eliminates the manual effort that is necessary to turn down (or off) air conditioning usage during peak periods (either via NEST or otherwise). Second, such automation obviates the need to make an effort-reward mental trade-off and calculus in terms of a combination of discomfort due to a lack air-conditioning on a hot summer afternoon, the effort required for a manual intervention, and the monetary and non-monetary rewards associated with saving energy. Third, consumers can save money due to such automatic energy conservation and at the same time feel rewarded for their environmentally friendly behavior in terms of fossil fuel usage and emissions as well as reduced battery storage when fossil fuels are replaced with solar and wind power. To complete the loop,

our consumer survey shows that consumers are willing to pay more for such a system-wide solution for the convenience it offers.

Our framework contributes to the literature by considering how the different components of the 4 Ps may need to work together. This complements prior studies that focused on the role of individual techniques and overlooked the role of the broader system. Our work thereby addresses recent calls for more research on "s-frame" (i.e., "system") solutions that can advance societal wellbeing and goals, beyond "i-frame" (i.e., "individual") solutions examined in prior research (Chater and Loewenstein, 2023). Furthermore, the insights generated by our framework and empirical results point to the importance of overlooked factors within the 4 Ps – Product and Place – in facilitating clean energy adoption. Finally, our work paves the way to numerous interesting opportunities for future research, which we outline next.

Future Research Directions

Key insights that emerge from our findings on the importance of examining a combination of tools within the 4 Ps, open the door to interesting research questions (Table 11). We organize the questions by each component of the marketing mix (Price, Product, Promotion, Place) along with examples of empirical methods and data sources that could illuminate them. While the list of questions is not exhaustive, it illustrates how scholars may identify and examine new opportunities and strategies that may advance the understanding and dissemination of clean energy consumption behaviors. We discuss a few of these in more detail below.

| 4 1 8 | Examples of research questions | Examples of empirical methods |
|-------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| | | and data to utilize |
| Price | 1. What pricing structures (e.g., rise in carbon-based energy prices vs. affordable | Lab experiment |
| | clean energy prices; one-time fee vs. monthly fee, cost sharing with a third party) | Consumer survey |
| | would be most effective in encouraging consumers' clean energy adoption and | Natural or field experiment with |
| | carbon emission reduction? | instances when pricing changed |
| | | or varied across segments. |
| | 2. To what degree do the heterogeneity in consumer perceptions of privacy affect | _ |
| | their perceptions of acceptable automation-related data collection/usage practices | Lab experiment |
| | for determining dynamic pricing structures, the propensity to defect, and | Consumer survey |
| | expectations of compensation? | |
| | 1 1 | Lab experiment |
| | 3. What policies would show the largest versus smallest behavior change: financial | Consumer survey |
| | penalties and mandates (e.g. carbon tax) or rewards (e.g. cost savings from | Natural experiment with instances |
| | reduced consumption selling power to the grid or tax credit for purchasing | when incentives changed or |
| | hatteries for power storage)? | varied across segments |
| | | |
| Product | 1. How may the use of certain technologies (e.g., smart homes, solar panels, | Observational study, natural |
| | electric vehicles) impact energy conservation practices and will there be | experiment, or field experiment, |
| | heterogeneous impacts across different consumer groups? | involving introduction of the focal |
| | | product/ solution /technology. |
| | 2. What level of automation offered by firms (e.g., automated notifications about | |
| | peak times with manual usage adjustment versus automated adjustment) would | Lab experiment |
| | provide optimal balance between the level of effort vs. control consumers may | Consumer survey |
| | want to exert over their energy consumption regulation? | |
| Promotion | 1. Which consumer segments may be more compelled by the affordability vs. | Lab experiment |
| | effortlessness framing of system-wide solutions in promotional campaigns, and for | Consumer survey |
| | which segments might effortlessness promotion messages backfire? | Field experiment featuring a |
| | | campaign |
| | 2. What kind of information within the "system-wide" solution information loop | |
| | would consumers be the most interested in tracking and most responsive to in their | Consumer survey |
| | consumption behavior? Which of these dimensions would be more vs. less | Lab experiment |
| | amenable to the provision of social norms, and for which of these dimensions | Conjoint study |
| | would social norms have the potential to backfire? | |
| | | |
| | 3. What sources of communication and spokespeople (utility providers, peer | Lab experiment |
| | consumers, technology companies, policy makers) would be more effective in | Field experiment featuring a |
| | persuading consumers to adopt clean-energy solutions? Would exposure to single | communication campaign |
| | messaging from one source or multi-layered messaging from multiple sources be | |
| | more effective? | |
| Place | 1. Would uptake for clean energy solutions be different depending on the type of | Lab experiment |
| | provider that delivers it (e.g., public utility vs. private company; small start-up vs. | Consumer survey |
| | large firm; government vs. private sector)? | - |
| | | Lab experiment |
| | 2. How might segment characteristics influence the success of distinct clean | Consumer survey |
| | energy solution providers? How does distinct providers' success further vary by | Field experiment involving |
| | the characteristics of the solution and category? | distinct segments. |
| Product Promotion Place | It what degree up the hereogenetic in consumer preceptions of pirvay affect their perceptions of acceptable automation-related data collection/usage practices for determining dynamic pricing structures, the propensity to defect, and expectations of compensation? What policies would show the largest versus smallest behavior change: financial penalties and mandates (e.g., carbon tax) or rewards (e.g., cost savings from reduced consumption, selling power to the grid, or tax credit for purchasing batteries for power storage)? How may the use of certain technologies (e.g., smart homes, solar panels, electric vehicles) impact energy conservation practices and will there be heterogeneous impacts across different consumer groups? What level of automation offered by firms (e.g., automated notifications about peak times with manual usage adjustment versus automated adjustment) would provide optimal balance between the level of effort vs. control consumers may want to exert over their energy consumption regulation? Which consumer segments may be more compelled by the affordability vs. effortlessness framing of system-wide solutions in promotional campaigns, and for which segments might effortlessness promotion messages backfire? What kind of information within the "system-wide" solution information loop would consumers be the most interested in tracking and most responsive to in their consumption behavior? Which of these dimensions would be more vs. less amenable to the provision of social norms, and for which of these dimensions would social norms have the potential to backfire? What sources of communication and spokespeople (utility providers, peer consumers, technology companies, policy makers) would be more effective in persuading consumers to adopt clean-energy solutions? Would exposure to single messaging from one source or multi-layered messaging from multiple sources be more effective? Would uptake for clean ene | Lab experiment Consumer survey Lab experiment Consumer survey Natural experiment with instau when incentives changed or varied across segments. Observational study, natural experiment, or field experiment involving introduction of the f product/ solution /technology. Lab experiment Consumer survey Lab experiment field experiment featuring a campaign Consumer survey Lab experiment Conjoint study Lab experiment Field experiment featuring a communication campaign Lab experiment Consumer survey Lab experiment Consumer survey Lab experiment Field experiment featuring a communication campaign |

Table 11: Examples of Future Research Questions

Price Q1. An intriguing application of system-wide technological solutions for clean energy delivery is in consumer-level pricing. Currently, in most locations, consumers pay a flat fee per kilowatt-hour, a tiered system based on monthly usage, or a peak period premium. We propose that an automated system with consumer-level manual override could establish a more affordable and environmentally sustainable pricing strategy. While the potential is captivating, it remains uncertain how well this approach can accommodate diverse consumer preferences in clean energy delivery. In essence, the question of whether an automated clean energy delivery solution can effectively incorporate consumer preferences to achieve optimal pricing is an exciting avenue for future research.

Price Q2. While embracing automated critical peak pricing raises data privacy concerns, many consumers seem willing to trade privacy for comfort and convenience (Dawar, 2018). For instance, conducting a Google search sacrifices privacy for quick access to seemingly free information. While some disregard privacy, a recent survey indicates that about a third of global consumers care and this behooves companies to convince their customers about their data privacy policies (Redman and Waitman, 2020). In the absence of such efforts, companies may face a consequence where a significant number of their consumers may abandon doing business with firms that breach their data usage and privacy expectations. Furthermore, companies using automation to gather consumer data may face calls to compensate users (Whitaker, 2019). In our context, electric utility companies using our automation solution would implicitly compensate consumers with lower prices. Such price savings may be complemented with promotional messaging which influence responses to persuasion efforts (Freistad and Wright, 1994). Therefore, a reasonable question in this context is to what degree do consumer perceptions of privacy affect their perceptions of acceptable automation-related data collection/usage practices, the propensity to defect, and expectations of compensation?

Product Q1. Smart technologies are increasingly prevalent in education, transportation, entertainment, and finance. However, the energy sector, which powers homes, lags behind. Current electricity use primarily relies on fossil fuels, sometimes from inefficient generators harming the environment. An opportunity arises to shift energy sources to renewables and

encourage solar panel adoption. Future research could explore how home technologies influence energy-saving efforts and segment-specific reactions. Data on regional energy practices and household technology usage are essential for addressing this issue.

Product Q2. Consumers increasingly value their data due to rising awareness of automation-related data breaches. Two main concerns arise. Firstly, privacy worries intensify alongside the growth of data protection laws like General Data Protection Regulation (GDPR) in Europe and similar regulations in California. Secondly, granting consumers control over integrated system-wide solutions is important. Privacy and control issues may deter consumers from allowing firms to automatically manage their home thermostats, hindering energy-saving automated systems that require data (Goldfarb and Tucker, 2011). One solution is shifting control partially to users, enhancing consumer control and reducing the need for data transfer to firms (e.g., preferred thermostat settings). This may involve algorithms learning from limited data or integrating individual user data with broader metadata. Compensation for user data might be necessary, increasing analysis costs. This approach's effectiveness depends on local Internet infrastructure, varying across regions and countries. Thus, addressing consumer reluctance to cede control and share data with utility providers is a critical research question.

Promotion Q1. Given the relatively complex nature of the clean energy construct and the multi-faceted, often abstract nature of its benefits for consumers and society, devising effective communications to facilitate broad adoption is critical. First, similar to other forms of disruptive innovation, emphasizing more concrete and immediate benefits may be beneficial to bring more consumers on board with adoption. A "system-wide" solution involving dynamic pricing and automation could potentially address key barriers to adoption, such as effort and affordability. Indeed, proactively tracking variation in households' energy needs, energy supply and prices is

taxing, and manually adjusting one's consumption to these factors in real time is effortful. Thus, emphasizing the effortlessness of an automated solution may be appealing to consumers. However, it would also require relinquishing control over one's energy consumption data. Therefore, the effortlessness frame could appeal to some consumers more than others.

Promotion Q2. Prior work (Andor et al., 2020) promotes the importance of education and information provision about social norms pertaining to energy consumption habits. Yet, the evidence on the effectiveness of these tactics is mixed. Whereas in some cases information provision, particularly involving social comparison information (e.g., upward comparison to more energy-efficient households), was deemed effective in lowering energy consumption (Allcott, 2011), in other cases it was ineffective or even counterproductive (e.g., downward comparison to less energy-efficient households; Schultz et al., 2007). Thus, identifying the education and information provision techniques that would be effective is important. And given that a "system-wide" solution involves change along multiple dimensions (price, energy supply and use during certain periods, automation, clean energy sources), consumers may respond to information provision about these various dimensions differently. Therefore, future research is needed to further delve into which types of promotion strategies will be most effective for various consumer or industry groups.

Place Q1. The involvement of multiple stakeholders is required in the provision of an integrated "system-wide" solution, and different stakeholders may take on different roles in the delivery process. For instance, while government subsidies are often needed to spur investment and innovation in the development, production, and supply of clean energy solutions, the private sector is taking on an increasable prominent role. A growing number of start-ups as well as prominent firms across sectors (e.g., energy, technology, automotive) are developing and

introducing clean energy solutions relevant to their sphere of operations. In this increasingly diverse landscape, consumers may consider offerings from different types of providers of energy and related solutions. For instance, they may have opportunities to choose between public vs. private utility providers with distinct renewable/clean energy offerings. Likewise, they may consider offerings from providers of technology involved in automation solutions (e.g., NEST vs. other brands of smart home devices) as well as information provision and privacy (e.g., start-ups vs. larger firms offering to perform data management, privacy, and feedback functions). Yet, consumers may hold distinct beliefs and attitudes toward different types of providers (e.g., large vs. small, public vs. private).

Place Q2. Different segments of consumers respond to distinct providers differently depending on their personal beliefs. For instance, consumers who endorse (vs. oppose) the freemarket ideology have greater trust in the free market and private firms, and they disapprove of government regulation (Jost et al., 2003). Consumers who believe in the fairness of the economic system appreciate offerings from entrepreneurs (e.g., start-ups) (Cakanlar and Ordabayeva, 2023). And consumers who question economic inequality find underdog offerings such as crowdfunded options more appealing, but only in categories that involve little (financial, physical) risk (Acar et al., 2021; Paharia et al., 2011). Such segment differences may contribute to the varying success of distinct clean energy solution providers in different segments.

Conclusion

To conclude, this research examined the appeal and effectiveness of some marketing (i.e., 4 P) tactics, including critical-peak pricing, in conjunction with informational and technological solutions (NEST) in facilitating carbon emission reduction. The findings indicate that affordability-focused tactics alone may be insufficient to encourage the transition to clean

energy, and embedding affordability in broader system-wide solutions may be necessary to achieve lasting change. We hope the insights generated by our multi-method approach will inspire novel ideas for possible clean energy solutions and future research.

References

- Abrahamse, W., Steg, L., Vlek, C., and Rothengatter, T. (2005). A Review of Intervention Studies Aimed at Household Energy Conservation. *Journal of Environmental Psychology*, 25 (3), 273–91.
- Acar, O. A., Dahl, D. W., Fuchs, C., & Schreier, M. (2021). The signal value of crowdfunded products. *Journal of Marketing Research*, 58 (4), 644–661.
- Allcott, H. (2011), 'Social norms and energy conservation', *Journal of Public Economics*, 95 (9-10), 1082–1095.
- Allcott, H. and Rogers, T. (2014), 'The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation', *The American Economic Review* 104 (10), 3003–3037.
- Andor, Mark A., Andreas Gerster, Jörg Peters, and Christoph M. Schmidt. "Social norms and energy conservation beyond the US." *Journal of Environmental Economics and Management* 103 (2020): 102351.
- Andor, M. A., Gerster, A. and Peters, J. (2022), 'Information campaigns for residential energy conservation', *European Economic Review* 144, 104094.
- Ayres, I., Raseman, S. and Shih, A. (2013), 'Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage', *Journal of Law, Economics, and Organization* **29**(5), 992–1022.
- Aspara, J., Luo, X., and Dhar, R. (2017). Effect of Intelligence on Consumers' Responsiveness to a Pro-environmental Tax: Evidence from Large-scale Data on Car Acquisitions of Male Consumers. *Journal of Consumer Psychology*, 27 (4), 448–55.
- Beale, J. R., and Bonsall, P. W. (2007). Marketing in the Bus Industry: A Psychological Interpretation of Some Attitudinal and Behavioral Outcomes. *Transportation Research Part F*, 10, 271–287.
- Brandon, A., List, J., Metcalfe, R., Price, M. and Rundhammer, F. (2018), 'Testing for crowd out in social nudges: Evidence from a natural field experiment in the market for electricity', *Proceedings of the National Academy of Sciences* forthcoming, 1–6.
- Bollinger, B., Leslie, P. and Sorensen, A. (2011), 'Calorie posting in chain restaurants', *American Economic Journal: Economic Policy*, 3 (1), 91–128.
- Bollinger, B. and Gillingham, K. (2012). Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Marketing Science*, 31 (6), 873–1025.
- Bollinger, B. and Hartmann, W. (2020), 'Information versus automation and implications for dynamic pricing', *Management Science* 66(1), 290-314.
- Bull, J. (2012). Loads of Green Washing—Can Behavioural Economics Increase Willingness-to-Pay for Efficient Washing Machines in the UK? *Energy Policy*, 50, 242–52.
- Busse, Meghan, Jorge Silva-Risso, and Florian Zettelmeyer. "\$1,000 cash back: The passthrough of auto manufacturer promotions." *American Economic Review* 96.4 (2006): 1253-1270.
- Burkhardt, J., Gillingham, K., and Kopalle, P. K. (2023). Field Experimental Evidence on the Effects of Information and Pricing on Residential Electricity Conservation. Forthcoming, *Management Science*.
- Çakanlar, A., & Ordabayeva, N. How Economic System Justification Shapes Demand for Peerto-Peer Providers. *Journal of Consumer Psychology*, in press.
- Caves, D., Christensen, L. and Herriges, J. (1984), 'Consistency of residential customer response in time-of-use electricity pricing experiments', Journal of Econometrics **26**, 179–203.

- Cacioppo, John T., Richard E. Petty, and Chuan F. Kao. "Need for Cognition Scale--Short Form." *Journal of Personality Assessment* (1984).
- Camilleri, A. R. and Larrick, R. P. (2014). Metric and Scale Design as Choice Architecture Tools. *Journal of Public Policy and Marketing*, 33 (1), 108–25.
- Chater, N., & Loewenstein, G. (2023). The I-frame and the S-frame: How Focusing on Individual-level Solutions Has Led Behavioral Public Policy Sstray. *Behavioral and Brain Sciences*, *46*, E147.
- Coelho, G. L. D. H., Hanel, P. H. P, and Wolf, L. J. (2018). The Very Efficient Assessment of Need for Cognition: Developing a Six-Item Version. *Assessment, online first*, 1-16.
- Cuddy, A. J.C., Doherty, K. T., and Bos, M. W. (2010). OPOWER: Increasing Energy Efficiency through Normative Influence (A). *Harvard Business School Case* 911-016, September.
- Dawar, N. (2018). Marketing in the Age of Alexa. Harvard Business Review, May-June.
- 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.
- Ferraro, P. J. and Price, M. K. (2013), 'Using nonpecuniary strategies to influence behavior: Evidence from a large-scale field experiment', The Review of Economics and Statistics 95(1), 64–73.
- Friestad, M., & Wright, P. (1994). The Persuasion Knowledge Model: How people cope with persuasion attempts. *Journal of Consumer Research*, 21 (1), 1–31
- Gillingham, Kenneth and Karen Palmer (2014), "Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence," Review of Environmental Economics and Policy 2014 8:1, 18-38.
- Gleim, M. R., Smith, J. S., Andrews, D., and Cronin Jr., J. J. (2013). Against the Green: A Multi-Method Examination of the Barriers to Green Consumption. *Journal of Retailing*, 89 (1), 44–61.
- Gneezy, U., and Rustichini, A. (2000). A Fine Is a Price. Journal of Legal Studies, 29 (1), 1–18.
- Goldfarb, A., & Tucker, C. E. (2011). Privacy Regulation and Online Advertising. *Management Science*, 57 (1), 57–71.
- Griskevicius, V., Tybur, J. M., and Van den Bergh, B. (2010). Going Green to Be Seen: Status, Reputation, and Conspicuous Conservation. *Journal of Personality and Social Psychology*, 98 (3), 392–404.
- Grubb, M. and Osborne, M. (2015), 'Cellular service demand: Biased beliefs, learning, and bill shock', *American Economic Review*, 105 (1), 234–271.
- Hansen J., Stiglitz J., Pachauri R.K., Rosenzweig C. (2008, January). *How the Nobel Was Won: Advances in the Science of Climate Change*. Panel discussion, Columbia University, New York, NY.
- Hardisty, D. J., Johnson, E. J., and Weber, E. U. (2010). A Dirty Word or a Dirty World? Attribute Framing, Political Affiliation, and Query Theory. *Psychological Science*, 21 (1), 86–92.
- Hardisty, D. J. and Weber, E. U. (2009). Discounting Future Green: Money Versus the Environment. *Journal of Experimental Psychology: General*, 138 (3), 329–40.
- Haws, K. L., Winterich, K. P., and Naylor, R. W. (2014). Seeing the World Through GREENtinted Glasses: Green Consumption Values and Responses to Environmentally Friendly Products. *Journal of Consumer Psychology*, *24*(3), 336-354.

- Heberlein, Thomas A., and G. Keith Warriner (1983), "The influence of price and attitude on shifting residential electricity consumption from on- to off-peak periods," Journal of Economic Psychology, 4 (1–2): 107-130.
- Hughner, R. S, McDonagh, P., Prothero, A., Shultz, C. J., and Stanton, J. (2007). Who Are Organic Food Consumers? A Compilation and Review of Why People Purchase Organic Food. *Journal of Consumer Behavior*, 6 (2), 94–110.
- Ito, K. (2015). Asymmetric Incentives in Subsidies: Evidence from a Large-scale Electricity Rebate Program. *American Economic Journal: Economic Policy*, 7, 209–237.
- Ito, K., Ida, T. and Tanaka, M. (2018), 'Moral suasion and economic incentives: Field experimental evidence from energy demand', *American Economic Journal: Economic Policy*, 10 (1), 240–267.
- Jachimowicz, J. M., Hauser, O. P., O'Brien, J. D., Sherman, E., and Galinsky, A. D. (2018). The Critical Role of Second-order Normative Beliefs in Predicting Energy Conservation. *Nature Human Behaviour*, 2 (10), 757–64.
- Jessoe, K. and Rapson, D. (2014), 'Knowledge is (less) power: Experimental evidence from residential energy use', *The American Economic Review*, 104 (4), 1417–1438.
- Jost, J. T., Blount, S. Pfeffer, J., & Hunyady, G. (2003). Fair Market Ideology: Its Cognitive-Motivational Underpinnings. *Research in Organizational Behavior*, 25, 53–91.
- Jost, J. T. (2006). The End of the End of Ideology. American Psychologist, 61 (7), 651.
- Kallbekken, S., Sælen, H., and Hermansen, E. A. T. (2013). Bridging the Energy Efficiency Gap: A Field Experiment on Lifetime Energy Costs and Household Appliances. *Journal of Consumer Policy*, 36 (1), 1–16.
- Klöckner, C. A., Nayum, A., and Mehmetoglu, M. (2013). Positive and Negative Spillover Effects from Electric Car Purchase to Car Use. *Transportation Research Part D: Transport and Environment*, 21, 32–38.
- Kraft-Todd, G. T., Bollinger, B., Gillingham, K., Lamp, S., and Rand, D. G. (2018). Credibility-Enhancing Displays Promote the Provision of Non-normative Public Goods. *Nature*, 563, 245–48.
- Laskey, A. and Kavazovic, O. (2011). OPOWER. Crossroads (Association for Computing Machinery) 17 (4), 47–51
- Lee, Z. A. and Zhang, K. M. (2022). Unintended Consequences of Smart Thermostats in the Transition to Electrified Heating. *Applied Energy*, 332 (September). 119384.
- Min, J., Azevedo, I. L., Michalek, J., and de Bruin, W. B. (2014). Labeling Energy Cost on Light Bulbs Lowers Implicit Discount Rates. *Ecological Economics*, 97 (C), 42–50.
- Paharia, N., Keinan, A., Avery, J., & Schor, J. B. (2011). The underdog effect: The marketing of disadvantage and determination through brand biography. *Journal of Consumer Research*, 37 (5), 775–790.
- Pitts, R. E., and Wittenbach, J. L. (1981). Tax Credits as a Means of Influencing Consumer Behavior. *Journal of Consumer Research*, 8, 335–338.
- Redman, T. C., & Waitman, R. M. (2020). Do You Care About Privacy As Much As Customers Do? *Harvard Business Review*, January 28.
- Reiss, P. C. and White, M. W. (2008), 'What changes energy consumption? prices and public pressures', *The RAND Journal of Economics*, 39 (3), 636–663.
- 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), 429–34.

- Schwartz, D., Bruine de Bruin, W., Fischhoff, B., and Lave, L. (2013). Advertising Energy Saving Programs: The Potential Environmental Cost of Emphasizing Monetary Savings. Paper presented at the Preconference EACR '*Moral Dynamics and Socially Responsible Consumer Behavior*', Barcelona, July 3, 2013.
- Sebastian, D. (2021), 'Mercedes-Benz plans to go all-electric by end of decade', *Wall Street Journal*.
- Sexton, R. J., Brown Johnson, N., and Konakayama, A. (1987). Consumer Response to Continuous-display Electricity-use Monitors in a Time-of-use Pricing Experiment. *Journal of Consumer Research*, 14, 55–62.
- Spector, Y., Tishler, A. and Ye, Y. (1995), 'Minimal adjustment costs and the optimal choice of inputs under time-of-use electricity rates', *Management Science*, 41 (10), 1679–1692.
- Tuballa, M. L., and M. L. Abundo (2016), "A review of the development of Smart Grid technologies," Renewable and Sustainable Energy Reviews, Volume 59, 710-725,
- Van Houwelingen, J. H., and Van Raaij, W. F. (1989). The Effect of Goal-Setting and Daily Electronic Feedback on In-home Energy Use. *Journal of Consumer Research*, 16 (1), 98– 105.
- Whitaker, Zack (2019). OzoneAI wants Companies to Pay You for Your Data, Upending the Ad Model. *TechCrunch*, *October 2* https://techcrunch.com/2019/10/02/ozoneai-pay-dataprivacy-battlefield/Wilhite, H. and Ling, R. (1995). Measured Energy Savings from a More Informative Energy Bill. *Energy and Buildings*, 22 (2), 145–55.
- Winnett, R. A., Love, S. Q., and Kidd, C. (1982–1983). The Effectiveness of an Energy Specialist and Extension Agents in Promoting Summer Energy Conservation by Home Visits. *Journal of Environmental Systems*, 12 (1), 61–70.
- Wolak, F. (2011), 'Do residential customers respond to hourly prices? Evidence from a dynamic pricing experiment', American Economic Review: Papers and Proceedings **101**(3), 83–87.
- Wolske, K.S., Gillingham, K.T. & Schultz, P.W. (2020), Peer influence on household energy behaviours. Nature Energy 5, 202–212.