Essays on Retail Electricity Pricing and Markets

by

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Committee in charge:

Professor Meredith Fowlie, Chair
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Professor Severin Borenstein

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Abstract

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In this thesis, I investigate economic inefficiencies related to residential electricity pricing and rate design. Two papers focus on firms' pricing behavior in restructured retail markets, and one focuses on the impact of electric rate design on consumers' incentives to make greenhouse gas-reducing investments.

The first chapter studies the causes and consequences of pricing heterogeneity in markets for residential electricity, a nearly homogeneous good. I uncover adverse efficiency and distributional impacts of competition when consumers face heterogeneous search frictions. I show that consumers pay different prices for electricity in the same market, with low-income households and marginalized communities paying systematically higher electricity prices than their higher-income counterparts. These pricing patterns are consistent with a model of firms price discriminating on search frictions through marketing. Using data from Baltimore, I estimate a structural model that shows that this marketing leads to an annual welfare loss of 14% of industry-wide variable costs. Despite having only slightly larger search frictions, low-income households pay substantially higher prices than high-income households primarily due to lower marketing costs in low-income communities. Auxiliary analyses rule out alternative explanations, such as differing underpayment risks or preferences for differentiated product attributes. The model demonstrates that policy implications are nuanced: while marketing restrictions can increase consumer surplus, they may also increase average market prices by reducing consumers' attention to their own prices.

The second chapter analyzes two key components of consumer welfare under government versus market provision of a private good: price levels and price uncertainty. The electricity sector provides a policy-relevant setting to plausibly causally estimate the directional effect of ownership on retail prices. Specifically, this paper investigates the question: Do residential consumers face higher retail price levels and greater exposure to wholesale prices when supplied electricity by their local government or by a private electricity supplier subject to competitive forces? Using 2005-2017 data from 13 U.S. states that had both local government

and retail electricity markets, with the former's geographic locations determined decades earlier and the latter entering the leftover markets, I compare within-state differences in price levels and pass-through of marginal costs across the two supplier types. I find evidence that retail prices and price pass-through of volatile wholesale prices were lower under government electricity provision than competitive retail provision during this timeframe.

The third chapter summarizes joint work with Andrew Satchwell and Chandler Miller on an under-studied impact of increasingly popular time-based rates. While time-based electricity rates can improve the economic efficiency of short-run consumption decisions, they can also have unintended consequences on consumers' incentives to make long-run investments in greenhouse gas-reducing technologies. This chapter quantifies the impacts of time-based rates on a diverse set of energy efficiency, rooftop solar, and electrification investment incentives. We capture heterogeneity across households, geographies, and real-world rate designs using National Renewable Energy Lab's ResStock database and 14 implemented electric rate schedules. Our analysis broadly shows that the average rate level matters more for bill savings and economically efficient investment signals than the rate design. We also find that time-based rates have highly heterogeneous effects on bill savings and welfare across investments, geographies, and households. Our analysis also provides some uplifting results for policymakers aiming to electrify buildings. Contrary to conventional wisdom, we find that electrification can reduce consumer bills, especially when paired with energy efficiency investments.

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Meredith's mentorship and encouragement has shaped my career path and helped build my confidence and discipline as a researcher. My research benefited from her readiness to delve into the minutiae of my work one moment and provide large-picture advice another. She especially helped me learn how to strike a balance between complexity and tractability. Her efforts to find time to meet despite her busy schedule, even during odd hours of the day, are also a testament to her dedication.

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All errors are my own.

Chapter 1

Competing for (In)attention: Price Discrimination in Residential Electricity Markets

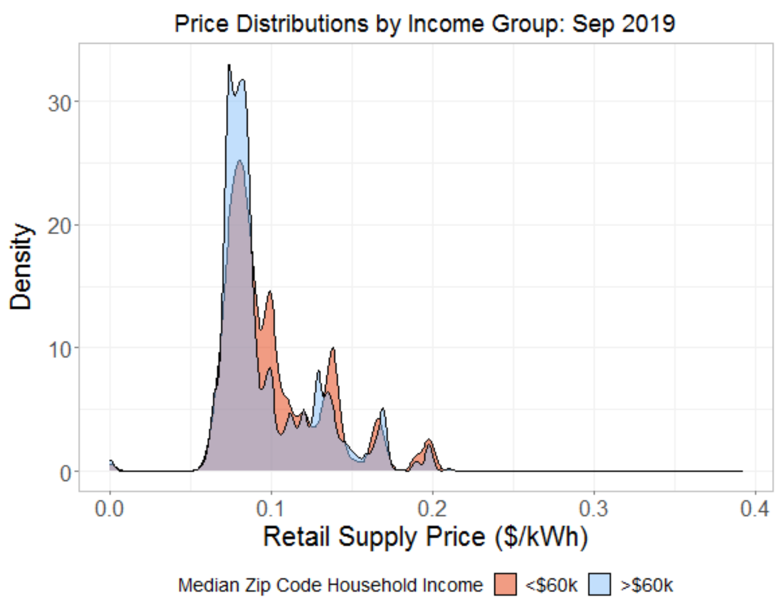
1.1 Introduction

From telecommunications to airlines and energy, policymakers have introduced competition into many industries since 1970. In many markets, deregulation has led to large price heterogeneity. This paper explores price discrimination as a cause of price heterogeneity in deregulated residential electricity markets. Price discrimination can increase economic efficiency in many markets by enabling firms to serve new market segments (Varian, 1985; Schmalensee, 1981). Since willingness to pay and ability to pay are often positively correlated, price discrimination also frequently results in wealthier consumers paying relatively high prices. However, price discrimination can also be inefficient, especially when firms price discriminate on consumer inattention or search frictions (Gabaix and Laibson, 2006). In the residential electricity context, I highlight an additional pathway through which price discrimination on search frictions generates economic inefficiency: incentivizing unproductive marketing. I also show that marketing causes low-income and marginalized communities to pay relatively high prices.

Inefficient and regressive pricing may be particularly concerning in the electricity context. Researchers have linked high energy prices to mortality (Chirakijja et al., 2019). Many low-income households keep their homes at unsafe temperatures and sacrifice food or medical care due to high energy costs (NEADA 2018). Inefficiently high electricity prices may also deter all households from investing in greenhouse-gas-reducing electrification (Borenstein et al., 2021).

This paper begins by documenting key patterns in a deregulated residential electricity market. Retail electricity restructuring created markets where financial intermediaries compete to buy wholesale electricity and sell this electricity to individual households. I show that competition resulted in firms charging households very different prices for the same electricity. Figure 1.1 shows a one-month cross-section of households' electricity prices in the restructured Baltimore market by zip code median annual household income.[1] This market is not concentrated by traditional metrics and exhibits limited product differentiation. However, a quarter of households pay prices more than 35% higher than the median price, and the top 5% pay at least double the median price, or roughly $75 more per month. Figure 1.1 also shows that households who live in low-income areas pay higher prices, on average, than households in high-income areas. I find that these pricing patterns hold more broadly across other states, time, data sources, and metrics of marginalized communities.

Figure 1.1: Estimated Monthly Marginal Costs



Probability density of generation supply prices for residential retail choice customers in Baltimore Gas and Electric Company service territory by 2019 American Community Survey zip code tabulation area median annual household income.

I present evidence that price heterogeneity in this market arises from firms price discriminating on two consumer distortions. First, firms price discriminate on inattention-driven inertia, which they achieve through price updating over a customer's tenure with the firm. Second, firms price discriminate on barriers to search, which they achieve through direct marketing, including in-person and telemarketing. Firms charge higher prices through in-person marketing than through active search channels. Firms also market disproportionately in low-income areas.

[1] The figure excludes prices for the small percentage of households on quantity or time-differentiated price structures.

Next, I develop a theory that can explain the evidence. In this model, direct marketing enables firms to gain information about consumer types and implement third-degree price discrimination, but marketing is costly. The result is a separating equilibrium where only consumers with high search frictions sign up through marketing, and marketing offer prices are relatively high. Among consumers with high search frictions, consumers who live in areas with relatively low marketing costs are more likely to interact with a marketer and, thereby, choose to participate in the market over the outside option of a regulated price. This causes higher average sign-up prices in areas with lower marketing costs in equilibrium. At the same time, marketing also puts downward pressure on prices. By causing frequent attention shocks that limit firms' ability to take advantage of consumer inattention, marketing mitigates the impact of price discrimination on inattention-driven inertia. Price markups can be sustained in equilibrium in a market with free entry because firms spend their expected economic profits on marketing to acquire consumers. This economically unproductive marketing creates a welfare loss, which I later estimate to be 14% of industry variable costs.

This model suggests that low-income communities could face higher prices than high-income communities due to demand- or supply-side drivers. On the demand side, the income-price gap could be driven by low-income households having especially high barriers to search, choice error, taste for marketing, or inattention to their own prices and bills. On the supply side, a difference in marketing costs across geographic areas is sufficient to create an income-price gap. I argue that firms face relatively low direct marketing costs in low-income communities. Door-to-door and other in-person marketing tend to be cheapest in densely-populated areas, and low-income households in Baltimore tend to live in especially dense areas.[2]

To test these hypotheses, I estimate this model of consumer demand and firm marketing and pricing decisions. I decompose the income-price gap and find that the largest driver is supply-side differences in marketing costs across geographic areas, explaining about 85% of the total gap. Approximately 30% of the gap comes from combined differences in taste for marketing and choice error in marketing interactions, and 5% comes from differences in barriers to search. Taken together, these positive contributions sum to more than 100% due to offsetting negative effects. Differences in preferences for premium attributes reduce the income-price gap by 14%. In the absence of marketing, a counterfactual suggests that differences in inattention-driven inertia across income groups would cause an income-price gap equal to roughly 32% of the status quo income-price gap. However, this effect is more than offset by the interaction effect between marketing and inertia. In the presence of marketing, the net effect of price discrimination on inattention-driven inertia, is a 6% reduction in the income-price gap.

A counterfactual scenario suggests that ending direct marketing would increase aggregate consumer surplus, primarily due to more consumers choosing the outside option, which is a regulated rate. However, ending marketing would also increase average market prices for low- *and* high-income households that remain in the market because these households would

[2] There may also be meaningful geographic differences in labor costs or legal risks.

experience fewer attention shocks.

I also consider alternative explanations for the income-price gap, including differing costs to serve, differing risks of underpayment, and differing preferences for premium bundled attributes. The analyzed market provides a unique setting where firms bear a negligible portion of the risk of their own customers' underpayment. Cost of service also varies negligibly across geographic areas, and any differences in temporal electricity usage patterns should result in low-income households being cheaper to serve.

To my knowledge, this is the first paper to analyze price discrimination through marketing in retail electricity markets. In doing so, this paper contributes to four literatures. First, there is an extensive literature rationalizing the existence of price variation in unconcentrated markets. The literature is mainly theoretical with some notable exceptions that empirically test select theories (Puller et al., 2015; Escobari and Gan, 2007; Orlov, 2011; Baylis and Perloff, 2002). This paper builds on and combines the heterogeneous search cost (Salop and Stiglitz, 1977; Varian, 1980) and costly marketing (Butters, 1977) theories, allowing firms to use marketing as a means to identify consumers with high search costs or other search-related frictions. In addition, I empirically estimate welfare and distributional implications of price discrimination.

A second literature studies the effects of poverty on household financial decision-making. Researchers have argued that poverty causes more present-biased behavior, tunneled focus on urgent tasks, and neglect of longer-term financial planning (Ong et al., 2019; Carvalho et al., 2016; Shafir and Mullainathan, 2013; Haushofer and Fehr, 2014; Spears, 2011; Loibl, 2017; Campbell, 2016; Handel and Kolstad, 2021). Mendoza (2011) offers some reasons households in poverty may pay higher prices even under identical decision-making processes. In many contexts, identifying the role of price discrimination on price disparities is confounded by differing risks of underpayment, large differences in the cost to serve across geographic areas, or unobserved variation in marginal costs. The retail electricity markets I analyze provide a particularly clean setting to study price discrimination that is largely free of these confounders.

Third, this paper also contributes to a long debate in the marketing literature on whether marketing is welfare-improving or welfare-reducing (e.g., Chamberlin, 1933; Kaldor, 1950; Ozga, 1960; Stigler, 1961).[3] Evidence is mixed but primarily supports the welfare improvement theory (Dubé and Manchanda, 2005; Ackerberg, 2001; Garthwaite, 2014; Carpio and Isengildina-Massa, 2016; Benham, 1972; Glazer, 1981; Milyo and Waldfogel, 1999). Analysis of door-to-door marketing is scarce. My paper builds on ideas from the persuasive theory of advertising (Braithwaite, 1928; Robinson, 1933; Kaldor, 1950) and on targeting advertising to consumers less likely to comparison shop (Iyer et al., 2005) to empirically estimate a door-to-door marketing setting where marketing appears to be welfare decreasing.

Fourth, I build on previous literature on pricing and decision-making in retail electricity choice markets. Much of this literature analyzes how average prices have changed with the implementation of restructuring (e.g., Dormady et al., 2019; Hartley et al., 2019; Ros,

[3]See Bagwell (2007) and Schmalensee (1988) for literature reviews.

2017; Borenstein and Bushnell, 2015; Su, 2015; Joskow, 2006; Taber et al., 2006). Results are mixed and tend to vary across locations and time periods. Under weak assumptions, my results suggest that restructuring increased prices for some households and decreased prices for others across several U.S. states. I, therefore, focus on two key parts of the overall pricing question: incidence and underlying mechanisms. A small body of research on retail restructuring documents consumer inertia and search costs (Hortaçsu et al., 2017; Giulietti et al., 2014, 2005; Flores and Price, 2013; Davis, 2021) and unexplained consumer decision error in plan selection (Wilson and Price, 2010). Researchers have explored firm responses to inattentive or behavioral consumers in other markets (Gabaix and Laibson, 2006; Ericson, 2014; Agarwal et al., 2014, 2015; Houde, 2018; McCoy, 2015), but research in the retail choice market is limited (Gugler et al., 2018; Byrne et al., 2022).

The closest paper in terms of research question is Byrne et al. (2022). The authors conduct an audit study of consumers searching by phone for a retail marketing supplier. They find no evidence that electricity suppliers explicitly discriminate on low-income subsidy status by charging higher prices to consumers who receive electricity subsidies. In contrast, I study firms' decisions to actively market to consumers since direct marketing is responsible for most switching. I find evidence of structural discrimination: profit-driven marketing strategies interact with pre-existing residential segregation to disproportionately harm marginalized communities.

This research may have applications to many other markets, particularly markets for subscription products where consumers demonstrate substantial inattention and heterogeneous search. Examples may include markets for mortgages and other loans, cell phone service, Internet service, newspaper subscriptions, gym memberships, and health, automobile, and life insurance.

1.2 Background on Retail Electricity Choice Markets

Under traditional electric utility regulation, one regulated monopoly provides electricity generation, distribution, transmission, and retail supply. Of these four services, only distribution and transmission are currently considered natural monopolies. Around the turn of the 21st century, many countries and U.S. states deregulated the electric generation function ("wholesale restructuring") and the retail supply function ("retail restructuring" or "retail choice").[4] Restructuring opened these electricity services to competition from other for-profit firms.

Under retail restructuring, these for-profit firms ("suppliers") compete to purchase wholesale electricity and sell it to households. Economists who pushed for retail electricity restructuring argued that it would reduce prices, improve incentives for innovation, and reduce monopsony power in wholesale markets (Bohi and Palmer, 1996; Littlechild, 2000). However, other economists raised skepticism about the ability of retail suppliers to reduce electricity

[4]As of 2022, Texas, Ohio, Illinois, the District of Columbia, and ten states in the New England and Mid-Atlantic regions had restructured residential electricity markets.

supply costs and argued that the opportunities for other value-added services were likely small for residential consumers (Joskow, 2000).

Politicians and regulators in multiple states have recently raised concerns about the high prices that low-income households pay in restructured markets. These concerns led to some market reforms. Multiple states banned or heavily restricted the participation of low-income subsidy recipients in the retail choice market.[5] As of September 2022, another state is actively considering ending the retail choice market entirely, largely due to its impact on low-income households.[6]

This paper focuses on the Baltimore Gas and Electric Company (BGE) market in Maryland and, to a lesser extent, markets in Connecticut and Maine. In these areas, consumers have a default option, which is a regulated rate. There are no limits on the prices suppliers can charge consumers for non-default products in these states. In this paper, I will treat the default and regulated option as the outside option and consider the market of non-utility suppliers (henceforth, "suppliers") and consumers who actively decide to participate in the retail choice market. In 2019, about 24% of all BGE residential customers participated in the retail choice market. All of these customers participate in the individual retail choice market. There were no areas where local governments or communities bargained with suppliers on behalf of households ("Community Choice Aggregation" or "Municipal Aggregation") during the period I study.

By traditional competition metrics, the BGE residential retail choice market appears reasonably competitive. Seventy-nine suppliers, owned by 65 unique companies, served households during the 38-month analysis timeframes. During this short period, 12 firms (i.e., parent companies) entered the market, and seven firms exited. Consumers have access to all suppliers. The Herfindahl Hirschman Index (HHI) classifies the market as unconcentrated in almost all analysis months.[7]

The regulatory agencies governing the retail electricity markets in Maryland and Connecticut, Maryland Public Service Commission (PSC) and Connecticut Public Utilities Regulatory Authority (PURA), run free websites that allow suppliers to publicly post electricity plan offers. Households can view and compare these offers. While electricity is typically considered a homogeneous good, the products offered on the comparison websites show that suppliers differentiate products by bundling electricity with other attributes. Common attributes include renewable energy certificates (RECs) and financial products, such as gift cards (e.g., Walmart, Amazon) and price stability for a given contracted time period.[8] Sup-

[5]See State of New York Public Service Commission CASE 15-M-0127 and Connecticut Public Utilities Regulatory Authority Docket 18-06-02.

[6]See Massachusetts Senate Bill No. 2150.

[7]A market is considered unconcentrated if it has an HHI below 1,500. The median HHI is 1,423, and the maximum HHI is 1,538. In general, the market exhibited a downward trend in market concentration between 2019 and 2022. In comparison, the Connecticut market is classified as unconcentrated, and the Maine market is classified as highly concentrated throughout the entire relevant timeframe. A market is considered highly concentrated if it has an HHI above 2,500.

[8]Renewable energy certificates are tradeable permits that give the owner financial rights to the renewable

pliers may also differentiate themselves as a company, for example, by offering superior customer service.

Differentiation through electric rate design or bill design is limited. As of 2022, all households in Connecticut and Maine and most households in Maryland receive one bill from their utility that includes the utility's charges *and* the supplier's charges. Some industry members have argued that this practice reduces suppliers' ability to differentiate their products.[9] Maryland does allow suppliers to send their customers a separate bill for supply charges, but this practice is very uncommon.

In addition to consumers actively searching for new electricity plans, suppliers may acquire customers through direct marketing, such as door-to-door marketing, tabling, telemarketing, and mail marketing. Suppliers frequently outsource this marketing to third parties, but regulators hold suppliers fully responsible for the behavior of marketers acting on their behalf. In this paper, I treat a supplier and its marketing partners as one entity. Policymakers have expressed concerns about misleading and aggressive marketing tactics.[10] Of the 283 supplier-related complaints the Maryland PSC reported in 2021, 49% were about disputing an enrollment or misrepresentation of the supplier or marketer.[11]

When consumers sign up with a supplier, they sign up at a price that is fixed for a specified number of months. Based on the frequency of price changes in the BGE data set, the median sign-up price duration is two months. When the initial contract ends, most contracts automatically renew at a potentially updated price. In the BGE data set, the median renewal contract lasts one month, suggesting that most contracts automatically renew on a month-to-month basis.

Sometimes a consumer cannot pay their entire bill, but the consumer's supplier does not bear much—if any—of this underpayment risk in Maryland and Connecticut. Through a program known as "Purchase of Receivables" (POR), the PSC and PURA require consumers' utilities to purchase suppliers' receivables at a regulated industry-wide percentage discount. Under this program, a supplier will receive the same revenue, equal to the amount they charged less this regulated discount, whether or not a customer pays their bill. This configuration is analogous to a risk-free market with a tax. In the short run, any additional underpayment is socialized across consumers. In the long run, the state regulator updates the percentage discount in a regulatory proceeding based on historical underpayments, thereby socializing costs across suppliers.

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content of electricity previously generated by a renewable generator.

[9]e.g., See the Retail Energy Supply Association (RESA) comments in Maryland Public Service Commission Case No. 9461.

[10]e.g., See the Massachusetts Joint Committee on Telecommunications, Utilities, and Energy Hearing. Available at: https://malegislature.gov/Events/Hearings/Detail/3891/Video1

[11]See Maryland Public Service Commission. "Retail Energy Supplier Complaint Reports." Accessed July 2022. Available at: https://www.psc.state.md.us/retail-energy-supplier-complaint-reports/

1.3 Data

The primary data set used in this paper is Baltimore Gas and Electric Company (BGE) billing data for December 2018 through March 2022. The data set includes billing information for all residential BGE accounts that participated in retail choice during this timeframe. The billing information includes total electricity supply bill ($), monthly electricity usage (kWh), rate structure, supplier, zip code, and whether the customer applied to participate in a low-income program through the Maryland Office of Home Energy Programs. These data include 96,014, 101,357, and 205,773 accounts, respectively, for households in zip codes with median annual income below $60,000, $60,000-80,000, and above $80,000. I supplement these data with historical prices for consumers on the default rate from BGE, Maryland Office of People's Council, and MD PSC Case No. 9064.

The Maryland PSC also provided data from their MDElectricChoice.gov offer comparison website. These data allow me to analyze search behavior and preferences for plan attributes. While consumers do not sign up on the comparison website, they can click on a plan to be directed to the relevant supplier's website and start signing up. I have weekly data on all residential offers on the website and all clicks on the website by plan and rough IP address geography from late January through July 2022. I map these geographies to zip codes for comparisons by median zip code annual household income. Figure A1 shows a screenshot of the website.

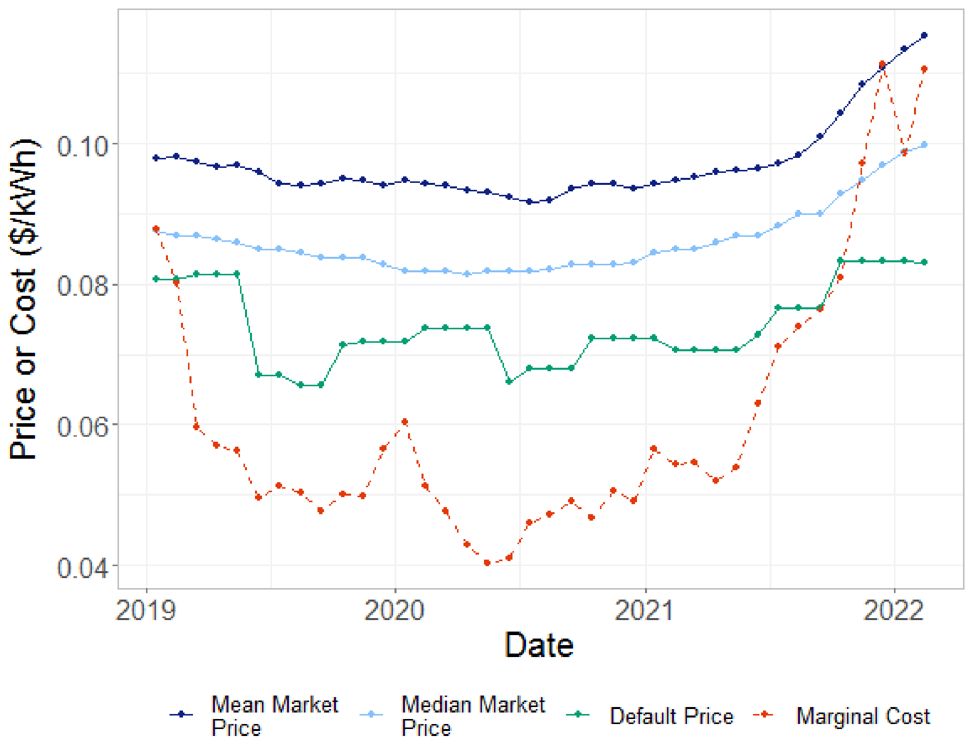
To analyze geographic variation in marketing presence, I use a cross-section of data on door-to-door marketing presence in the Baltimore metropolitan area. These data come from the PSC (PSC 2020). The PSC requires all suppliers to report when and for how long they plan to conduct marketing activity by zip code. The PSC report documents the number of suppliers that reported marketing door-to-door in each zip code from November 2019 through October 2020.

I estimate suppliers' marginal cost of supplying one additional kWh by cost component and month. Suppliers' marginal costs include wholesale electricity costs scaled up for losses, payments for grid-balancing ancillary services, and the cost of meeting Maryland's Renewable Portfolio Standard. Although capacity costs only vary with kWh usage at certain times in the year with a one-year delay, I also treat generation capacity-related costs as marginal costs for simplicity. In this sense, it may be more appropriate to consider the marginal costs as the incremental cost per kWh of supplying a consumer with electricity. This incremental cost excludes any customer service or administrative costs. See Appendix A.7 for a detailed discussion of cost calculations.

Figure 1.2 displays one-month-ahead estimated marginal costs for each month of the analysis timeframe. The figure also shows default prices and summary statistics of market prices for comparison.

Finally, I also conducted a consumer survey of 905 Baltimore and Maryland households in August and September 2022 to gain additional information about consumer behavior, beliefs, and experiences searching for and signing up with electricity suppliers. Roughly two-thirds of the participants also received one of two randomized information interventions. Of the

Figure 1.2: Prices and Estimated Marginal Costs



Market prices reflect electricity supply prices of consumers who are active in the Baltimore retail choice market. The default rate is the BGE Standard Offer Service (SOS) rate. Estimated marginal costs are one-month ahead estimates.

baseline survey participants, 471 responded to a one-month follow-up survey. MFour Mobile Research administered the surveys using their mobile application. Eligible participants lived in an area of Maryland, Connecticut, or the District of Columbia open to retail choice, were over 18 years old, and made decisions about their electricity bill. To facilitate comparison across low- and high-income communities, I undersampled zip codes with median household income between $60,000 and $80,000. Of the 905 respondents, 25.6%, 44.5%, and 29.8%, respectively, come from zip codes with median annual income below $60,000, $60,000-80,000, and above $80,000. See Appendix A.8 for a copy of the survey instruments and Appendix A.9 for all survey response summary tables.

See Appendix A.6 for information on data sources used to analyze other states.

1.4 Descriptive Evidence

This section presents some descriptive and reduced-form evidence to support six key facts about the BGE residential electricity market. The first two facts document the extent of price heterogeneity and provide evidence of adverse implications on social equity. The remaining facts illuminate the importance of price discrimination based on inattention-driven inertia and price discrimination through marketing for explaining this price heterogeneity.

Stylized Fact 1: Markets exhibit large price variation

Figure 1.3 presents cross-sectional distributions of all billed prices in the BGE retail choice market in four months.[12] Looking across all months, the standard deviation in residualized prices after controlling for time fixed effects is \$0.041/kWh or roughly \$37/month at the mean 2019 BGE household electricity usage of 903 kWh.[13] I observe substantial pricing variation within firms as well as across firms. Adding controls for supplier parent company fixed effects reduces the standard deviation in residualized prices by only 14% to \$0.035/kWh.

The months included in Figure 1.3 are typical of the price distributions in a random month during the analysis timeframe. I selected these months to capture variation over time and seasons, excluding the atypical period near the beginning of the COVID-19 pandemic.

Stylized Fact 2: Low-income households and marginalized communities face particularly high prices

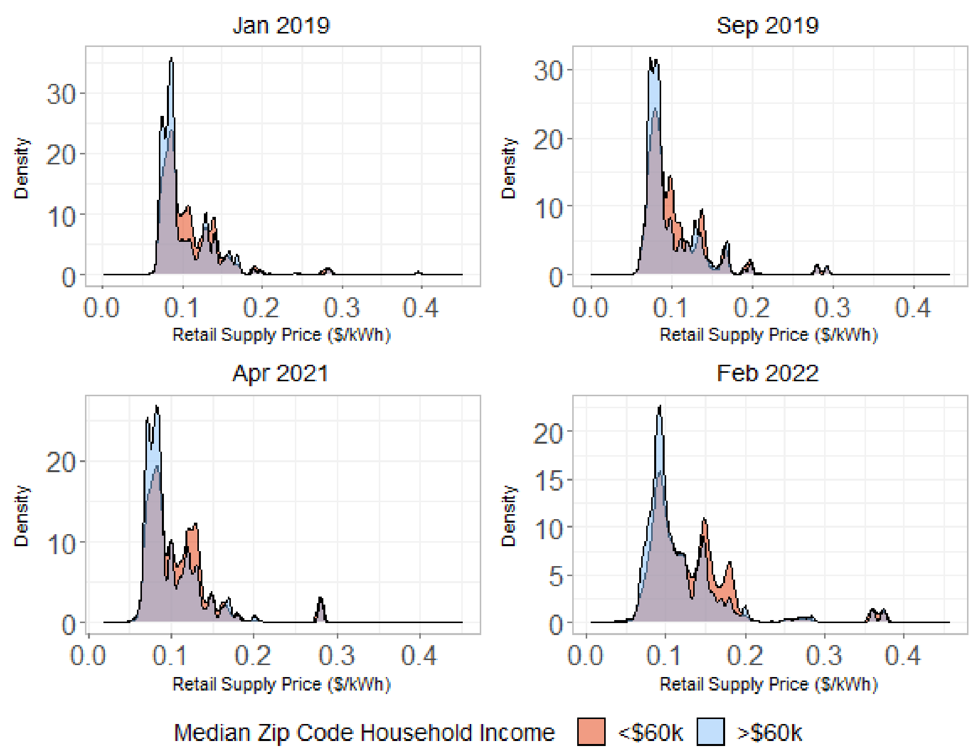
Figure 1.4 shows plots of mean and median prices over time by three zip code-level annual median household income categories: below \$60,000, \$60,000-80,000, and above \$80,000. Across all months of the analysis timeframe, households in the lowest-income category paid the highest mean and median prices, and households in the highest-income category paid the lowest mean and median prices. On average, households in zip codes with a median income below \$60,000 and between \$60,000-80,000 face \$0.0094/kWh ($t = 53$) and \$0.0042/kWh ($t = 26$) higher mean prices, respectively, than households in zip codes with a median income above \$80,000. These estimates come from a regression of price on income group and time fixed effects with errors clustered on consumer. A similar regression at an individual household level shows that households who applied for low-income electricity bill assistance face \$0.008/kWh higher prices, on average, than other households ($t = 41$).

I also observe relatively high prices in zip codes with a large percentage of Black, Latino and Hispanic, and immigrant households as well as few high school graduates, many rented housing units, and low English proficiency. Figure 1.5 displays coefficients and 95% confidence intervals from regressions of price on zip code demographics across all time periods, controlling for time fixed effects and clustering standard errors by supplier. For example, the linear model predicts that households in a zip code with exclusively Black residents will pay \$0.019/kWh (≈20%) more than households in a zip code with only white residents. It also predicts that households in the BGE zip code with the highest percent of non-U.S. citizens,

[12] These distributions do not include prices on the default regulated rate or BGE charges for electricity delivery.

[13] Source: Energy Information Administration Form EIA-861.

Figure 1.3: Price Distributions in Four Months by Income Group



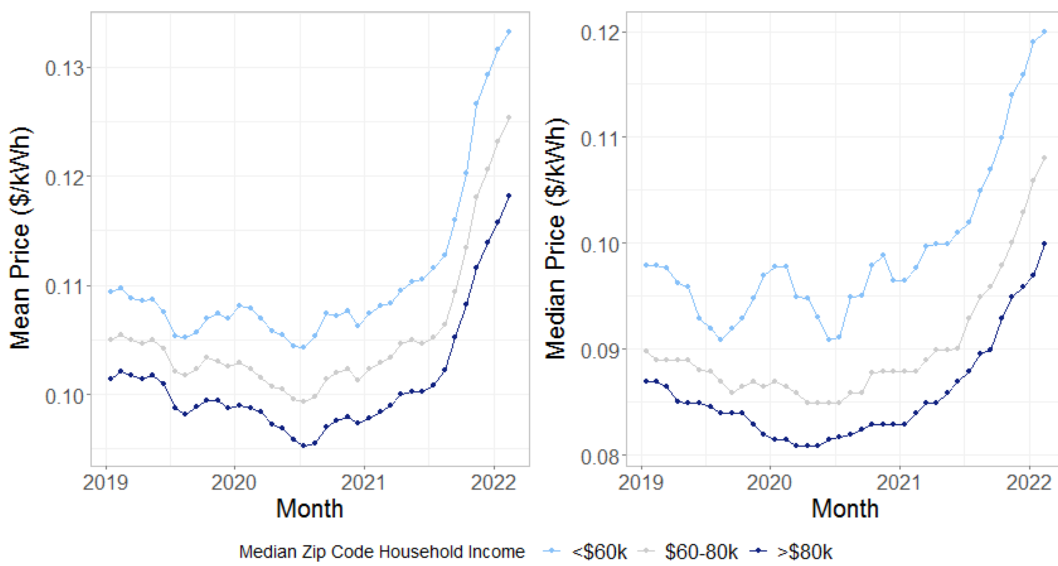
Probability density plots of electricity supply prices billed in Baltimore Gas and Electric Company service area in four months. Excludes standard offer service prices. Only includes prices for consumers on linear tariffs that are not time-differentiated. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

about 18%, will pay \$0.016/kWh (≈15%) more than households who only live around U.S. citizens. Figure A2 shows scatterplots of mean zip code price by the percentage of the zip code population that falls into each of four demographic groups in September 2019. The percentage of Black residents is a particularly strong metric for predicting variation in mean price across zip codes. This variable can explain 45% of the variation in mean September 2019 prices across zip codes.

Many of these demographic variables are correlated. Median household income is highly correlated with metrics of wealth, such as the percentage of occupied homes that are rented (r=-0.46), and with education metrics, such as the percentage of households without a high school diploma (r=-0.48). Median household income is also correlated with race, such as the percentage of Black residents (r=-0.19). For simplicity, I focus only on the income-price gap for the remainder of this paper.

The aggregate price distributions shown in Figure 1.3 combined contracts that started in different months as well as "new" and "renewal" contracts. When a consumer switches

Figure 1.4: Mean and Median Prices Over Time by Income Group



Mean (left) and median (right) electricity supply prices billed in Baltimore Gas and Electric Company service area by month and zip code median household income. Only includes prices for consumers on linear tariffs that are not time-differentiated. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

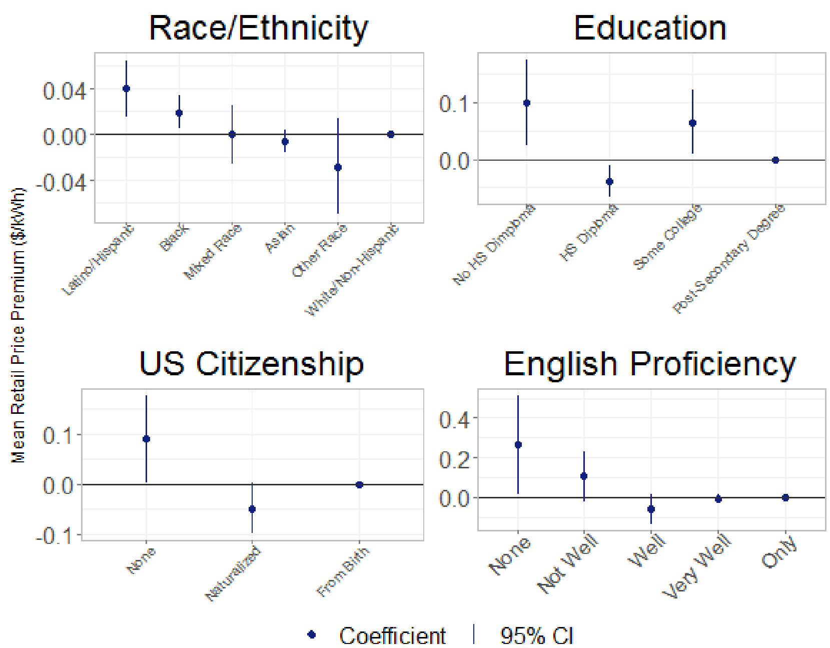
suppliers, they execute a "new" contract with the new supplier. When a consumer's initial contract term with a supplier ends, they either switch suppliers or execute a "renewal" contract.

The income-price gap also exists in the restricted sample of new contracts. Figure 1.6 shows the sign-up price distributions by median zip code household income. Across all months, the mean sign-up price difference between households in zip codes with median household income below $60,000 and above $80,000 is $0.0091/kWh ($t = 68$). Moderate-income households have a sign-up price premium of $0.0052/kWh ($t = 38$).[14]

Contracts that were renewed display an even larger income-price gap. As an approximation, I identify contract renewals as any instance in which a consumer has the same supplier but a different price than they had the previous month. This definition includes households who actively renewed a contract and households who passively allowed their contracts to renew automatically. Across all months, households in zip codes with a median income below $60,000 and between $60,000-80,000 face $0.0102/kWh ($t = 34$) and $0.0044/kWh ($t = 16$) higher renewal prices, respectively, than households in zip codes with a median income above $80,000.

[14]See Figure A5 for a map of mean sign-up price by Baltimore City zip code.

Figure 1.5: Coefficient Estimates from Regressions of Price on Key Zip Code Demographics



Coefficients and 95% confidence intervals from regressions of electricity supply price on time fixed effects and zip code tabulation area (ZCTA) demographics from the 2019 American Community Survey. Baltimore Gas and Electric Company service territory residential customer accounts on retail choice only.

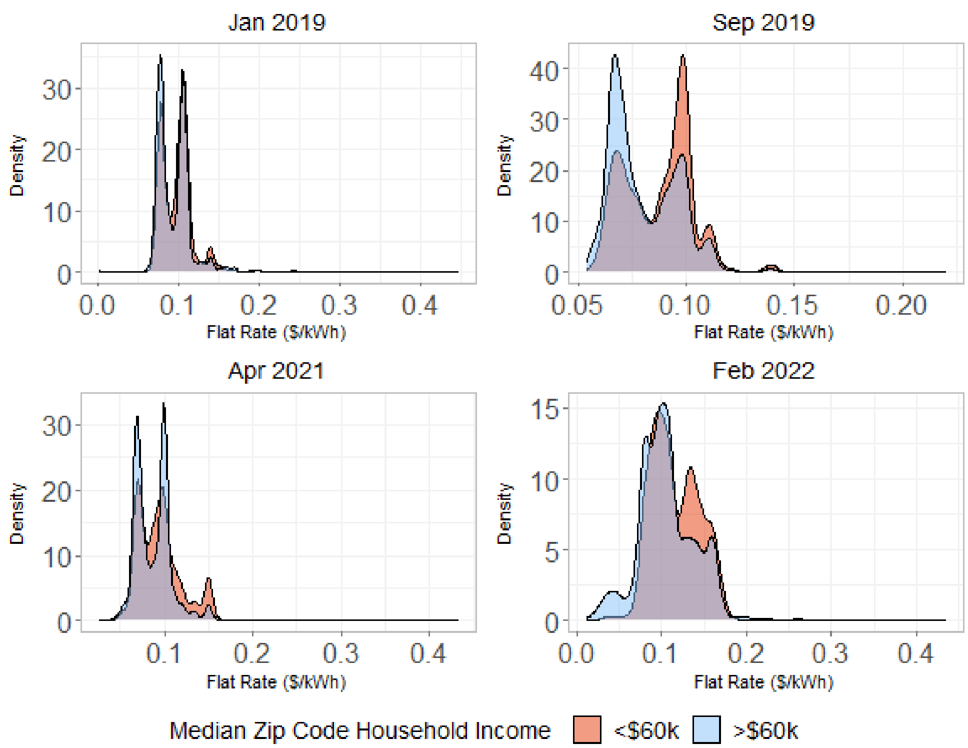
Stylized Fact 3: Households in low-income areas switch suppliers more frequently and are more likely to opt into retail choice

One potential hypothesis for the income-price gap is that low-income households are less active in the market and switch suppliers less frequently. However, I observe the opposite: households in low-income communities are significantly *more* likely to participate in the market and switch suppliers than other households. About 24% of households in low-income communities participated in the retail choice market in a given month, on average.[15] Comparable participation rates in moderate- and high-income communities were 22% and 20%, respectively.[16] Households in low-income communities were also more than twice as likely as households in high-income communities to switch their electricity supplier in a given

[15]Calculations exclude the early COVID-19 pandemic period from February 2020 through September 2020.

[16]These estimates equal the ratio of residential accounts in the BGE billing data to total households in the 2019 American Community Survey by zip code median annual household income category, scaled proportionately to the total residential accounts in the BGE service territory from Energy Information Administration Form EIA-861.

Figure 1.6: Sign-up Price Distributions in Four Months by Income Group



Probability density plots of electricity supply prices for consumers who switched suppliers in four specific months in Baltimore Gas and Electric Company service area. Excludes standard offer service prices. Only includes prices for consumers on linear tariffs that are not time-differentiated. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

month. Mean monthly switching rates were 8.0%, 5.3%, and 3.3% for low-, moderate-, and high-income communities, respectively.

Survey responses suggest that these differences in switching and participation are not due to systematic differences in search cost-benefit calculations. While respondents in low-income zip codes tend to report higher expected benefits of searching than respondents in high-income zip codes ($t = 2.5$), these differences are almost perfectly offset by differences in reported search costs. Table A7 reports the mean and median responses by income group of expected one-month bill savings from an hour of searching, one-month bill savings required to justify an hour of searching, and the differences between these two values. The mean net expected cost of searching for one hour differs across low and high-income households by less than $1 ($t = 0.05$).

Survey results shown in Table A8 provide evidence that consumers are partially inattentive to their own prices and bills. However, attention levels appear similar across low-and high-income zip codes. Among respondents who reported ever being active in the retail choice market, only 51% reported ever switching suppliers due to a change in price or bill amount. Only 77% reported looking at their bill approximately every month, and 53% reported looking at their price approximately every month. When asked to guess their electricity price, 84% of households guessed a price outside of the reasonable range, defined as a price above the maximum price charged in the Connecticut retail choice market in that month.[17] While point estimates may suggest low-income households look at their prices especially frequently, this does not translate to better price estimates.

Stylized Fact 4: Prices increase with contract renewals, with larger price increases in low-income communities

Suppliers appear to be aware that consumers are partially inattentive to price, and they seem to price discriminate on this inattention through gradual price increases over a customer's tenure. The renewal price distributions discussed in Stylized Fact 2 described renewal prices irrespective of customers' tenures. To analyze price discrimination on attention, I segment these price distributions further by the number of times a consumer has—actively or passively—renewed their contract with an individual supplier (e.g., 1 = sign-up price, 2 = first renewal, etc.). Figure 1.7 shows estimates and 95% confidence intervals from a regression of renewal and sign-up prices on the number of renewals, zip code income group, their interactions, and time fixed effects. All values are relative to sign-up prices of households in zip codes with a median household income above \$80,000.[18]

As shown in Figure 1.7, prices tend to increase with the number of renewals for all income groups. The magnitudes are large. A household that renews their contract for the 11th to 20th time can expect to pay an extra \$0.035/kWh, or roughly \$32 per month, relative to the price they would get if they switched suppliers that month. At the mean sign-up price, this reflects a 38% price increase.[19]

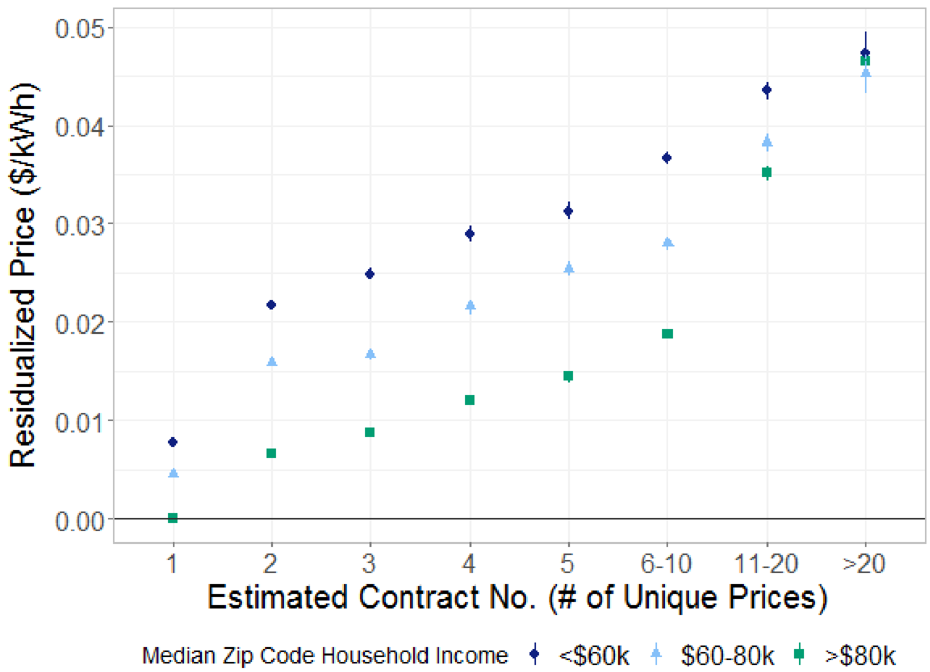
This result suggests that suppliers price discriminate on consumers' attention to their prices. For example, suppose consumers rarely notice small price increases. Then suppliers would have an incentive to increase their prices a small amount with each renewal. This strategy would explain the observed pricing pattern. In contrast, conventional search or switching costs cannot create this pricing pattern of continued price increases over time. After initial sign-up, conventional search and switching costs remain constant. As a result, profit-maximizing renewal prices under search and switching costs alone would increase on the first renewal but then cease to change with additional renewals.

[17]Increasing this cutoff to \$0.50/kWh only reduces this proportion to 82%.

[18]For example, a dark blue dot at an estimated contract number of 3 captures the difference between the mean second renewal price for a household in a below $\$60,000$ income zip code and the mean sign-up price for households in an above $\$80,000$ income zip code.

[19]It is common for consumers to experience many renewals. See Figure A3 for shares of consumers on each renewal contract number.

Figure 1.7: Residualized Price by Number of Contract Renewals



Estimates from a regression of electricity supply price on time fixed effects, number of unique prices a consumer has faced since last switching suppliers, and income group. Excludes standard offer service prices. Only includes prices for consumers on linear tariffs that are not time-differentiated. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

Figure 1.7 also shows that the income-price gap increases on renewal. The gap almost doubles between sign-up and the first contract renewal and persists at some magnitude through the 14th renewal.

The result that the income-price gap increases on renewal may seem contradictory to some of the earlier findings about switching and attention. If low-income households were relatively inattentive, we might also expect them to switch relatively infrequently. Section 1.7 shows that marketing can reconcile these findings.

Stylized Fact 5: Suppliers appear to offer low prices online and high prices through marketing

This subsection further explores the sign-up price gap by asking two questions about consumers' sign-up methods: 1) How do consumers sign up with electricity suppliers? 2) Do prices differ by sign-up method? I cannot explicitly observe sign-up prices by the associated sign-up method. Instead, I use survey evidence to answer the first question. For the second question, I use activity on MDElectricChoice.gov to analyze how sign-up prices from comparison website search differ from sign-up prices from other methods. I then leverage COVID-19 restrictions that prohibited in-person marketing to analyze how sign-up prices through in-person marketing differ from sign-up prices from other methods.

Among survey respondents, the most commonly reported method of signing up with an electricity supplier was through an in-person marketing interaction. Significantly more respondents report signing up through an in-person marketer (43%) than from actively searching (36%) within the past ten years ($\chi^2 = 8$). In addition, 27% reported signing up through a telemarketer, and 29% reported signing up through other types of marketing, such as mail or online marketing.

To explore how sign-up prices through comparison website search differ from sign-up prices from other sign-up methods, compare two sets of price distributions: 1) prices associated with each plan click on the comparison website, and 2) *all* sign-up prices in the BGE service territory. Figure 1.8 plots these two price distributions in February 2022, and Table 1.1 displays associated summary statistics.[20] The mean and variance of website click prices are lower than the overall price distribution of new contracts ($t = -19$, $F_{93,5437} = 0.09$). These results suggest that firms can price discriminate on sign-up method. Consumers who sign up through methods other than online tend to receive higher prices.

Table 1.1: Summary Statistics by Price Distribution

Price Distribution	Mean Price ($/kWh)	Price Variance ($/kWh)
Comparison Website Clicks	0.086	0.0001
New Contracts	0.111	0.0014

I formally test the hypothesis that high sign-up prices predominantly come from in-person marketing while low sign-up prices come from other sign-up methods, such as active search. I use COVID-19 marketing restrictions as a natural experiment. To achieve this, I first estimate the distributions of low and high sign-up prices for each month in the analysis timeframe. I then assess whether COVID-19 marketing restrictions have a larger effect on the number of high-price sign-ups than the number of low-price sign-ups.

To estimate the distributions of low and high sign-up prices, I leverage the bimodal nature of sign-up price distributions demonstrated in Figure 1.6.[21] I assume the higher mode reflects the mode of marketing-related sign-up prices and the lower mode is the search-related sign-up price mode. Assuming each of these distributions is symmetric, I estimate the two underlying sign-up price distributions. For more estimation details, see Appendix A.5.

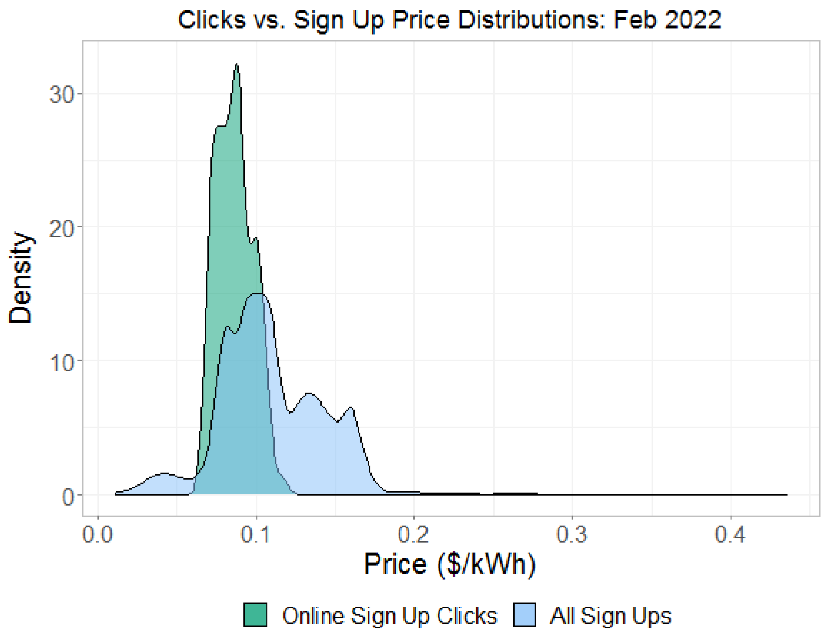
Figure 1.9 shows the resulting estimates of the number of presumed marketing-related (i.e., high-price) and search-related (i.e., low-price) sign ups.[22] Each observation is a daily estimate based on a two-week rolling average. The orange-shaded region indicates when

[20] See Table A4 for a comparison to renewal prices.

[21] The February 2022 sign-up price distribution is an outlier in this respect.

[22] Comparing cross-sectional variation across zip codes, I find an 89% correlation between these estimates

Figure 1.8: Comparison Website Click Prices vs. All New Contract Prices



In blue, probability density of sign-up prices for all consumers who switched electricity suppliers in February 2022 in the Baltimore Gas and Electric Company (BGE) service area. In green, probability density of prices associated with plan-specific clicks on the MDElectricChoice.gov website in February 2022 in the BGE service area. Excludes standard offer service prices. Only includes prices for consumers on linear tariffs that are not time-differentiated.

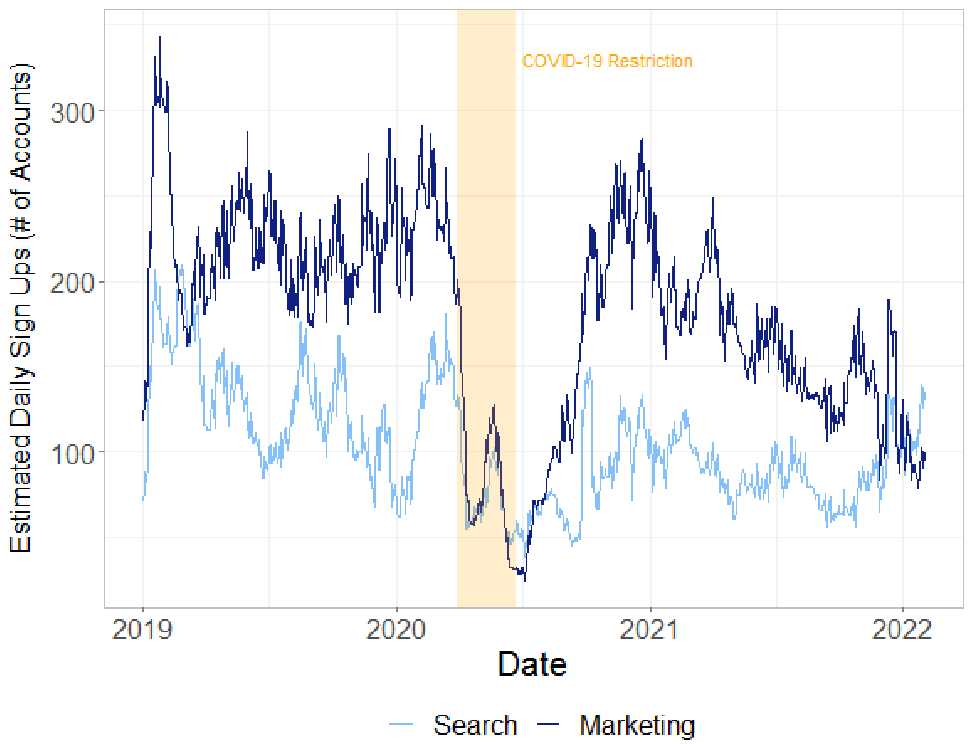
suppliers were not allowed to market in person in Baltimore City due to COVID-19 restrictions. This restricted period began on March 30, 2020, and ended on June 22, 2020, with a Baltimore City executive order that lifted restrictions on non-essential businesses.[23]

To test whether the estimated marketing- and search-related distributions are picking up meaningful variation in sign-up method, I conduct two tests. The first test is a difference-in-differences analysis. I analyze differences in the reduction of marketing-related sign-ups relative to search-related sign-ups during days when Maryland or Baltimore City restricted non-essential business operations due to COVID-19 relative to other days. All observations received treatment simultaneously, from March 30 through June 22. The short nature of the treatment period relative to the analysis timeframe minimizes potential concerns about

of the number of suppliers marketing door-to-door by zip code and the reported numbers in the administrative marketing activity data.

[23]Maryland's shelter-in-place executive order began on March 30, 2020. When the Maryland governor lifted these restrictions, Baltimore City imposed its own restrictions on non-essential business operations until the June 22, 2020, executive order.

Figure 1.9: Estimated Daily Sign Ups by Type and Date



Estimated number of search- and marketing-related sign ups in the Baltimore Gas and Electric Company service area based on an assumption that bimodal sign-up price distributions reflect a mixture of two underlying distributions: a high-price distribution from marketing and a low-price distribution from search. Shaded region portrays the time between the Maryland COVID-19 shelter-in-place ordinance and the lifting of Baltimore City COVID-19 restrictions on non-essential businesses.

parallel trends. Specifically, I estimate the following linear probability model:

$$y_{ijt} = \beta_1(Marketing)_i + \beta_2(Shelter)_t + \beta_3(Marketing)_i \times (Shelter)_t + \delta_j + \varepsilon_{ijt}$$

where y_{ijt} is an indicator of whether consumer i switches to supplier j in period t, $(Marketing)_i$ equals one if the sign-up occurred at a high price, $(Shelter)_t$ equals one during the treatment period and zero otherwise, and δ_j denotes supplier fixed effects. I also test specifications without supplier fixed effects. Our parameter of interest is β_3.

Difference-in-differences results in Table A1 suggest that shelter-in-place reduced estimated marketing-related switching probability by about 2.7 percentage points more than that of search-related switching. This estimate is about 83% of the overall mean switching rate in the data set. Excluding supplier fixed effects reduces these estimates slightly to 2.6 percentage points and 80%.

I also perform regression discontinuity analysis of search- and marketing-related sign-up rates when Baltimore City allowed non-essential businesses to open. Specifically, I estimate the following linear probability model using data from the 38 days before and after June 22, 2020:

$$\begin{aligned} y_{ijt} = \beta_1(After\ Event)_t + \beta_2(Date_t - Event\ Date) \\ + \beta_3(After\ Event)_t \times (Date_t - Event\ Date) + \delta_j + \varepsilon_{ijt} \end{aligned}$$

where $Event\ Date$ is June 22, 2020, $Date_t$ is calendar date, $(After\ Event)_t$ is an indicator for whether the calendar date falls after June 22, and y_{ijt} and δ_j have the same interpretations as in the Difference-in-Differences model. I estimate the difference $Date_t - Event\ Date$ in days. The coefficient of interest is β_1. Assuming suppliers could not influence the timing of the June 22 executive order, we can interpret this estimate as the immediate effect of allowing in-person marketing to resume.

Table A2 presents the results of the regression discontinuity analysis. Marketing-related switching increased by 0.54 percentage points due to Baltimore City lifting restrictions on non-essential businesses. There was no significant discontinuity in search-related switching on June 22, 2020. With 95% confidence, I can rule out an increase greater than 0.22 percentage points, which is half the estimated increase for marketing-related switching. This provides further evidence that suppliers offer higher prices through in-person marketing than through other sign-up methods, such as online search.

Stylized Fact 6: There is more marketing in low-income areas

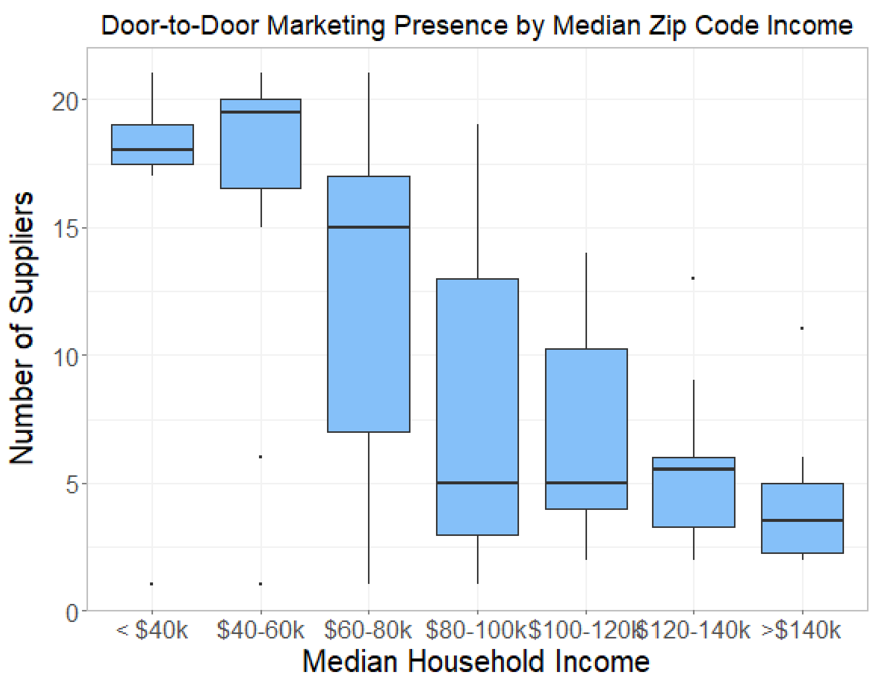
Sign-up prices in Figure 1.7 (i.e., contract #1) show that even when consumers actively choose to switch suppliers, low-income consumers tend to sign up at higher-priced plans than high-income consumers, on average. Is this because consumers in low-income zip codes are relatively more likely to sign up through marketing than through active search? Figure 1.8 showed that no consumers clicked on a plan on the comparison website in February 2022 that had a price above \$0.1165/kWh. Comparing this result with the bottom right quadrant of Figure 1.6, observe that low-income households were particularly likely to sign up with a new supplier at a price above this \$0.1165/kWh threshold price in February 2022. I can reject the null of equal proportions of sign-up prices above and below \$0.1165/kWh in low vs. high-income zip codes ($\chi^2 = 85$). In addition, only 19% of comparison website clicks come from low-income areas, while 32% of overall February 2022 sign-ups come from low-income areas ($\chi^2 = 6.2$).[24] This suggests that low-income households may be particularly likely to sign up with a new supplier through methods that do not involve full search.

Suppliers disproportionately market in low-income areas. Figure 1.10 shows box-and-whisker charts of the number of suppliers that marketed door-to-door in each Baltimore metropolitan area zip code by zip code median household income bin between November

[24] Areas defined as closest zip code based on Google Analytic's city tag for each user.

2019 and October 2020. There is a strong negative correlation between income and door-to-door marketing presence. At least 15 suppliers marketed door-to-door in almost every zip code with a median household income below \$60,000, and fewer than 15 suppliers marketed door-to-door in every zip code with a median household income above \$100,000.

Figure 1.10: Number of Suppliers Marketing Door-to-door by Zip Code Median Household Income



Box-and-whisker plots of number of suppliers reporting door-to-door marketing activity in each Baltimore metropolitan area zip code by 2019 American Community Survey zip code tabulation area median annual household income bin.

The survey confirms that there is more direct marketing in low-income areas. As shown in Table A9, about 77% of respondents in low-income areas reported being approached by an in-person marketer within the past two years. Marketing is significantly lower in high-income areas, where only 57% met an in-person marketer ($\chi^2 = 33$). Low-income households are also more likely to be approached by a telemarketer ($\chi^2 = 18$). This difference in marketing probability translates to more marketing-related sign-ups in low-income areas. As shown in Table A10, 57% percent of respondents in low-income areas report signing up through an in-person marketer in the past ten years, compared to 35% in high-income areas ($\chi^2 = 22$). Telemarketing led to 35% and 28% consumers signing up in low- and high-income areas, respectively ($\chi^2 = 2.9$). Respondents in low- and high-income zip codes were roughly equally likely to have signed up through active search.

Why do consumers sign up with marketers? I find evidence of persuasive marketing.

Among consumers who signed up through direct marketing, the majority (59%) said they signed up to save money, 24.5% selected plan attributes, and 54-61% cited an aspect of the marketing interaction itself.

To what extent can these marketing level differences be explained by differences in population density-driven marketing costs? It is difficult to disentangle these potential drivers since population density and income are highly correlated. Within the Baltimore metropolitan area, the correlation between population density and whether a zip code has a median household income below $60,000 is -0.59. However, as an initial exploration, Table A3 shows results from regressions of the number of suppliers that marketed door-to-door on zip code income metrics with and without controlling for population and population density. Adding these controls reduces the coefficients on the income variables by 68-84%, although most of these coefficients remain statistically significant. This result suggests that differences in marketing costs may be an important driver, but they cannot fully explain differences in door-to-door marketing presence across zip codes. Section 1.8 explores the individual contributions of marketing costs and demand-side drivers in detail.

Discussion

This section presented six key facts about the Baltimore market. The market exhibits large price variation. Low-income and marginalized communities pay especially high prices despite switching more frequently and being more likely to opt into the market. Evidence suggests that suppliers price discriminate on inattention-driven inertia, with larger price increases on renewal for low-income households. Suppliers also appear to price discriminate on search by offering low prices online and high prices through marketing. They also market disproportionately in low-income areas.

Some of these results may initially appear contradictory. For instance, relative to high-income communities, low-income communities pay higher prices and face higher price increases on renewal, which may suggest they also have greater inertia. However, households in low-income communities switch more frequently and are more active in the market. Section 1.7 shows that differential marketing across areas can explain how these facts may hold simultaneously.

These results generally appear to hold within the Northeastern and Mid Atlantic regions of the U.S. Appendix A.6 presents results for other states. I corroborate the result that low-income household pay especially high prices in four other states. In Maine and Connecticut, I also test and corroborate other stylized facts. Renewal prices tend to be significantly higher than prices of new contracts, and households in low-income areas have particularly high levels of retail choice participation and especially frequent switching. The proportion of clicks coming from low-income areas on the official Connecticut plan comparison website is significantly and substantially smaller than the overall proportion of sign-ups from low-income areas. See Appendix A.6 for details.

1.5 Alternative Theories

This section presents a brief overview of auxiliary facts and analyses that largely rule out alternative explanations as key drivers of the income-price gap. See Appendix A.4 for additional details.

Underpayment Risk

Low-income consumers may be particularly likely to underpay their bills. In many industries, firms may need to charge these high-risk consumers higher prices to account for the additional risk. In Maryland, however, the "Purchase of Receivables" program discussed in Section 1.2 insures retail electricity suppliers against such underpayments. The BGE Purchase of Receivables discount was zero throughout the period I study. Suppliers received exactly the amount they billed.

Quantity- and Time-differentiated Rate Designs

Some suppliers charge consumers quantity-differentiated rates, such as two-part tariffs or rates that differ by time of day or day of the week. If differences in electricity usage cause low-income consumers to benefit relatively less from these rate designs, they may pay high average prices despite facing identical price schedules. However, during the analysis timeframe, 95% of consumers in the BGE service area faced linear per-kWh rates, 5.0% had plans with fixed charges, and 0.006% were on time-differentiated rates.[25]

I restrict the analysis to consumer-months where consumers faced a flat per-kWh rate. I also drop about 3.9% of consumer-months because they are on budget billing. Under budget billing, a consumer's BGE bill may differ from the amount they owe.[26] This applies to all results presented in other sections of this paper, so quantity- and time-differentiated rates cannot explain price heterogeneity shown in Section 1.4.

Cost to Serve

Differences in marginal costs across geographic areas also cannot explain difference prices. Per-kWh marginal electricity costs are similar across geographic locations within the BGE service area. The entire BGE service area is located within the same transmission zone and locational deliverability area within the PJM market, so there is no capacity cost variation and limited transmission-related cost variation.

[25] Estimates are averages across across a subset of 94.4% of consumer-months for which I observe the full rate structure.

[26] Budget billing is an attempt to reduce the month-to-month variability in bill amounts by smoothing an expected annual bill over months of the year. While budget billing for transmission and distribution service is mandatory for BGE customers receiving low-income subsidies, there is not a similar mandate for electricity supply.

Marginal cost may vary with the timing of a consumer's electricity consumption since suppliers' marginal costs differ by time of a day and day of year. However, both literature (e.g., Zethmayr and Makhija, 2019) and external data sources suggest that, if anything, low-income consumers use relatively less of their electricity during high-cost hours.

If suppliers recover fixed administrative or customer service costs in a variable price,[27] This hypothesis is inconsistent with the finding of more direct marketing in low-income areas since suppliers should find these consumers less profitable. In addition, the correlation between residualized price and customer-specific usage after controlling for time fixed effects is small (r =-0.089). Furthermore, the variable price income gap persists in the restricted subset of consumers on two-part tariffs. Finally, I estimate that fixed costs can account for less than one-hundredth of a cent per kWh of the income-price gap. See Appendix A.4 for details.

Preferences for Premium Attributes

Another theory is that low-income households have a higher willingness to pay (WTP) for some attributes that suppliers bundle with electricity. However, on the MDElectricChoice comparison website,consumers in low-income areas click on *lower*-priced plans, on average, than do consumers in high- and moderate-income areas ($t = 2.2$). The mean price difference is $0.0038/kWh. Furthermore, as shown in Table A4, there is no statistically significant differences between income groups in WTP for any attribute. Point estimates suggest that, if anything, high-income households have larger WTP for most attributes. Low-income households may have a stronger distaste for fixed charges, but differences in electricity usage can fully rationalize this result. See Appendix A.4 for details.

Subsidies

The government offers some low-income consumers electricity bill subsidies. These subsidies may explain an income-price gap if they change low-income consumers' price responsiveness. However, Baltimore's electricity bill assistance subsidies are generally lump-sum transfers that do not vary with electricity price.[28] The income-price gap only decreases slightly (4%) when I exclude subsidy recipients. This result is consistent with the results of Byrne et al. (2022), who find no evidence that suppliers price discriminate based on low-income subsidy recipient status in Australia. See Appendix A.4 for a detailed analysis of pricing differences between low-income program applicants and non-applicants.

[27]The term "variable price" in this context refers to the charges that vary with a consumer's electricity usage. The term does not take the industry meaning of a price that may change each month.

[28]Subsidy amounts vary with household income, type of fuel used for heating, and electricity usage.

Negotiation

Consumers can negotiate their prices with suppliers. If low-income households are less willing to negotiate or have less negotiating power than high-income households, this could explain the income-price gap. I do not find any evidence for this theory. Among survey respondents, there is no statistically significant difference across low- and high-income households in the probability of having ever negotiated price ($\chi^2 = 0.3$; see Table A14). Recall that negotiation is not very common in the market, with 66% of surveyed retail choice participants reporting that they had never negotiated their electricity price.

1.6 Theoretical Model

Overview

This section outlines the general model I will use in Section 1.7 to explain the stylized facts and then estimate in Section 1.8 to conduct income-price gap decomposition, counterfactual, and welfare analyses. I will later make simplifying assumptions and add additional structure for these purposes, but the underlying model is the same.

In this model, firms compete for a homogeneous subscription product under imperfect information and costly marketing. There are two demand-side market distortions: 1) heterogeneous search frictions and 2) inattention-based inertia. Although barriers to search and inattention-driven inertia both reduce search, it is important to distinguish between factors affecting a consumer's binary decision to consider alternative electricity plans ("inattention-based inertia") and factors governing the consumer's search process conditional on considering alternative electricity plans ("search frictions"). In this model, inattention-driven inertia determines the binary outcome, while search frictions determine choice sets.

There is also one supply-side distortion: marketing is costly. Despite the costs, the presence of consumers with high search frictions may make it profitable for suppliers to provide price information by marketing directly to consumers. I build on the marketing model in Varian (forthcoming).

In the model, marketing reveals a single price to a prospective customer. The marketing interaction may also temporarily increase the consumer's willingness to pay (WTP) for the marketed plan due to persuasive marketing or decrease it due to a distaste for the interaction. Notably, the interaction does not affect the consumer's WTP for any of the supplier's other plans or for the same plan offered at another time. There are no network effects; the interaction does not impact other consumers' WTP for the plan. Marketing also does not create market power through product differentiation.

In equilibrium, suppliers price discriminate. This creates a separating equilibrium in which consumers with low or no search frictions search and receive a low price, while consumers with high search frictions sign up with marketers at a high price. Arbitrage is cost prohibitive. Moreover, inattention-driven inertia enables suppliers to charge renewal prices above sign-up prices for all customers. Suppliers compete away all ex-ante expected inattention-related profits from consumers who search in sign-up prices. While I do not model entry formally, I assume there is sufficient entry for suppliers to compete away ex-ante expected profits from consumers who do not search through marketing.

Consumer Behavior

Each consumer has a fixed type. There are two consumer types: 1) a proportion $\alpha \in (0,1)$ search fully whenever they pay attention ("searchers"), and 2) a proportion 1-α never search but have access to a default outside option ("non-searchers"). Consumers can participate in the market or stick with the default outside option, a regulated rate. Consumers who choose to participate in the market can select a supplier by searching in a competitive marketplace or purchasing from a direct marketer who comes to their door. Searching in the competitive marketplace is prohibitively costly for non-searchers and free for searchers. Talking to a direct marketer is free for all consumers.

All consumers, including searchers, are partially inattentive to their price and bill unless they receive an attention shock. Any marketing interaction creates an attention shock. Consumers may also receive a "bill shock" from an unexpectedly high price or bill. Formally, a consumer i will pay attention in period t if $A_{it}(\{p_{i\tau}\}_{\tau=1}^{t}, \{Bill_{i\tau}\}_{\tau=1}^{t}) > 0$ where $\{p_{i\tau}\}_{\tau=1}^{t}$ and $\{Bill_{i\tau}\}_{\tau=1}^{t}$ are the entire histories of the consumer's prices and bills. The following sections will add more structure to this latent attention function A_{it}.

When a marketer attempts to contact a consumer, the consumer interacts with them with some fixed probability ϕ. For door-to-door marketing, we can think of ϕ as the probability that a consumer will open their door when a stranger knocks on it. A consumer who does not answer their door does not receive an attention shock.

Conditional on receiving an attention shock, consumers will select the plan in their choice set that provides them with the highest utility. All consumers have their current plan and the outside option in their choice sets. Searchers also have competitive marketplace offers. If marketing stimulates a consumer's search, the consumer also has the marketing offer. Marketing offers are sequential with no recall; consumers cannot receive another marketing offer before accepting or rejecting an existing offer. However, accepting one marketing offer does not preclude consumers from accepting any future marketing offer.[29] Searchers may compare the marketing offer with the competitive marketplace offers.

Consumer i's latent utility for a supplier's plan j is:

$$u_{ijt} = -p_{ijt} + \gamma \mathbb{1}\{j \text{ is a marketing offer}\} + \varepsilon_{ijt}$$

where ε_{ijt} is a random error term with some known distribution and γ captures the direct impact of the marketing interaction on a consumer's perceived utility of signing up for plan j. A positive γ may reflect persuasive, aggressive, or misleading marketing, while a negative γ captures distaste for marketing.

[29] I abstract from consideration of early termination fees. This abstraction is reasonable if suppliers are typically willing to pay another supplier's termination fee to acquire a customer.

For simplicity, I assume electricity usage is perfectly price-inelastic. This assumption is common in electricity models.

Supplier Behavior

I assume there are many suppliers that are each small relative to the market. An individual supplier's actions negligibly impact aggregate marketing levels and price distributions. The market also exhibits free entry and exit.

For each geographic area, suppliers simultaneously choose marketing levels $M > 0$, marketing offer prices p_m, competitive marketplace offer prices p_o, and renewal prices p_{ri}. Renewal prices can vary by observable consumer characteristics and history. Marketing levels reflect the number of marketing attempts or, specifically, the number of doors marketers knock on.

Suppliers can fully observe their competitors' prices and marketing levels, and they have rational expectations about all underlying demand distributions. Suppliers can observe the types of their existing customers but not prospective customers. They can observe the other components of consumers' attention and decision-making processes (i.e., A_{it}, u_{ijt}) up to consumer-specific attention error, choice error (i.e., ε_{ijt}), and marketing availability draws.

Suppliers are risk neutral and maximize expected profits subject to costs. Suppliers face costs c_t and marketing costs $C(M) \geq 0$ with $C'(M), C''(M) > 0$. While the model could be adapted to include a fixed entry cost, the analytical or structural model results treat the number of suppliers as fixed and do not explicitly analyze supplier entry and exit decisions.

To summarize, play proceeds as follows:

1. Nature determines the outside option price
2. Suppliers choose sign-up offer prices, marketing offer prices, marketing levels, and renewal prices
3. Nature determines bill shock attention error draws, choice error draws, marketing availability draws, and which consumers receive marketing visits given the marketing level in their area
4. Consumers who receive an attention shock each make a choice from their choice sets
5. Suppliers receive period profits

Discussion

This simple model can explain a lot of the price heterogeneity in the market. The following section uses a simplified version of this model to demonstrate some simple dynamics that are useful for explaining the stylized facts. Section 1.8 discusses the empirical estimation of the underlying model parameters.

This model allows consumers to be rationally or irrationally attentive as well as naive or sophisticated about their inattention. For example, rationally inattentive consumers may perceive a specific cost of paying attention and hold beliefs about the money they could save if they paid attention and switched plans. Price or bill changes may cause consumers to update these beliefs. To the extent that consumers are also sophisticated about their inattention, their default plan utility would embed these beliefs.

Incorporating negotiation and product differentiation may explain even more of the price heterogeneity, but survey evidence supports focusing on search costs, inattention, and marketing. Most survey respondents who indicated ever participating in the retail choice market reported never having considered negotiating price with a supplier. Only 34% had ever negotiated any electricity price. Survey evidence also suggests that consumers have heterogeneous preferences for attributes, but these preferences only drive a minority of consumers' decisions to sign up with a supplier. When asked in an open-response question about the most influential factors in their decisions to sign up with a non-default supplier, 62% of respondents who said they participated in retail choice mentioned price or cost, 8% mentioned a plan attribute, and 7-9% cited a characteristic of the supplier itself. The income-price gap decompositions will relax the homogeneous good assumption.

1.7 Analytical Model to Explain Stylized Facts

Simplifying Assumptions

This section uses a simplified version of the model outlined in the previous section to present a coherent explanation for the stylized facts in Section 1.4. As a key simplification, this version considers only one geographic area and one time period. We can still gain insights about differences across geographic areas through comparative statics with respect to marketing costs and consumer search. To easily perform comparative statics on marketing costs, I rewrite marketing costs as $\lambda C(M)$ where $\lambda > 0$.

Consider also a simplified choice and attention setting where there is no choice error, persuasive marketing, or non-zero taste for marketing, i.e., $\gamma = 0$, $\varepsilon_{ij} = 0 \; \forall i, j \neq D$ where D denotes the default and outside option plan. Assume further that consumers are only inattentive up to a common price threshold $\bar{p} >> c$.[30] Formally, I write this attention assumption as $A_i = p_{ri} - \bar{p}$. A consumer will search if and only if they receive a price above $\bar{p}$. To ensure that consumers still switch away from their current supplier in equilibrium with this simplified attention assumption, I also add an exogenous attention shock, which occurs with fixed probability, ζ. We can think of ζ as capturing the probability that a consumer has a negative interaction with their supplier. When this occurs, a searcher will switch to another competitively-priced plan, but a non-searcher will return to the outside option. Assume also that consumers have full marketing availability (i.e., $\phi = 1$). Without loss of generality, I also normalize each consumer's electricity usage to one.

[30] The threshold $\bar{p}$ must be greater than the optimal marketing price in the single-period model.

For notational convenience, define r_i as the threshold market price at which consumer i would be indifferent between taking that price and being on the exogenous outside option plan with price p_D. This reservation price has density $f(r_i)$ and cumulative density $F(r_i)$ such that $f(r_i) > 0\ \forall r_i > 0$. Reservation prices are independent of consumer type.

For simplicity, the following subsection demonstrates the key theoretical results using a single-period model. I also discuss findings with the addition of pricing dynamics. See Appendices A.2 and A.3 for a detailed discussion and proofs for the dynamic case.

Single-period Model

Equilibrium

First, observe that the online market is a perfectly competitive market with no distortions. This means that all suppliers are price takers and set price p_o equal to the common constant marginal cost c.

Next, observe that free disposal requires a supplier's marketing price to be above p_o. Because the supplier faces marketing costs, charging a price at or below c would cause the supplier to lose money. This price difference creates a separating equilibrium in which no searchers will sign up with a marketer. The probability that a randomly chosen consumer will sign up with a marketer at price p_m is, therefore, $D(p_m) \equiv (1-\alpha)(1-F(p_m))$.

Since suppliers face symmetric problems, consider the marketing problem of a representative supplier. The firm's marketing problem is to choose marketing price and marketing level to maximize expected period profit:[31]

$$\max_{p_m, M}(p_m - c)\left((1-\alpha)D(p_m) + \mathbb{1}\{p_m \leq c\}\alpha D(p_m)\right)M - \lambda C(M)$$

We start by considering the firm's marketing offer price. The firm's first order condition with respect to p_m is

$$(p_m^* - c)(1-\alpha)D'(p_m^*)M + (1-\alpha)D(p_m^*)M = 0$$

This simplifies to

$$(p_m^* - c)D'(p_m^*) + D(p_m^*) = 0$$

and is independent of M (Varian forthcoming). Marketing costs are sunk at the time consumers choose to accept or reject the price offer.

Knowing this optimal price, the firm chooses M using the following first-order condition:

$$(p_m^* - c)(1-\alpha)D(p_m^*) = \lambda C'(M^*)$$

The firm will stop marketing when the marginal cost of another marketing interaction equals the expected revenue from that marketing interaction.

[31] Note that this specification assumes non-searchers will select the representative firm's offer if it is weakly better than all other offers in the market. The results are robust to making this inequality strict.

Comparative Statics

We now consider comparative statics of key market outcomes on search frictions and marketing costs. I model an increase in marketing costs as an increase in λ. Proposition 1 formalizes the key marketing level, market participation, and average price comparative static results. For notational ease, define π_M as the equilibrium probability that a consumer will experience a marketing interaction.

Proposition 1. *Let R^* be the equilibrium proportion of non-searchers who are active in the market, and let p^* be the average price in the market. The following comparative statics hold:*

$$\frac{\partial M^*}{\partial \lambda}, \frac{\partial M^*}{\partial \alpha}, \frac{\partial R^*}{\partial \lambda}, \frac{\partial p^*}{\partial \lambda}, \frac{\partial p^*}{\partial \alpha} < 0$$

Proof. See Appendix A.3. □

It is intuitive that marketing level decreases with marketing costs and the percentage of consumers in society who are searchers (i.e., α). The marketing price first-order condition shows that the optimal marketing price is independent of marketing costs and α. The online offer price is also independent of marketing costs and search frictions. The average price in the market, however, decreases with marketing costs and increases with search frictions. Since consumers with search frictions pay higher prices than consumers without search frictions, an increase in the ratio of non-search friction to search friction consumers in the market will increase *average* price. Marketing costs impact average price by changing the composition of consumers who are active in the market. More marketing causes more non-searchers to enter the market, causing the composition of the market to change in the direction of more non-searchers.

Additional Dynamic Results

Appendix A.2 shows how Proposition 1 also holds under the simple dynamic model of partial inattention outlined above.

In the dynamic model, we also obtain a few additional intuitive results about inattention-driven inertia. First, we find that renewal prices are higher than sign-up prices for each consumer type, i.e., $p^*_{r1} > p^*_o$ and $p^*_{r2} > p^*_m$. Second, with an additional assumption on the reservation price density and an upper bound on marketing levels, suppliers will never be incentivized to purposefully produce a bill shock. In this case, we also have the intuitive result that renewal prices increase with inattention, i.e., $\frac{p^*_{r1}}{\bar{p}}, \frac{p^*_{r2}}{\bar{p}} > 0$. Since suppliers know how their customers sign up, they perfectly observe their customers' types and can theoretically charge different renewal prices by type. However, with this simple attention model, they charge both consumer types the highest price they can without causing an attention shock.

In the dynamic case, we can also show that the probability of switching decreases with marketing costs, λ. This result comes from a combination of two effects. First, the logic of participation in the single-period model applies to participation in this dynamic model. Higher marketing costs reduce marketing, which reduces market participation of non-searchers ($\frac{\partial R^*}{\partial \lambda} < 0$). Second, marketing creates attention shocks. A reduction in marketing reduces the frequency at which consumers pay attention and switch ($\frac{\partial prob(switch)}{\partial \lambda} < 0$).

See Appendix A.2 for formal propositions and Appendix A.3 for proofs of these results.

Discussion

Combining these theoretical results with evidence about differences across low- and high-income areas can explain the stylized facts in Section 1.4. Recall that we observe a relatively higher door-to-door marketing presence, higher average sign-up prices, higher average renewal prices, higher market participation, and more frequent switching in low-income areas than in high-income areas. In the model, this would be true if low-income areas exhibited lower marketing costs and low-income households had especially high search costs and higher inattention. Within the urban and suburban markets I analyze, low-income households tend to live in particularly densely populated areas. Door-to-door marketing is likely cheaper in densely populated areas since traveling from one door to the next takes less time. In addition, the poverty literature suggests that financially-constrained households have particularly high search frictions and tunneled focus on urgent tasks (e.g., Shafir and Mullainathan, 2013). The model also explains why renewal prices are generally higher than sign-up prices in the presence of inattention.

In a more general attention model, it is possible to attain all of these results with only a difference in marketing costs across low- and high-income areas. In particular, if door-to-door marketing costs are lower in low-income areas than high-income areas and consumers are otherwise identical, the comparative static results predict more door-to-door marketing ($\frac{\partial M}{\partial \lambda} < 0$), higher retail choice participation ($\frac{\partial R^*}{\partial \lambda} < 0$), more switching ($\frac{\partial prob(switch)}{\partial \lambda} < 0$), and higher average sign-up prices ($\frac{\partial p^*}{\partial \lambda} < 0$) in low-income areas. While the simple attention model presented in this section requires demand-side differences to explain a difference in renewal prices, consider a case of the more general model with a non-degenerate distribution of attention thresholds. Recall that firms can observe the aggregate attention threshold distribution but cannot observe the attention thresholds of individual customers. In this case, an increase in marketing costs has two primary opposing impacts on renewal prices. On the one hand, it increases the one-period benefit of a price increase due to the higher expected customer retention rate. On the other hand, it also increases the attention-related cost of increasing price due to the increase in expected future profit from retaining a customer. With a sufficiently high discount factor and attention derivative at the optimal price, the net effect will be to decrease renewal prices. Hence, marketing costs alone could explain why renewal prices are higher in low-income areas, conditional on renewal number. This explanation is consistent with the survey results on attention and search costs net of beliefs about the benefits of searching.

The extreme consumer search types modeled are useful for fixing ideas. However, in reality, some consumers may have moderate search frictions that result in partial search.

As long as marketers have some market power over some consumers and not others, these results should translate to this less extreme case.

For simplification, this section assumed away some demand drivers present in the general model that could also contribute to the income-price gap: choice error, taste for marketing, and other factors influencing the propensity to be persuaded by a marketer. These factors all impact the probability that a consumer will sign up with a marketer at a given price and, thereby, the marketing price and marketing level. As a result, a difference in any of these factors across low- and high-income households could cause price differences by income group.

Suppliers can sustain markups in this model despite free entry. Suppliers charge markups on renewal prices and possibly also on marketing offer prices. Suppliers compete away ex-ante expected profits from searchers by reducing prices in the competitive marketplace to levels below marginal costs. While similar price competition occurs for non-searchers, marketing-related price competition is less fierce. Suppliers compete away the remaining ex-ante expected profits from non-searchers through spending more on marketing.

1.8 Structural Model

By adding more structure to the model in Section 1.6, I decompose the income-price gap into six potential determinants and find that the largest driver is differences in marketing costs across geographic areas. I use the model to explore the impacts of additional consumer protection policies that eliminate direct marketing. Without marketing, welfare and consumer surplus increases, but some consumers pay higher market prices.

Additional Model Assumptions

I now assume functional forms for the general model presented in Section 1.6 and modify consumer choice set assumptions to better reflect survey evidence.

Marketing costs are given by:

$$C(m_{jzt}) = (C_1 + C_2/(PopDensity)_z)m_{jzt} + C_3 m_{jzt}^2$$

where m_{jz} denotes the marketing level for supplier j in zip code z at time t and $(PopDensity)_z$ is the average 2019 population density in the zip code. The squared term allows marketing costs to be convex in marketing level. Since population density varies within a zip code, marketers may initially prioritize marketing in the zip code's most densely-populated areas. At higher marketing levels, they may expand to less dense areas. Since the distance between door-to-door marketing interactions decreases with population density, the marginal marketing interaction will be more costly. As a result, marketing costs are convex conditional on average population density.

Consumers who do not receive a marketing offer pay attention to prices if their price is sufficiently high, their bill increases sufficiently, or they receive a random attention shock. I allow the impact of a bill change to be asymmetric around zero. Thus, latent attention takes the form:

$$\begin{aligned} A_{ijt} = \beta_1 p_{i,j,t-1} &+ \beta_2 \log(Bill_{i,j,t-1} - Bill_{i,j,t-2}) \mathbb{1}\{Bill_{i,j,t-1} - Bill_{i,j,t-2} > 0\} \\ &+ \beta_3 \log(Bill_{i,j,t-2} - Bill_{i,j,t-1}) \mathbb{1}\{Bill_{i,j,t-1} - Bill_{i,j,t-2} < 0\} + \beta_4 (Tenure)_{ijt} + \nu_{ijt} \end{aligned}$$

where p_{ijt} denotes renewal price for consumer i with supplier j in period t, q_{ijt} is the consumer's electricity usage in period t, $Bill_{ijt} = p_{ijt} q_{ijt}$, $(Tenure)_{ijt}$ is the number of consecutive months the consumer has been with supplier j, and $\nu_{ijt} \sim F_\nu = \mathcal{N}(\mu_\nu, 1)$. I assume consumers do not know their bill and price the month that they switch. The price term reflects the price on the last bill they received. The bill terms are the positive and negative components of the difference between that bill's total electricity supply charges and the previous bill's supply charges. We can think of the error term, ν_{ijt}, as capturing random variation in attention needed for competing priorities. The duration term aims to capture any serial correlation in the error term. Recall that, absent a marketing interaction, consumer i pays attention if and only if A_{ijt} is positive.

I assume the error terms in consumer i's latent utility from plan j in time t are i.i.d. Extreme Value 1. Recall that latent utility from the outside option is $r_{it} = p_{Dt} + \varepsilon_{iDt}$ where p_{Dt} is the price of the default regulated plan (i.e., the outside option).

Among retail choice participants, I assume that only non-searchers consider the outside option and only when they receive a price- or bill-related attention shock. This assumption reflects survey evidence that only 10% of respondents reported considering both their current price and the outside option before accepting a marketing offer. For searchers, revealed preference of being in the market suggests that they can find a market offer that they prefer to the outside option.

Following Berry and Pakes (2000) and Hansen and Singleton (1982), I assume suppliers have rational expectations about future profits from acquiring or retaining a customer:

$$V_{jzt} + \epsilon_{jzt} = E_i \left[\sum_{\tau=t}^{T} \delta^t \pi_{ijz\tau} \right]$$

with $E[\epsilon_{jzt}] = 0$. Here, $V_{jzt} + \epsilon_{jzt}$ is firm j's expectation of the value of having a customer in zip code z at time t, δ is a common discount factor, and T is February 2025. For months through February 2022, π_{ijzt} is the observed period profit for consumer i and supplier j in period t. For subsequent months, π_{ijzt} is the estimated period profit. See Appendix A.5 for post-February 2022 profit estimation detail. I continue to treat suppliers as identical up to this random prediction error about the impact of keeping or maintaining a customer on future profit.

Estimation

The demand primitives of the model are $\theta = \{\gamma_g, \sigma_{1g}, \sigma_{2g}, \beta_{1g}, \beta_{2g}, \beta_{3g}, \beta_{4g}, \mu_\nu\}$. These capture the direct impact of a marketing interaction on choice probabilities, decision error in plan selection for each consumer type, and all attention parameters. The subscript g denotes the income group. I estimate the demand parameters separately for consumers in zip codes with a median household annual income below \$60,000 and above \$80,000. I exclude areas between these two income thresholds.

I impose a few parameter values from outside the model estimation. The discount factor, δ, is 0.96. I impose the survey estimates of α, ϕ, and the percent of households in low-income areas which receive a marketing interaction in a month. I estimate the average percentage of households in high-income areas interacting with a marketer by multiplying the low-income estimate by the ratio of the median number of suppliers marketing in low- versus high-income zip codes in the MD PSC data.[32] Since renewal prices tend to be substantially higher than initial offers, I further assume that consumers always switch following a price or bill attention shock. This assumption may also capture behavioral choice considerations, such as a bill shock reducing a consumer's taste for their current supplier.

Estimation begins with two pre-processing steps to estimate partially-unobservable outcomes. Next, I estimate the demand primitives and use these results to estimate the marketing cost primitives. Estimation proceeds as follows:

1. **Assign consumer types**: Categorize each consumer as a searcher or non-searcher based on sign-up prices
2. **Estimate truncated continuation profit**: Non-parametrically estimate continuation renewal profit after the analysis period ends to avoid selection bias due to truncation
3. **Estimate demand primitives**: Find the primitives that maximize the probability of observed switching decisions
4. **Estimate marketing costs primitives**: Find the primitives that best match suppliers' observed marketing levels given demand primitives and rational expectations

The remainder of this subsection discusses each step in detail.

Step 1 leverages the bimodal nature of sign-up prices and follows the procedure discussed in Section 1.4 and described in detail in Appendix A.5 to identify consumer types. After obtaining an initial estimate of search-related and marketing-related price distributions each month, I estimate the probabilities that a searcher and non-searcher would each sign up at their observed sign-up prices. I then assign the consumer to the higher probability type. For consumers who had the same supplier throughout the entire analysis period, I use a matching method to estimate types. See Appendix A.5 for more detail.

Step 2 aims to correct selection bias due to truncation at the end of the analysis period. I estimate net present value continuation profit for an additional three years after the end of the analysis timeframe. I use a non-parametric function of marginal costs and observable

[32]Survey estimates of this marketing percentage in high-income areas would likely be biased due to a disproportionate selection of low-income households into the survey. The wealthiest households may be especially unlikely to install an application to take surveys for compensation of only a few dollars each.

consumer characteristics, including type, location, total bill, and duration with the supplier. See Appendix A.5 for more detail.

Step 3 estimates demand primitives via maximum likelihood. Bringing together the attention and choice frameworks, I parametrically estimate the probability of switching conditional on a price change and the probability of signing up with a marketer. Estimated switching renewal probabilities vary by period, consumer type, zip code, customer tenure with the supplier, and the consumer's recent prices and electricity usage:

$$\begin{aligned} &prob(n_{i,j,t+1} = 0 | n_{ijt} = 1, p_{ijt}, q_{ijt}, p_{i,jt-1}, q_{i,j,t-1}, Duration_{ijt}, \theta) = \\ &\quad 1 - (1 - A(p_{ijt}|\theta, q_{ijt}, p_{i,j,t-1}, q_{i,j,t-1}, Duration_{ijt}))(1 - (M_{zt}/N_{zt})\phi\pi_{st}(p_t)) \end{aligned}$$

where n_{ijt} equals one if consumer i is a customer of supplier j in period t and zero otherwise, $M_{zt}/N_{zt}\phi$ is the probability of a marketing interaction in zip code z at time t,[33] and $\pi_{st}(p_{ijt})$ is the probability of switching conditional on receiving a marketing interaction by consumer type s. Choice sets and latent utilities imply the following switching probabilities conditional on a marketing interaction and a current price p_t:

$$\pi_1 = 1 - \int_0^\infty \frac{exp(-p_t/\sigma_1)}{exp(-p_t/\sigma_1) + exp(-y/\sigma_1) + \sum\limits_{j\in\mathcal{J}} exp(-p_j/\sigma_1)} g_{p_m}(y)dy$$

$$\pi_2(p_t) = \int_0^\infty \frac{exp((\gamma - y)/\sigma_2)}{exp(-p_t/\sigma_2) + exp((\gamma_1 - y)/\sigma_2)} g_{p_m}(y)dy$$

where $s = 1$ for searchers and $s = 2$ for non-searchers, $g_{p_m}(\cdot)$ is the distribution of equilibrium marketing offers, $\mathcal{J}$ indexes the set of potential offers in the competitive marketplace, and consumer and supplier subscripts have been left out for simplicity. I estimate $\{p_j\}_{j\in\mathcal{J}}$ by sampling 94 prices from each monthly search distribution estimated in Step 1.[34]

Marketing sign-up decisions vary by zip code and whether the consumer switches from another supplier or from the default option.[35] The unconditional probability of switching when engaging with a marketer given a marketing offer p_t is

$$\begin{aligned} D(p_t) = (1-\alpha)\Bigg(& d\frac{exp((\gamma - p_t)/\sigma_2)}{exp(\gamma - p_t/\sigma_2) + exp(-p_{Dt}/\sigma_2)} \\ & + (1-d)\int_0^\infty \frac{exp((\gamma - p_t)/\sigma_2)}{exp(\gamma - p_t/\sigma_2) + exp(-x/\sigma_2)} h_{p_b}(x)dx \Bigg) \end{aligned}$$

where d is the percent of non-searchers on the outside option, and $h_{p_b}(\cdot)$ represents the distribution of all non-searchers' prices in the retail choice market. Recall that marketers

[33] I impose $M_{zt}/N_{zt} = 0$ during April and May 2020. I exclude March, June, July, and August 2020 from the analysis.

[34] This number reflects the median number of plans listed on MDElectricChoice.gov from February through July 2022.

[35] I assume all consumers not participating in the retail choice market receive the default price.

never offer a price that would attract a searcher. The two terms in parentheses are a weighted average of the probability that a consumer prefers the marketing offer to the default option and the probability that a consumer prefers the offer to the price offered by their current supplier, integrated over the density of all market prices.

After estimating the demand parameters, I also estimate the three marketing cost parameters. I follow Berry and Pakes (2000) and Hansen and Singleton (1982) and combine suppliers' marketing level first-order conditions and rational expectations to find:

$$\begin{aligned} 0 &= E[(\pi_{jzt} + \sum_{\tau=t}^{T} \delta^t \pi_{jz\tau})\phi D(p_{jzt}) - C'(m_{jzt})] \\ &= E[(\pi_{jzt} + \sum_{\tau=t}^{T} \delta^t \pi_{jz\tau})\phi D(p_{jzt}) - C_1 - C_2/(PopDensity)_z - C_3 m_{jzt}] \end{aligned}$$

where the expectation is taken across firms' valuation errors. With estimates of demand parameters and truncation values, this becomes a linear function of the cost parameters. I estimate marketing coefficients using two-stage least squares. I use the mean electricity usage of market participants by zip code and the month of year to instrument for expected profit from a marketing interaction.

Broadly, identification of γ and σ_2 comes from variation in sign-up probability with marketing offer prices, variation in the billed price distribution and the default price over time, and the mean marketing interaction probability. Identification of the attention primitives, β_1, β_2, and β_3, come from variation in non-searcher switching probabilities conditional on a price change with renewal price, bill increase, and bill decrease, respectively. The β_4 term captures a linear trend in this probability over customer tenure, and μ_ν captures the hypothetical intercept conditional on no price or bill change. Identification of the decision error variance for searchers, σ_1, comes from variation in switching with renewal price conditional on a marketing attention shock.

Results

Tables 1.2 and 1.3 show the resulting primitive estimates. The choice parameters suggest a distaste for marketing that is especially large in high-income areas. Choice variance is also larger for marketing interactions than non-marketing interactions.

To further facilitate choice probability comparisons across income groups, Figure 1.11 shows probabilities that non-searchers in low- and high-income zip codes would sign up with a marketer in September 2019 by marketing offer price and last-period retail choice participation. The assumed aggregate distributions of billed prices do not vary across income groups, so all differences in the choice probabilities are driven exclusively by differences in choice parameters. Among households on the default outside option, low-income households are more likely than high-income households to sign up with a marketer when offered a relatively low marketing price. However, the relation reverses at high marketing prices.

Table 1.2: Demand Primitive Estimates

Demand Primitives	Low income	High Income
Choice		
γ (taste for marketing)	-0.018	-0.042
	(0.00005)	(0.00102)
σ_{ϵ_2} (choice standard deviation, non-searchers)	0.026	0.041
	(0.00008)	(0.00070)
σ_{ϵ_1} (choice standard deviation, searchers)	0.0006	0.0030
	(0.0014)	(0.0026)
Attention		
β_1 (price on last bill)	1.23	-[1]
	(0.10)	
β_2 (bill increase from prior bill)	0.019	0.004
	(0.004)	(0.004)
β_3 (bill decrease from prior bill)	-0.0092	-0.0090
	(0.0036)	(0.0037)
β_4 (customer tenure, months)	-0.058	-0.038
	(0.0002)	(0.0003)
μ_ν (attention constant)	-1.29	-1.51
	(0.013)	(0.011)

[1] $\beta_1 = 0$ for high-income due to negative sign and statistical insignificance.
Standard errors in parentheses.

Table 1.3: Cost Primitive Estimates

Marketing Cost Parameter	Low and High Income
C_1 (constant)	2.53
	(0.139)
C_2 (inverse population density)	314
	(9.52)
C_3 (squared marketing level)	0.011
	(0.0004)

Parametrically bootstrapped standard errors in parentheses.

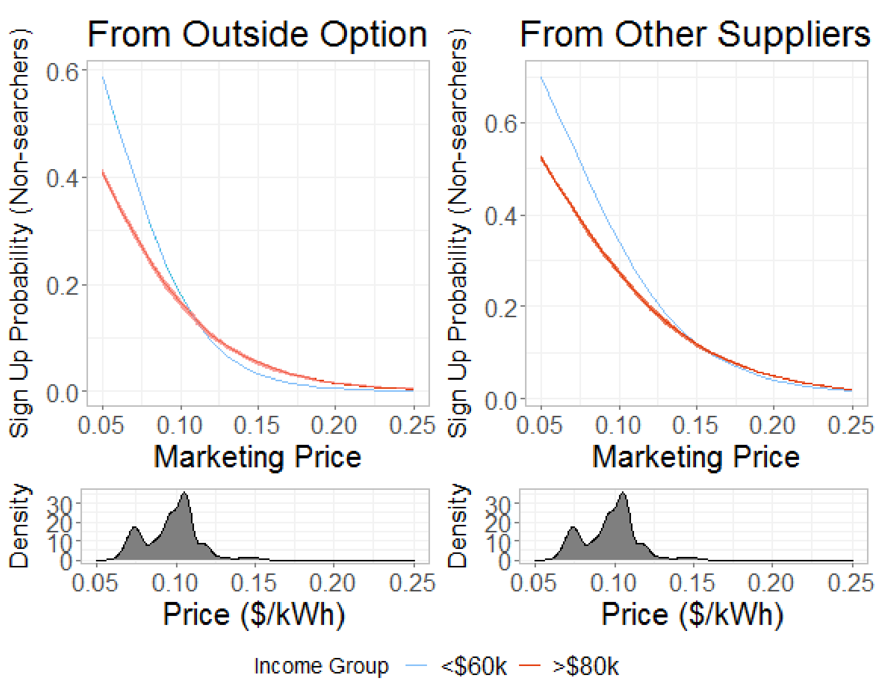
Among retail choice market participants, low-income households are more likely to sign up with a marketer at all except for the highest observed marketing offers.

Attention parameters suggest that bill increases have an especially large impact on attention. Figure 1.12 shows the probability of paying attention by bill change and price for low-income households who have been with their supplier for one year. The probability of attention is close to zero at all prices if the price change does not result in a bill change. The probability of attention increases rapidly with bill increase for larger bill changes. Relative to the impact of bill changes, the impact of moving from a low to a high price on attention probability is small.

Marginal marketing costs are convex in marketing level and decreasing in population density. Figure 1.13 shows marginal marketing cost by population density for a marketing level of 100 marketing interactions. For comparison, the chart also includes the population density distributions for low- and high-income zip codes. Marginal marketing costs are especially high in the least dense Baltimore zip codes, which tend to be richer areas.

Estimated average marketing acquisition costs are a little under \$300 per customer. This value is roughly in line with suppliers' informal estimates.

Figure 1.11: Estimated Non-searcher Marketing Sign-up Probability: April 2019

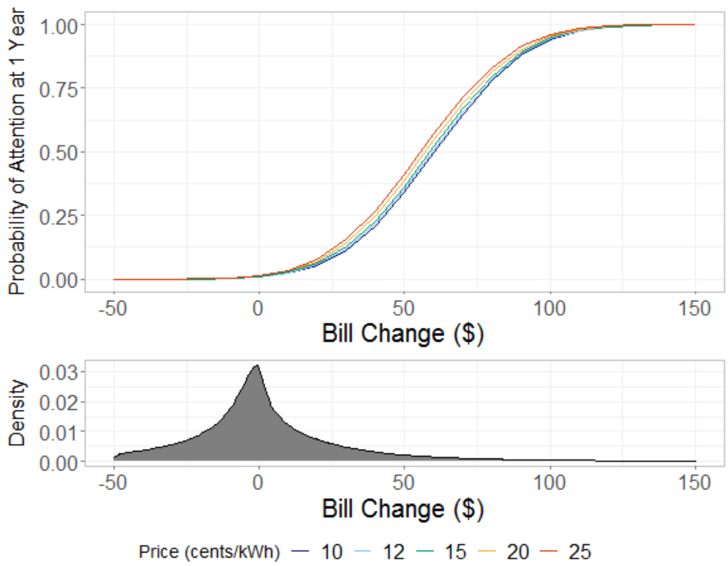


Width of curves reflect 95% confidence intervals estimated via parametric bootstrap. Top charts show estimated probabilities that a non-searcher will sign up with a marker by marketing offer price and whether the consumer is on the outside option (left) or active in the market (right). Bottom charts are identical and show the probability density of marketing offer prices.

Counterfactual Analysis

The analytical model demonstrated the importance of interaction effects between price discrimination through marketing and price discrimination on inattention-driven inertia. This subsection explores these effects empirically by analyzing the impacts of eliminating marketing. Consider the partial equilibrium where the distributions of search-related sign-

Figure 1.12: Attention Probability by Bill Change and Price: Low-Income



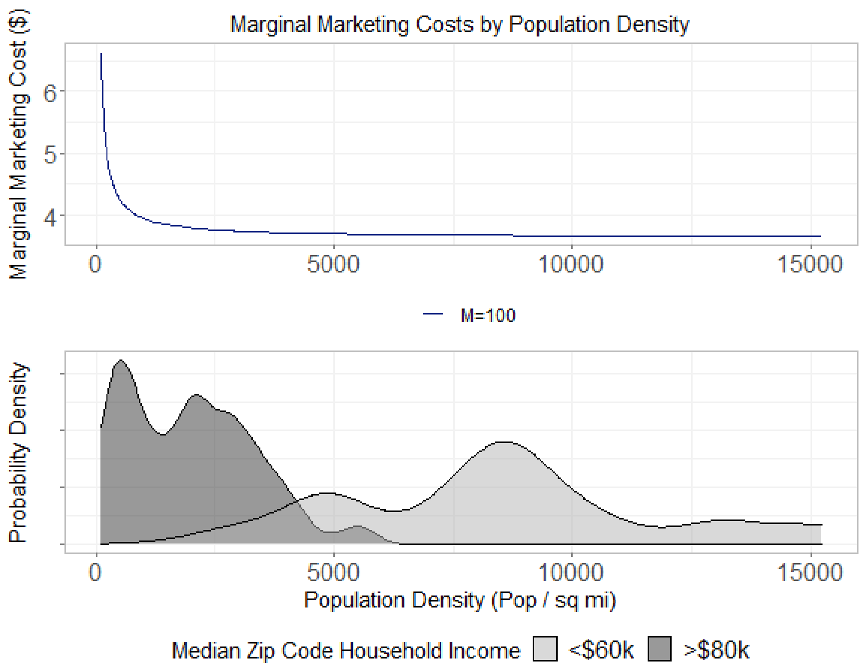
Top chart shows the estimated probability that a consumer in a low-income zip code who has been with their supplier for one year will pay attention to their electricity plan options given renewal price and bill change. Bottom chart shows the probability density of observed bill changes given a renewal price update in low-income zip codes.

up and renewal prices remain unchanged conditional on income group, bill change, and a consumer's tenure with a supplier. I remove marketing shocks from the model and explore the evolution of prices paid. I fix the state at September 2019 levels and assume all contracts last one month.

What happens when marketing ends? Market prices increase, market participation decreases, and switching decreases. Low-income households would still pay a premium in the absence of marketing due to attention differences. As Figure 1.14 shows, the income-price gap disappears initially and then gradually increases over time. This result is due to two opposing effects. The sign-up income-price gap is immediately eliminated, aside from differences in preferences for premium attributes, since only searchers sign up with new suppliers. However, low-income households are also especially inattentive to prices and bills. Mean market prices increase across low- and high-income communities since eliminating marketing also reduces the frequency of attention shocks. The price impact of inattention differences increases with time as the impact of previous marketing on customers' tenures diminishes. Despite these higher prices, aggregate consumer surplus increases in all periods relative to the counterfactual with marketing due to the lower prices of consumers who choose the regulated rate. Supplier profits decrease because they have fewer customers.

We can also consider the hypothetical counterfactual scenario without marketing where no non-searchers ever entered the market. Relative to the marketing status quo, market

Figure 1.13: Marginal Marketing Costs by Population Density



Top chart shows estimated marginal marketing cost for the one hundredth marketing attempt by average 2019 American Community Survey zip code tabulation area (ZCTA) population density. Bottom chart shows probability densities of population density by ZCTA median annual household income.

participation is lower in this equilibrium, with the largest participation reductions occurring in low-income areas. Estimated participation rates are 13.1% in high-income areas and 9.7% in low-income areas. Low-income households that stay in the market would still pay higher prices than high-income households, on average, due to larger inattention to prices and bills. Estimated equilibrium market prices are 18% higher than current prices in low-income areas and 23% higher in high-income areas.[36] I estimate the income-price gap in this equilibrium to be about $0.004/kWh, which is less than half of the status quo income-price gap.

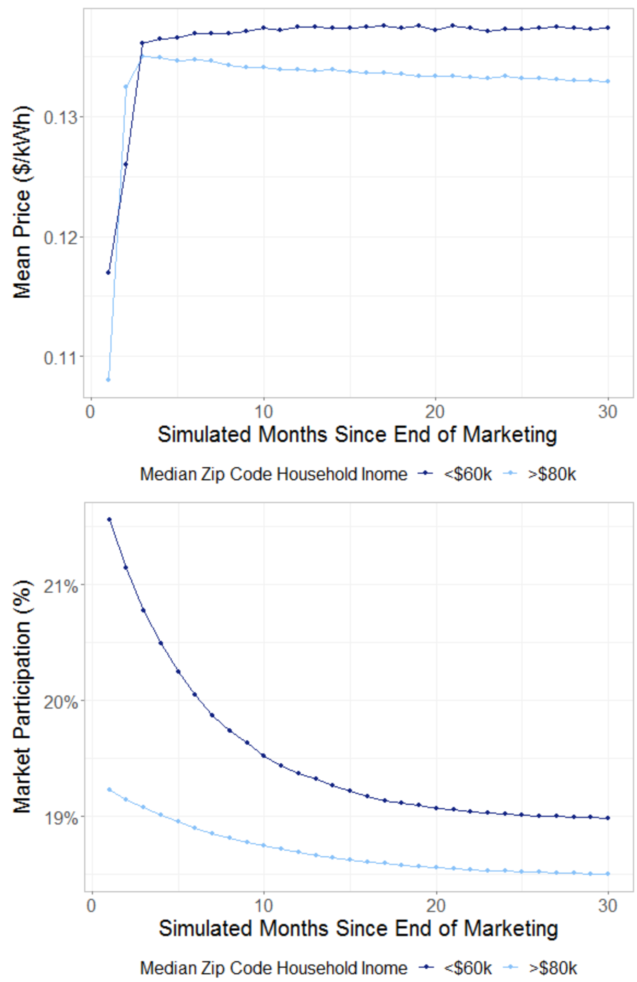
In sum, eliminating marketing reduces the income-price gap and increases aggregate consumer surplus, but it also increases prices for the remaining market participants.

Price Decompositions

Using this model and the counterfactual results, I can decompose the price gap into six components: active search, marketing costs, marketing efficacy, preferences for premium

[36]These estimates may be high relative to the general equilibrium where suppliers can adjust their price-setting methods in response to the absence of marketing shocks.

Figure 1.14: Simulated Mean Prices and Market Participation by Income Group: No Marketing



Mean electricity supply prices (left) and retail choice market participation (right) in the simulated counterfactual scenario where all direct marketing ceased at month one. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

attributes, inattention-driven inertia in the absence of marketing, and interaction effects of marketing and inattention-driven inertia. Active search captures differences across low- and high-income zip codes in the proportion of the population who actively search (i.e., ratio of searchers to non-searchers). Marketing costs capture supply-side differences across low- and high-income zip codes in the cost of marketing due to population density. Marketing efficacy captures differences in tastes for marketing and choice error in marketing interactions. Premium attributes captures differences in willingness to pay for plan attributes. Finally, I separately estimate the impact of inattention-driven inertia in the absence of marketing and interaction effects when marketing and inattention-driven inertia simultaneously exist.

Table 1.4 summarizes the decomposition results and describes how I identify each effect from model parameters and observed prices. These results show that marketing costs (i.e., population density) is the largest driver of the income-price gap with cheaper marketing in low-income areas. Marketing efficacy (i.e., choice error and taste for marketing) is also a large driver. As shown in Figure 1.11, low-income non-searchers are more likely than high-income non-searchers to sign up with a marketer given identical choice sets. While low-income households are also less likely to search per capita, this difference has a relatively small impact on the income-price gap. Differences in preferences for premium attributes across income groups reduce the income-price gap. Without marketing, differences in inattention-driven inertia across income groups would lead to an income-price gap equal to roughly 32% of the status quo income-price gap. However, this effect is more than offset by the interaction effect between marketing and inertia. The net effect of price discrimination on inattention-driven inertia in the presence of marketing is a 6% reduction in the income-price gap.

Table 1.4: Income-price Gap Decomposition

Underlying Difference	Price Gap Contribution (Cents/kWh)	(%)	Description
Active Search	0.05	5%	Effect of switching from α_H to α_L on mean sign-up price
Marketing Costs	0.84	85%	Effect of switching from the high-income to low-income population density distribution on mean sign-up price
Marketing Efficacy	0.30	30%	Effect of switching from γ_H and $\sigma_{\epsilon_2,H}$ to γ_L and $\sigma_{\epsilon_2,L}$ on mean sign-up price
Attribute Preferences	-0.14	-14%	Difference in mean search-related sign-up price across groups
Inattention-driven Inertia	0.32	32%	Difference in billed price premiums over sign-up prices across groups under counterfactual without marketing
Marketing/Inertia Interaction	-0.37	-38%	Difference in billed price premiums over sign-up prices across groups plus effect of switching from V_H to V_L on mean sign-up price less isolated inattention-driven inertia effect

Welfare Losses from Unproductive Marketing

Marketing costs represent a welfare loss relative to a scenario without price discrimination through marketing. While a marketing interaction may benefit both the supplier and consumer involved in the marketing interaction, this comes at the expense of other suppliers and consumers since electricity demand is ubiquitous and inelastic. Eliminating price discrimination through marketing would not change consumption, and price differences would only result in monetary transfers between parties. The primary change would be the elimination of marketing costs.

The model results imply a combined annual welfare loss due to unproductive marketing of $1.5 million across low- and high-income Baltimore zip codes.[37] This value is 14% of total variable industry costs. These variable costs reflect all electricity-related costs suppliers pay on behalf of their customers.

This result relies on the assumption that marketing only provides information about prices. It does not capture any welfare increase from providing information about available non-financial attributes, such as renewable energy certificates,[38] or any direct welfare reduction from engaging in a marketing interaction.[39]

1.9 Information Interventions

The model and results presented in this paper indicate that the root of the market inefficiencies and adverse distributional outcomes is lack of information. However, survey results suggest that information interventions may be insufficient to eliminate these undesirable outcomes. In a randomized information intervention, I provided select survey respondents with information about their local plan comparison website and other respondents with information about the true price distribution in the market. Respondents who received these information interventions showed no significant difference in reported switching decisions from the control group in the month following the survey. If anything, point estimates show a reduction in switching with additional information. Point estimates suggest that these interventions may be partially effective at increasing attention to prices and encouraging negotiation, but substantial inattention remains.[40] See Appendices A.8 and A.9 for details.

1.10 Conclusion

This paper explored determinants of pricing heterogeneity in the restructured Baltimore residential electricity market. It uncovered evidence that suppliers price discriminate on consumer inattention and search barriers. Suppliers achieve price discrimination through two channels: 1) marketing and 2) price updating after the initial contract. The first channel of price discrimination causes households to pay higher average prices in low-income areas than in high-income areas. This income-price gap can be primarily attributed to supply-side differences in marketing costs, although demand-side differences in choice behavior also play a large role. This marketing channel also reduces economic efficiency. I estimate this

[37]This estimate excludes zip codes with a median annual household income of $60,000-80,000.

[38]Among survey respondents who signed up with a marketer, 25% said a plan characteristic contributed to their decision. This result suggests that 75% of marketing is fully unproductive.

[39]Model parameter estimates in Table 1.2 suggest a large distaste for marketing. Survey evidence corroborates this result. Among respondents who signed up with a marketer, 14% said they signed up because they wanted the marketer to leave, and 15% said they misunderstood the price or terms of the plan from the marketing interaction.

[40]These results are not statistically significant at conventional levels with multiple hypothesis correction.

welfare loss to be 14% of total industry variable costs. While these results indicate that the root of the market inefficiencies and adverse distributional outcomes is lack of information, survey results suggest that information interventions may be insufficient to eliminate these undesirable outcomes.

The model results also highlight the importance of interaction effects between the two price discrimination channels. Counterfactual analysis suggests that policies that restrict direct marketing may increase consumer surplus and reduce the income-price gap. However, they may also increase market prices if they fail to address price discrimination on inattention-driven inertia.

In some U.S. states, concerns about high prices in retail electricity markets have already led to policy reforms or proposed legislation. At an extreme, Massachusetts legislators have proposed ending retail electricity markets entirely.[41] Regulators in New York used price caps as a policy instrument.[42]

Many of these consumer-protection policies present a trade-off between protecting consumers from high prices and encouraging innovation. This paper found positive willingness to pay for premium product attributes, many of which may not exist without retail choice. Ending competition or capping prices may reduce similar future innovation. With a changing electricity grid and aggressive greenhouse gas goals, future market-driven innovation could provide more value going forward.

As legislators and regulators deliberate market reform and the value of retail electricity restructuring, it is important to keep in mind that these markets share similarities with markets for many other goods. It may be valuable to weigh the relative merits and drawbacks of competition and government interventions in other markets where consumers are inattentive and face high barriers to search, such as loan, insurance, and telephone service markets.

[41] e.g., see Massachusetts Senate Bill No. 2150.

[42] See State of New York Public Service Commission CASE 15-M-0127.

Chapter 2

Government vs. Competition: Residential Electricity Pricing and Pass Through

2.1 Introduction

Conventional economic theory suggests that consumer welfare should be higher under competition than under government provision of a private good. While consumer welfare would be identical in a first-best setting with a welfare-maximizing government, competitive suppliers have a greater incentive than government employees to reduce costs in practice. In the presence of market distortions, however, this relationship may be reversed.

The retail electricity sector provides a new, unique setting to analyze this classic debate about governments versus markets. Electricity is a homogeneous, ubiquitous good that is supplied pseudo-randomly by governments in some locations and competitive suppliers in others. Moreover, administrative data provide researchers with granular location- and time-varying information about marginal costs across both of these supplier types.

Consider two first-order determinants of consumer welfare: retail price level and retail price uncertainty. Two distortions obscure the theoretical comparison of retail price levels in an otherwise efficient setting:

1. Misalignment of government employee and consumer objectives
2. Consumer inertia and decision error in electricity provider selection (Wilson and Price, 2010; Hortaçsu et al., 2017; Giulietti et al., 2014, 2005; Flores and Price, 2013; Davis, 2021)

On one hand, if government employee incentives do not perfectly align with consumer incentives, government suppliers may have inefficiently high input costs relative to private firms. On the other hand, customer inertia may enable private firms in retail markets to charge prices substantially above their marginal costs.

Retail price uncertainty may have a first-order effect on consumer welfare in the presence of imperfect information or liquidity constraints. The general consensus in the literature is that risk averse consumers are unable to effectively understand and insure against electric price uncertainty (Beecher and Kihm, 2016). In this sector, the primary driver of uncertainty in retail prices comes from pass through of highly volatile and uncertain wholesale costs as the primary metric for price uncertainty. If public firms are more likely than private firms to hedge and pass hedging benefits on to consumers, as the theory section argues, risk averse consumers may be better off under government provision even if they face the same expected retail price levels in the two regimes. The actual effect of hedging on retail price levels is ambiguous, but likely positive in expectation.

Table 2.1 summarizes the hypothesized effects of each of these distortions on prices relative to the first-best setting.

Table 2.1: Key Distortions Differentially Affecting Consumer Welfare Under Government Electricity Provision and Retail Electricity Markets Relative to First-best Setting

Distortion	Hypothesized Equilibrium Retail Price Effect		Hypothesized Consumer Welfare Effect
	Private	Public	
Imperfectly aligned government and consumer incentives	N/A	Increase Average Price	Decrease for Public Firms
Consumer inertia in electricity supplier selection	Increase Average Price	N/A	Decrease for Private Firms
Consumer liquidity constraints or imperfect price uncertainty information	N/A[1]	Reduce Price Uncertainty[2], Ambiguous Level Effect	Ambiguous

[1]In practice, many private firms offer consumers fixed rate contracts, which provide consumers with price certainty. Firms tend to price these contracts considerably higher than other contracts. This may suggest that firms effectively act as insurers for some consumers, raising the average price and reducing price volatility. While the empirical analyses in this paper capture the effects of these behaviors, the theory section abstracts from the ability to offer fixed-rate contracts.
[2]Due to effect of the distortion on public firm hedging.

This paper investigates the question: Are residential consumers financially better off being supplied electricity by their local government or by a private electricity supplier subject to competitive forces? I focus on the effect of ownership on retail prices and answer the more pointed question: How do retail price levels and pass through of uncertain marginal costs differ across local government electricity suppliers and private electricity suppliers subject to competitive forces? Since public electricity suppliers were established decades earlier, with private firms only allowed to enter other markets, the geographic placement of provider type can be considered predetermined. I, therefore, compare pricing of local government providers and retail power marketers within the same state, using observed local wholesale electricity spot prices and electricity usage patterns to estimate local marginal costs. I show that the customers served by these two types of firms seem to consume similar amounts of electricity, which provides some evidence that the two consumer groups are similar in terms of the key unobservables. Specifically, it suggests that they experience similar weather, use the same heating fuel type, and have similar income levels. I estimate that government-owned suppliers have significantly lower retail prices and lower pass through of marginal costs. Tests of first-order stochastic dominance provide further evidence that consumer welfare is higher under government electricity provision.

This paper contributes to the literature contrasting private and government supply of private goods. Prior research on this topic has been largely theoretical (Besley and Coate, 1991; Epple and Romano, 1996). The residential electricity sector provides a unique setting that enables empirical comparison. This is also the first paper, to my knowledge, to consider the roles of consumer inertia and retail price uncertainty in the government-market comparison.

In addition, this paper extends a classic literature on electricity sector restructuring. Past empirical work has predominantly focused on wholesale market restructuring (e.g., Borenstein et al., 2000; Wolfram, 1999; Bushnell et al., 2008; Cicala, 2015). There has been much less ex-post empirical research on the retail sector. Most of the existing research compares prices under restructured markets and traditionally-regulated utilities, with mixed results (Hartley et al., 2019; Ros, 2017; Su, 2015; Joskow, 2006; Taber et al., 2006; Borenstein and Bushnell, 2015). While the regulated utility counterfactual may be difficult to identify causally due to selection of states into retail restructuring, the analysis of retail restructuring relative to municipal ownership does not suffer from this same bias. Another body of research on electricity restructuring has uncovered consumer inertia, and consumer decision error in plan selection (e.g., Wilson and Price, 2010; Giulietti et al., 2014; Hortaçsu et al., 2017; Gugler et al., 2018).

This paper proceeds as follows: Section 2 provides some background on retail provision of electricity in the U.S. and key related literature. Section 3 uses theory to better understand mechanisms that lead to consumer welfare differences. Section 4 discusses data used in the empirical analysis and marginal cost calculation. Section 5 discusses the paper's identification method. Section 6 presents results of a balance analysis. Section 6 presents empirical results. Section 7 discusses planned follow-on work and concludes.

2.2 Background

The U.S. residential electricity sector is experiencing a resurgence of retail electricity restructuring. The wave of retail restructuring around the turn of the 21st century focused on opening retail electricity markets to competitive suppliers. In contrast, the current transformation focuses on creating local government-owned electricity suppliers. In California alone, the electric utility regulator projects that up to 85% of consumers will leave their conventional regulated monopoly provider (e.g., PG&E) for a local government-owned provider by the mid 2020s (CPUC 2017).

Local government suppliers and firms in retail electricity markets impact the well-being of millions of consumers. Firms competing in retail electricity markets served over 15 million U.S. households in 2017 as well as customers in Canada, Australia, and throughout Europe. Government-owned electricity suppliers serve about 14 million U.S. households in 2017, and they are projected to serve about 21 million households by 2025 (EIA 2018; CPUC 2017). With unexpectedly low natural gas prices and concerns about inefficiency of regulated monopoly suppliers and regulatory capture, other areas are considering adopting one of these two regimes.[1].

Advocates for local government electricity supplier regimes and competitive retail market regimes both cite low prices as a primary motivation for restructuring (Littlechild, 2002, CalCCA 2017). However, these two types of firms have very different incentives. Private firms aim to maximize profits subject to competition from other firms, while economists often assume government-owned entities make decisions based on the well-being of the communities they serve and government employee benefits (Aidt, 1998; Oates and Portney, 2003). The relative merits of these two supplier regimes are not well understood. To the extent that policymakers may choose between these two regimes going forward, it is important to rigorously analyze the relative impacts of the regimes on consumers.

The residential electricity sector may be particularly ill-suited for competition relative to other industries. The residential electricity sector can be characterized by inelastic short-term demand (Reiss and White, 2005; Espey and Espey, 2004), limited opportunity for product differentiation Defeuilley (2009), large uncertainty in common marginal input costs (Beecher and Kihm, 2016), and barriers to competition due to inertia and decision error in consumer supplier selection (Wilson and Price, 2010; Salies and Price, 2004; Hortaçsu et al., 2017). Jointly, these characteristics suggest that 1) the non-financial innovation-related benefits of residential retail markets may be small, and 2) the potential for suppliers to mark up prices and have consumers bear the burden of high costs may be high. Common marginal input costs may also mitigate the potential for government providers to have inefficiently high input costs.

For causal identification, the empirical analysis includes the 13 U.S. states that have areas with local government electricity suppliers and areas with competitive retail markets. There are currently two different identifiable types of local government-owned retail electric suppliers in the U.S.: 1) vertically-integrated government-owned utilities ("Municipal electric utilities") that procure, transport, and sell electricity to consumers (e.g. Austin Energy); and 2) California community choice aggregators (CCAs) that only procure and sell electricity (e.g. East Bay Community Choice). While the latter type is growing, California does not have a large competitive residential electricity market, so I exclude CCAs from the empirical analysis. As long as the responsibility of transporting electricity does not affect electricity purchases and generation, the results here should extend to California CCAs.

[1]For example, see Arizona Corporation Commission Docket E-01345A-19-0236

Relatedly, several states have CCAs or municipal aggregation to assist communities with selecting competitive retail electricity suppliers, which is distinct from CCAs that procure and provide electricity directly to consumers. I incorporate these CCA customers and individual retail choice customers into the empirical analysis.

In the remainder of this paper, I refer to government electricity suppliers as 'public' firms and private electricity suppliers in deregulated retail markets as 'private' firms.

2.3 Theory

Introduction

The following simple model illustrates key mechanisms by which ownership may affect expected retail price, retail price variance, and, thereby, consumer welfare. The model answers the question: How may the relative expected prices, price variance, and consumer welfare under public and private electricity provision vary with the relative magnitudes of the key market distortions outlined in Section 2.1? To explore these outcomes, the model incorporates the three key mechanisms discussed above: inertia in supplier choice, public firm inefficiency, and cost hedging under average cost pricing and risk averse consumers.

While public firms may have numerous objectives, I focus here on the dual objectives of maximizing consumer welfare and minimizing effort to reduce administrative and billing costs. The model also allows for the possibility that the inframarginal wholesale price of electricity is higher for public firms than for private firms, which would be consistent with public firms signing ex-ante suboptimal contracts or owning inefficient generators. For simplicity, I assume these inframarginal wholesale prices are fixed. The model does not explicitly capture corruption, stakeholder capture, intergovernmental transfers, or inefficiencies in costs of marginal electricity procurement. To the extent that corruption and stakeholder capture can be measured as lump sum transfers to or from residential consumers, changing the interpretation of effort and administrative and billing costs could enable the model below to encompass these transfers. Sometimes municipalities use electricity rates to collect revenue for non-electricity expenses. This analysis ignores these intergovernmental transfers, implicitly assuming that each consumer would pay the same amount of money through taxes if the municipality switched to private electricity provision. Since public and private firms can purchase electricity from wholesale electricity spot markets, firms in the same geographic location should receive the same marginal electricity cost.

In terms of cost structure, this model assumes that electricity suppliers bear two types of costs: 1) per-unit (e.g. $/kilowatt-hour) costs, and 2) per-customer administrative and billing costs. None of the modeled public or private firms pay for electricity transportation. The model set up also obviates consideration of private firm customer acquisition and marketing costs. Adapting the model to incorporate these costs should not change the main conclusions about the potential relative signs of average retail price, retail price volatility, and consumer welfare.

Model Set Up

For each unit of electricity, suppliers can either 1) purchase electricity from the wholesale spot market at marginal cost $c \sim f(c)$ where $f(c)$ is continuous and differentiable, $E[c] = \mu$, and $Var[c] = \sigma^2$, or 2) hedge and buy electricity at a constant, known marginal cost $\bar{c}$. Because public and private firms may exert different, yet fixed effort levels to find low-price contracts, let there be two hedged prices, $\bar{c}_{pu}$ and $\bar{c}_{pr}$, for the public and private firms, respectively.

This are two periods. In period one, an electricity supplier chooses a hedging level $s \in [0, 1]$ where $s = 1$ denotes that all electricity supplied is hedged. In period two, suppliers purchase any remaining electricity at the realized wholesale price c.

Suppliers also choose an effort level $e \in [0, \infty)$ and incur administrative and billing cost $a(e)$ with $a(e) > 0$, $a'(e) < 0$, $a''(e) > 0$. Private firms incur costs of effort $k(e)$ $k(e) > 0$, $k'(e) < 0$, and $k''(e) > 0$ $\forall e > 0$. We denote the competitive equilibrium level of effort for private firms $\bar{e}$ and normalize the cost of exerting this effort level $(k(\bar{e}))$to zero. The employees of the public firm are lazier than employees of the private firm and incur effort costs $\gamma k(e)$ such that $\gamma > 1$.

There is one risk averse representative consumer with perfectly inelastic electricity demand q and constant switching cost ω. The consumer is unable to effectively insure herself against retail electricity prices. Let X be a numeraire good with price normalized to 1. Since demand for electricity is perfectly inelastic, the representative consumer always consumes $X = I - pq$ where I is endowed wealth. With loss of generality, let $q = 1$. Hence, ignoring the fixed utility from electricity consumption, we can represent the consumer's utility function as $U(I - p)$ such that $U'(I - p) > 0$ and $U''(I - p) < 0$.

Private Firm

First, consider the behavior of a representative private firm with risk-neutral preferences that competes with other firms in a market with free entry and customer switching cost ω. The firm has three decision variables: 1) average retail price to charge customers, denoted $p_1 \in \mathbb{R}$; and 2) the share of input costs to hedge $s \in [0, 1]$; and 3) the level of effort $e \geq 0$ to exert to reduce administrative and billing costs. There are still two periods. Play proceeds as follows: In the first period, the existing firm chooses s. Then, c is realized. In the second period, the existing firm decides whether to stay in the market or to declare bankruptcy and default on all existing contracts. If the firm stays in the market, it sets e and p_1, a potential entrant can then enter and charge p_2, the customer then decides whether to switch to receiving service from the entrant, and then the existing firm's profit is realized.

We first notice that the objective function of the private firm is additively separable in s and e conditional on staying in business and retaining the customer:

$$\pi|\text{operating} = (p_2 - c)q_r(p_2) - a(e) - k(e)$$

This implies that, conditional on staying in business, the firm will choose e such that $a'(e) = k'(e)$. We denote this effort level $\bar{e}$. Recall that $k(\bar{e}) = 0$.

To analyze optimal pricing, we first consider the consumer's problem:

$$\min_{p \in (p_1, p_2)} p + \omega * \mathbb{I}\{p = p_2\}$$

We observe that the customer will switch to the entrant if and only if $p_1 > p_2 + \omega$.

Next, we consider the problem of the potential new entrant, which faces residual demand

$$q_r = \begin{cases} 1 & \text{if } p_2 < p_1 - \omega \\ 0 & \text{if } p_2 \geq p_1 - \omega \end{cases}$$

The potential entrant faces the following problem:

$$\max_{p_2} \pi = \max_{p_2} [(p_2 - c) q_r(p_2) - a(\bar{e})] \mathbb{I}\{(p_2 - c) q_r(p_2) - a(\bar{e}) > 0\} \mathbb{I}\{p_2 < p_1 - \omega\}$$

So the potential entrant will enter the market and the consumer will switch to the entrant if and only if

$$p_1 > \omega + c + a(\bar{e})$$

Hence, in period two, the existing private firm faces the following problem:

$$\begin{aligned} \max_{p_1} \pi = \max_{p_1} & (p_1 - (s\bar{c}_{pr} - (1-s)c) - a(\bar{e})) \times \mathbb{I}\{p_1 > \omega + c + a(\bar{e})\} \\ & \mathbb{I}\{p_1 - s\bar{c}_{pr} - (1-s)c - a(\bar{e}) > 0\} \\ = \max_{p_1} & (p_1 - s\bar{c}_{pr} - (1-s)c - a(\bar{e})) \, \mathbb{I}\{p_1 \leq \omega + c + a(\bar{e})\} \times \\ & \mathbb{I}\{p_1 - s\bar{c}_{pr} - (1-s)c - a(\bar{e}) > 0\} \end{aligned}$$

The objective function is strictly increasing in p_1 $\forall p_1 \leq \omega + c + a(\bar{e})$. The objective function evaluates to zero for $p_1 > c + a(\bar{e}) + \omega$. The minimum possible profit is zero, as the firm can always default on its hedging contract and exit the market. This implies $p_1 = c + a(\bar{e}) + \omega$ is always an optimal solution to the firm's profit. It is also the unique solution since $s = 0$ implies $\omega + c + a(\bar{e}) > s\bar{c}_{pr} + (1-s)c + a(\bar{e})$, meaning the firm will not go bankrupt if it chooses not to hedge. The associated retail price variance is σ^2. Note that these results hold with more general demand functions unless $c + a(\bar{e}) + \omega$ is greater than the monopoly profit-maximizing price, in which case the private firm would charge the monopoly price.

Public Firm

Now, consider the problem of a public firm that chooses hedging level and effort costs to maximize expected consumer utility less effort costs. In period two, it charges average realized cost, $p = s\bar{c}_{pu} + (1-s)c + a(e)$. The public firm's problem is:

$$\max_{s,e} g(E[U(I-p)], k(e)) = \max_{s,e} g\left(E\left[U\left(I - s\bar{c}_{pu} - (1-s)c - a(e)\right)\right], \gamma k(e)\right)$$

Clearly, the utility will choose $s = 1$ and hedge fully if there is no price premium on hedging, i.e. $\mu \geq \bar{c}_{pu}$, as long as $\frac{\partial g()}{\partial U} > 0$.

To explore administrative inefficiency and hedging for the case where $\mu < \bar{c}_{pu}$, I impose functional forms on $g()$, $U()$, and the distribution of c. These assumptions are admittedly strong, but they create a tractable problem that is useful in demonstrating how public firm administrative inefficiency, uncertainty, and consumer risk aversion could affect price and consumer welfare. Suppose $c \sim N(\mu, \sigma^2)$, $g(U, k) = -\log(-U) - k$, and $U = -e^{-\lambda(I-p)}$ where λ is the Arrow-Pratt Index of absolute risk aversion. Since $I - p \sim N(I - s\bar{c}_{pu} - (1-s)\mu - a(e^*), (1-s)^2\sigma^2)$, we get the well known mean-variance utility result:

$$E[U(I-p)] = -e^{-\lambda(I - s\bar{c}_{pu} - (1-s)\mu - a(e^*) - \frac{\lambda(1-s)^2\sigma^2}{2})}$$

Hence, we can solve for s^* and e^* using the following monotonic transformation of the firm's objective function:

$$\max_{s,e} I - s\bar{c}_{pu} - (1-s)\mu - a(e) - \frac{\lambda(1-s)^2\sigma^2}{2} - \frac{\gamma k(e)}{\lambda}$$

This objective function is additively separable in e and s, so we can consider the two problems separately. The FOC with respect to e produces

$$-a'(e^*) = \frac{\gamma}{\lambda} k'(e^*)$$

Since $h(e) = a(e) - \frac{\gamma}{\lambda}k(e)$ is strictly decreasing, this implies $0 < e^* < \bar{e}$ as long as $\gamma > \lambda$. Hence, we have constructed a situation in which the public firm is less efficient than the private firm.

The FOC with respect to s is:

$$-\bar{c}_{pu} + \mu + \lambda(1 - s^*)\sigma^2 = 0$$

or, equivalently,

$$s^* = \frac{\mu - \bar{c}_{pu}}{\lambda\sigma^2} + 1$$

Thus, if $(\mu - \bar{c}_{pu}) \in (-\lambda\sigma^2, 0)$, an internal equilibrium exists. Note that $s = 1$ gives the (transformed) objective value $I - \bar{c}_{pu} - a(e) - \frac{k(e)}{\lambda}$. If $\mu \geq \bar{c}_{pu}$, then $s = 0$ gives the objective value $I - \mu - \frac{\lambda\sigma^2}{2} - a(e) - \frac{k(e)}{\lambda}$, which is strictly less than $I - \bar{c}_{pu} - a(e) - \frac{k(e)}{\lambda}$, and the public firm will hedge completely. In contrast, if $\bar{c}_{pu} - \mu > \lambda\sigma^2$, there will be no hedging.

Hence, the public firm may hedge fully, hedge partially, or not hedge at all depending on the relative values of $\bar{c}_{pu}$ and μ. The resulting expected retail prices are $p = \bar{c}_{pu} + a(e^*)$, $p = s^*\bar{c}_{pu} - (1 - s^*)c + a(e^*)$, and $p = c + a(e^*)$, respectively. The associated retail price variances are 0, $(1 - s^*)^2\sigma^2$, and σ^2, respectively. In this example, we also observe that the optimal level of hedging weakly increases with the index of absolute risk aversion λ and the variance of the wholesale electricity spot price. Hence, these parameters affect the price and variance associated with partial hedging and may also affect retail price levels and variance through their effect on the applicable hedging regime (i.e. full, partial, or none).

While the public firm chooses the level of hedging that maximizes consumer welfare, two potential inefficiencies may make consumer welfare suboptimal: 1) effort to reduce administrative costs may be lower than the consumer's preferred level, which increases retail price; and 2) the hedging cost may not equal the lowest attainable hedging cost, which raises retail price in the presence of hedging and reduces the level of hedging, thereby increasing retail price volatility.

Comparisons

This section compares expected price, price variance, and consumer welfare under the assumptions made in Sections 2.3 and 2.3.

Theorem 1. *If the public firms is perfectly efficient, consumers have no switching costs, and consumers can properly insure themselves against retail electricity price risk, then the public and private firm prices are identical.*

Proof. Consider the first-best case where the public firms is perfectly efficient (i.e. $e^* = \bar{e}$), consumers have no switching costs (i.e. $\omega = 0$), and consumers can properly insure themselves against retail electricity price risk, which we can represent as $\gamma = U''(I-p) = 0$. Then the public firm's problem reduces to minimizing expected price. Assuming $\bar{c}_{pu} \geq c$, the public firm charges average price $p = c + a(\bar{e})$, which matches the private firm price without switching costs. □

Comparing the results of the previous two subsections under $\omega > 0$, $U''(I-p) < 0$, and public firm inefficiency, it is evident that retail price variance must be weakly higher in the private electricity provision case, as formalized in the following theorem.

Theorem 2. *Retail price variance is weakly higher under the private firm than under the public firm.*

Proof. Since $\mathrm{Var}(p_1) = \mathrm{Var}(c + a(\bar{e}) + \omega) = \mathrm{Var}(c) = \sigma^2$, retail price variance under private provision always equals σ^2. Retail price variance under public provision equals σ^2 if the firm chooses not to hedge and equals $(1-s^*)^2\sigma^2 < \sigma^2$ if the firm hedges since $s^* \in (0, 1]$. □

Theorem 3. *A sufficient condition for the private firm's expected price to exceed the public firm's expected price is* $\omega > \bar{c}_{pu} - \mu - \frac{(\bar{c}_{pu}-\mu)^2}{\lambda\sigma^2} + a(e^*) - a(\bar{e})$

Proof. With partial hedging, the expected retail price under the public firm is:

$$E[p^*] = s^*\bar{c}_{pu} + (1-s^*)\mu + a(e^*) = \left(\frac{\mu - \bar{c}_{pu}}{\lambda\sigma^2} + 1\right)\bar{c}_{pu} + \frac{\mu - \bar{c}_{pu}}{\lambda\sigma^2}\mu + a(e^*)$$

This will be less than the private firm's expected retail price $E[p_1^*] = E[\omega + c + a(\bar{e})] = \omega + \mu + a(\bar{e})$ if and only if

$$\omega > \bar{c}_{pu} - \mu - \frac{(\bar{c}_{pu} - \mu)^2}{\lambda\sigma^2} + a(e^*) - a(\bar{e})$$

□

Hence, the relative expected retail prices depend on the switching cost ω, the level of consumer risk aversion, the wholesale spot market price variance σ^2, the public firm's inefficiency $a(e^*) - a(\bar{e})$, and the public firm's hedging premium $\bar{c}_{pu} - \mu$.[2] Assuming that the risk premium is weakly positive, which would hold if generators are risk neutral, a sufficient condition for a private firm charging prices higher than a public firm is that switching costs are greater than the risk premium plus the difference in charges to cover administrative costs, i.e. $\omega > (\bar{c}_{pu} - \mu) + a(e^*) - a(\bar{e})$.

Corollary 1. *Consumer welfare could be higher under public or private electricity provision.*

Proof. Consider the case where the public firm is perfectly efficient and chooses $e^* = \bar{e}$. Then consumer welfare is relatively higher under the public firm. In this case, the public firm chooses hedging level to maximizes expected consumer welfare and $E[U(I - p)] \geq E[U(I - c - a(\bar{e}))] > E[U(I - \omega - c - a(\bar{e}))]$.

Now, consider the case where the public firm is very inefficient, switching costs are small, and consumers are not very risk averse such that $a(e) - a(\bar{e}) > \omega$ and $\bar{c}_{pu} - \mu > \lambda\sigma^2$, then consumer welfare is higher under the private firm. □

Discussion

These theoretical results suggest that, depending on the relative levels of customer inertia, public firm inefficiency, and consumer risk aversion, consumer welfare could be higher under public or private electricity provision.

While this model used switching costs to explore firms' ability to charge prices above marginal costs, other conditions may lead to similar conclusions. The model assumes no fixed costs, or costs that do not vary if the firm serves a marginal customer. If we relax the assumption of one representative consumer and allow for fixed marketing and administrative costs, then the private firms have decreasing marginal costs and a perfectly competitive equilibrium cannot be sustained. Even in the absence of inertia, oligopoly power would enable firms to charge prices above marginal costs. Anecdotally, private firm marketing costs and fixed administrative costs are large relative to the non-fuel costs of serving a marginal customer. If this is true, this would imply that the perfectly competitive price should be close to marginal costs, yet perfect competition may not be attainable in practice.

[2] If we allowed q to deviate from one, it would also depend on the usage per customer q in terms of the average administrative costs per kWh.

One key finding of the theory is that government suppliers may have prices above or below marginal costs, depending on realizations of electricity spot prices, while private firms should always have prices above marginal costs in equilibrium. This paper now turns to an empirical analysis of retail prices and an important determinant of retail price variance: pass through of highly uncertain marginal costs. It is important to keep in mind that, with hydraulic fracturing ('fracking') and large declines in solar photovoltaic prices, it is likely that the realizations of spot market electricity prices covered in the analysis timeframe were generally lower than anticipated. As a result, theory suggests that the empirical analyses of retail prices in the coming sections are particularly favorable to competitive markets.

2.4 Data

Residential Retail Electricity Sales, Customer Accounts, and Average Prices

Annual residential electricity sales in Megawatt-hours (MWh), revenues in thousands of U.S. dollars, and number of residential customers, come from The Energy Information Administration (EIA) Form EIA-861 survey. I calculate average residential retail electricity prices in U.S. dollars per kilowatt-hour (kWh) by dividing residential retail electricity revenue by residential retail electricity sales for each entity.

I restrict this analysis to companies that provide energy or bundled service in states that had at least one municipal utility and at least three private firms serving residential customers in 2016. Thirteen states fit this description.

In 2012, the EIA altered their reporting system for small utilities. As a result, Form EIA-861 only provides post-2011 data on total sales, revenue, and number of customers across all customer types (e.g. residential, commercial) for many of the municipal utilities. I impute residential-specific data based on the 2011 ratios of residential to total sales. To test this method, I apply the same imputation method to data with known 2017 residential data. The imputations perform well on average. Paired two-sided t-tests do not reject the null hypotheses that the average revenues sales, and number of customers are significantly different at any conventional significance level (t = 0.05, 0.02, and 0.11, respectively). Nonetheless, I perform sensitivity analyses excluding these imputed data to address any remaining measurement error concerns.

I convert all financial data to real 2017 U.S. dollars using the GDP deflator from the US Bureau of Economic Analysis (2019).

See Appendix B.1 for more details on data cleaning.

Table 2.2 displays summary statistics for residential electricity sales in Gigawatt-hours (GWh) and annual number of residential customers for municipal and competitive suppliers in the states covered in this analysis.

Table 2.2: Data Summary Statistics

Ownership	Statistic	Retail Price ($/kWh)	Marginal Cost ($/kWh)	Wholesale Natural Gas Price ($/MCF)	Residential Customers (Thousands)	Residential Usage (GWh)
Public	Mean	0.11	0.05	6.49	6.96	78.06
	SD	0.03	0.02	2.13	32.99	422.75
	Min	0.03	0.02	2.08	0.08	0.62
	Max	0.26	0.12	14.89	725.46	9573.05
	N	4084	4084	4084	4084	4084
Competitive	Mean	0.10	0.04	5.70	143.01	1444.69
	SD	0.02	0.02	1.76	260.61	2707.42
	Min	0.04	0.02	2.08	0.00	0.01
	Max	0.24	0.10	14.89	2642.55	23949.64
	N	3401	3401	3401	3401	3401

Marginal Per-kWh Costs

The marginal cost of an additional kWh to an electricity supplier is the spot market price of electricity, which varies by location.[3]

I calculate annual wholesale electricity costs for each supplier by aggregating publicly-available hourly spot market electricity prices weighted by electricity usage at the closest (in Euclidean distance) geographic location (node) with available hourly electricity usage data. I obtained these spot prices and usage data from SNL Financial, which provides a centralized database of the relative region-specific administrative databases. Since I do not have data on the precise distribution of private providers' customers within a state, I calculate marginal costs for private providers in a given state as the average hourly locational marginal price weighted by hourly electricity usage in the closest area (load zone). See Appendix B.1 for a more detailed description of the annual marginal cost calculation and planned sensitivity analysis.

Measurement error is introduced in these calculations both due to the aggregation from hourly marginal costs to annual totals and because the relevant spot price for each firm is only estimated as the closest one. As a result, I use a variety of methods to account for this measurement error.

Wholesale Natural Gas Prices

I obtain monthly wholesale citygate natural gas prices by state in dollars per thousand cubic feet (MCF) from EIA. I aggregate these monthly data to the the annual level using

[3]Section 2.3 illustrates that any cost associated with long-term contracts for electricity or hedging-related derivatives are inframarginal.

a simple average. Future work may incorporate seasonal variation in use of natural gas for electricity generation.

T&D Costs and Government Transfers

I obtained municipal electric utility financial data from state public utility commissions and the municipalities themselves through a combination of public record requests and scraping data available online. In total, I collected data for 66% of the municipal utilities used in this analysis, although the coverage and granularity of data vary by municipality. Table 2.3 shows the number and percentage of municipal electric utilities by state.

Table 2.3: Municipal Electric Utility Data Collection Summary

State	Number in Analysis	Number Received	% Received
CT	7	7	100 %
DE	9	6	67 %
IL	41	19	46 %
MA	40	40	100 %
MD	5	0	0 %
ME	5	4	80 %
NH	5	0	0 %
NJ	9	4	44 %
NY	47	38	81 %
OH	84	84	100 %
PA	34	9	26 %
RI	1	1	100 %
TX	59	16	27 %
Total	346	229	66 %

While the empirical analysis primarily employs conservative estimates of T& D costs from Form EIA-861, I verify the results using a subset of these municipal electric utility financial data sets. The remainder of these data can be digitized and used in future work to improve the empirical estimates.

2.5 Methods and Identification

To empirically identify the causal effect of ownership on price levels and volatility of marginal costs to residential consumers, the geographic location of public versus private providers cannot be endogenous to the pricing decision. The municipal electric utilities are government-owned vertically integrated electricity suppliers, and the vast majority of them were established well before retail electricity markets opened to competitive firms.

The number of municipal electric utilities peaked in 1923 and has decreased by about a third since then Vince and Fogel (1995). No municipal utilities in the states covered in this analysis entered or exited during the analysis timeframe of 2005-2017 based Form EIA-861 data. When U.S. retail markets opened to competition between 1996 and 2002, states did not allow them to enter areas served by existing municipal electric utility service territories.[4] Since all data come from time periods at least three years after the opening of competitive retail markets, the analysis excludes the years that are most affected by transitional policies.[5]

Since consumers respond to average prices Ito (2014), not marginal prices, and electricity is a homogeneous good, average price — or, equivalently, average bill — is the appropriate metric for assessing the effect of pricing decisions on consumer welfare.

To analyze retail bill volatility, I focus on pass through of volatile and uncertain marginal costs: wholesale electricity spot prices. Drawing on theory, showing that pass through is larger under private electricity provision than public provision is sufficient to show that the underlying variance in retail prices must also be larger under private provision. Theoretically, the only source of retail price uncertainty under public firm average-cost pricing is uncertainty about future marginal costs. Under competition, there may be additional uncertainty in prices due to private firm profit-maximizing pricing strategies. To the extent that this pricing is correlated with marginal costs, it will be embedded in the pass-through results. If pricing behavior is orthogonal to marginal costs, it could only increase the variance of retail prices under competition.

Derivation of Estimating Equations

Industry knowledge and public firm financial documents provide insight into the data generating process. Public firms generally set average retail prices P using the following basic formula:

$$
\begin{aligned}
P =&(operating\ costs + depreciation\ of\ capital\ assets + interest\ on\ capital\\
&+ intergovernmental\ transfers)/(projected\ demand)\\
=&(transfers\ in\ lieu\ of\ taxes)(fuel\text{-}related\ costs\ incl.\ losses + billing\ and\ admin\ costs\\
&+ T\&D\ O\&M\ costs + depreciation\ of\ T\&D\ assets + interest\ on\ T\&D\ assets\\
&+ other\ transfers)/(projected\ demand)\\
=&\gamma_1(marginal\ fuel\ cost) + \gamma_3(hedged\ fuel\ cost\ premium)+\\
&[\gamma_4(non\text{-}T\&D\ billing\ and\ admin\ costs)\ + \gamma_5(T\&D\text{-}related\ depreciation\ and\ interest)\\
&+ \gamma_6(T\&D\ O\&M\ and\ admin)\ + \gamma_7(other\ transfers)]/(projected\ demand)
\end{aligned}
$$

A key difference between municipal utilities and private suppliers is that municipal utilities own and operate distribution and, in some cases, transmission facilities. In addition,

[4] This was typically because regulators had little to no jurisdiction over the municipalities in most states (Ando and Palmer, 1998).

[5] I do identify three municipalities that municipalized in the '90s, possibly in anticipation of the introduction of retail competition and exclude them from the analysis (Doane and Spulber, 1997).

many municipalities collect revenue through electricity bills to cover non-electric municipality expenses, such as fire department expenses.

Another important consideration is the timing of retail price setting. Municipal utilities likely have some fixed bureaucratic lag in adjusting retail prices to reflect unexpected cost changes. Pearson correlation coefficients of relationships between changes in marginal cost and changes in retail price suggest that municipal utilities revise retail prices annually to reflect costs from the prior year. To be cautious, I include a contemporaneous effect of marginal costs to capture any within-year updating.

For tractability, I make four assumptions: 1) the hedged fuel cost premium is constant, on average, across time and public firms; 2) non-T&D administrative and billing costs scale linearly with sales, are the same across all public firms in the same state, on average, and only exhibit year-to-year changes that are consistent across all firms; 3) there is no cross-subsidization across customer classes; and 4) aggregate error in estimation of these cost components, denoted $\epsilon_{i,t}$, is normally distributed and independent across suppliers.

This suggests the following data generating process:

$$\begin{aligned} P_{i,t} =& \gamma_0 + \gamma_1(marginal\ fuel\ cost)_{i,t-1} + \gamma_2(marginal\ fuel\ cost)_{i,t-1} + \\ & [\gamma_5(scheduled\ T\&D\ costs)_{i,t-1} + \gamma_6(other\ T\&D\ \ costs)_{i,t} \\ & + \gamma_7(non\text{-}tax\ transfers)i, t-1]/(electricity\ sales)_{i,t-1} + \phi_s + \psi_t + \epsilon_{i,t} \end{aligned}$$

where $P_{i,t}$ denotes supplier i's average retail price at time t, $(marginal\ fuel\ costs)_{i,t-1}$ indicates the consumption-weighted average wholesale electricity spot price for supplier i at time t, and ϕ_s and ψ_t are state and time fixed effects, respectively.

While the data generating process for private firms is not publicly available, the components of these firms' costs are generally known. For tractability, I assume that the firms charge a strategic pricing premium that is time-invariant in expectation and that all marketing and administrative costs scale roughly linearly with the firm's electricity sales. The strategic pricing premium may arise, for example, from consumers incurring supplier switching costs. Using a linear conditional expectation function, I assume the data generating process for private firm i takes the form:

$$P_{i,t} = \alpha_0 + \alpha_1(marginal\ fuel\ costs)_{i,t-1} + \alpha_2(marginal\ fuel\ costs)_{i,t} + \phi_s + \psi_t + \epsilon_{it}$$

where α_0 captures administrative, billing, and marketing costs as well as a strategic pricing premium. The normally distributed error term captures firm- and time-specific deviations from the state average strategic pricing premium and from mean billing, administrative, and marketing costs. Recall that private firms do not own or pay for electricity delivery and, therefore, do not incur any T&D costs.

This price setting process includes contemporaneous marginal fuel costs and the previous year's marginal fuel costs. I hypothesize that competitive firms would adjust prices for some customers within the year. Since many of these firms offer customers fixed price contracts that can last one year or longer, it is plausible that some portion of these costs would be collected in the years following the cost change. Pearson correlation coefficients suggest that competitive firms' retail prices are most highly correlated with contemporaneous marginal costs, although costs from the prior year may affect pricing decisions. Correlations of retail price and two-year lagged marginal costs suggest that limiting the analysis to one lag captures the vast majority of effects of marginal cost on price.

Combining the above public and private firm data generating processes produces:

$$\begin{aligned} P_{i,t} = (\alpha_0 - \gamma_0)(private)_i + \gamma_1(marginal\ fuel\ costs)_{i,t-1} + \gamma_2(marginal\ fuel\ costs)_{i,t} \\ +(\alpha_1-\gamma_1)(marginal\, fuel\, costs)_{i,t} \times (private)_i + (\alpha_2-\gamma_2)(marginal\, fuel\, costs)_{i,t} \times (private)_i \\ + [\gamma_4(scheduled\, T\&D\ costs)_{i,t-1} + \gamma_5(other\ T\&D\ \ costs)_{i,t} \\ + \gamma_6(non\text{-}tax\ transfers)i,t-1]/(electricity\ sales)_{i,t-1} + \phi_s + \psi_t + \epsilon_{i,t} \end{aligned} \quad (2.1)$$

where $(private)_i$ is a binary variable equal to one if supplier i is a retail power marketer.

This derivation shows that it is appropriate to interpret the coefficient on $(private)_i$ as the average effect on retail prices of private firm marketing, billing, and administrative costs plus the average premium from private firm strategic pricing less the average retail price effect of public firm non-T&D billing and administrative costs and hedging cost premiums. The interpretation of the sum of the coefficients on $(marginal\ fuel\ costs)_{i,t-1} \times (private)_i$ and $(marginal\ fuel\ costs)_{i,t} \times (private)_i$ is the average difference in the pass through of marginal costs to consumers between private and public firms.

The state and year fixed effects also capture any remaining time-invariant heterogeneity in price drivers across states or any time-varying factors that influence prices nationwide.

To isolate systematic differences in price level across public and private firms, I first estimate the coefficient on $(private)_i$ Equation in 2.1 restricting all firms to have the same marginal cost pass through, on average (i.e. $\alpha_1 = \gamma_1$ and $\alpha_2 = \gamma_2$). To isolate systematic differences in pass through across public and private firms, I estimate Equation 2.1 in first differences. While I assume the error term is independent across firms, it may follow a random walk. The estimate of interest is $\alpha_1 - \gamma_1 + \alpha_2 - \gamma_2$.

Addressing Threats to Identification

This section discusses three common potential threats to identification: measurement error, simultaneity, and selection.

Measurement Error and Reverse Causation

I estimate variants of Equation 2.1 using two-stage least squares (2SLS). Classical measurement error in estimated marginal costs could cause attenuation bias. In addition, although electricity demand is inelastic (Reiss and White, 2005; Espey and Espey, 2004), there is some concern about simultaneity with retail price affecting demand, which affects marginal costs. I instrument for marginal costs using state-specific citygate natural gas prices, which can be thought of as a cost shifter. The marginal electric generator uses natural gas in many hours of the year in all of the wholesale electricity spot markets included in this study. The instrument should also be uncorrelated with measurement error in estimated marginal costs.

The 2SLS estimates would be biased downwards if the exclusion restriction is violated due to reverse causation. This could happen if changes in average retail price cause short-run changes in electricity demand, which cause changes in natural gas usage of power plants, which cause changes in state citygate natugal gas prices. Since the share of residential electricity demand to total state demand is less than 5% for all firms in the analysis, short-run own-price electricity demand is inelastic, electric generation comprises only 12-50% of statewide natural gas demand, and the instrument is strong, this potential bias is likely to be small. Using an assumed average price elasticity of -0.35 (Espey and Espey, 2004) and conservative estimates for all other relevant factors, I calculate a bound for the potential bias of about -0.0001 (see Appendix B.2 for assumptions and calculation). As short-run cross-price elasticities for natural gas and electricity are small (Lavín et al., 2011), any bias from cross price effects should be smaller in magnitude and the opposite sign, which further limits the potential bias from violation of the exclusion restriction.

Endogenous Location

If the geographic areas where the public and private firms located within a state are different across unobservables related to retail price, then this analysis may be picking up these unobserved differences and not reflect differences in price-setting choices of public and private firms. This section addresses balance of observables related to electricity demand and supply unobservables.

Key factors that affect households' electricity demand include climate, income, heating fuel type, conditioned square footage, and household size. All of these factors are correlated with total per-household electricity consumption. Table 2.4 shows that a two-sample unpaired t-test cannot reject the null that, in aggregate, the municipal and competitive firms in this analysis have equal 2017 mean usage per household (t=0.410). There is some indication that mean usage of competitive providers is greater than that of municipal utilities in Pennsylvania and that the opposite relationship holds in Illinois, although these results do not survive Bonferroni multiply hypothesis correction. To be cautious, I perform a sensitivity analysis excluding these two states. This balance analysis provides some evidence that these household are balanced in terms of climate, income, heating fuel type, conditioned square footage, and household size. It is possible that usage per customer could be the same across these two populations despite systematic differences in electricity usage patterns if, for instance, areas served by public firms tend to have higher income and less conditioned square footage than households served by private firms such that the effect of these two differences on total annual usage perfectly cancel each other out. To help address any remaining concerns, I weight observations based on propensity scores from a logistic regression of firm ownership on mean electricity usage per household (Larivi{\`e}re and Lafrance, 1999). I also truncate the data based on usage per customer to ensure overlap of this key observable.

Table 2.4: Usage per Customer Balance Analysis

State	Mean 2017 Usage per Household		t-statistic
	Competitive	Public	
CT	9.5	8.1	0.5
DE	10.6	9.9	0.4
IL	8.0	9.3	-2.3
MA	8.4	8.5	-0.1
MD	11.2	12.0	-0.3
ME	8.4	6.3	1.2
NH	6.3	7.1	-0.7
NJ	9.9	7.5	0.8
NY	12.6	12.9	-0.1
OH	9.4	9.9	-1.1
PA	11.0	8.0	2.4
RI	6.1	7.7	-0.7
TX	14.9	13.0	1.4
Total	10.4	10.2	0.4

On the supply side, estimated marginal costs and year fixed effects should capture most of the within-state geographic cost variation. There could be some remaining geographic variation in factors that affect billing and administrative costs, marketing costs, or hedging cost premiums. The main potential factor that stands out is population density. Population density is correlated with usage per customer (Larivi{\`e}re and Lafrance, 1999), which appear to be similar across public and private firms. Moreover, Census data on 2010 county-level housing unit density by square mile suggests that public firms operate in counties that are more densely populated than other areas with the same state, on average. Hortaçsu and Madanizadeh, Seyed Ali (2012) and Giulietti et al. (2005) provide evidence that customers of private suppliers are also more likely to reside in more urban and densely-populated areas. While this is far from airtight evidence that public and private firms are balanced on population density, the common directional relationship is encouraging.

While there may be some differences in hedged fuel costs, these appear limited. All grid-connected households in a state should technically be able to sign a power urchase agreement with any generator within the state.[6] There could be cost differences if public firms signed long-term contracts prior to retail restructuring. To the extent that public firms signed long-term natural gas or solar contracts prior to restructuring that were still in effect during the

[6]FERC Order 888 requires transmission owners to offer nondiscriminatory transmission service to all others. There may be systematic geographic differences in the cost of transporting electricity due to transmission losses and congestion, but these are likely to be small given that public firms locate throughout the states (see Appendix B.4) and there is some evidence that population densities are similar across public and private firms.

analysis timeframe, this would most likely bias hedging costs in the direction of higher costs for public firms. However, any pre-existing access to hydropower could give public firms a cost advantage relative to private firms.[7] As shown in the EIA map in Appendix B.4, this is most likely to be a concern in New York, which has substantial hydroelectric generating capacity. For this reason, I perform sensitivity analysis excluding New York.

In addition, if the linear model is incorrect, it would be important to have overlap in marginal costs across public and private firms. The distributions of marginal costs appear to be similar across private and public firms. To eliminate concerns about overlap in estimated marginal costs, I perform a sensitivity analysis that excludes all observations with marginal costs that fall above or below the private firms' observed marginal cost range.

2.6 Results

Retail Price Levels

Column 1 of Table 2.5 shows estimates of the coefficients in Equation 2.1. To relax assumptions about how costs vary differentially across states over time, Columns 2 presents a variant of Equation 2.1 using OLS to control for state-by-year fixed effects, and Column 3 controls for state trend fixed effects. The last five columns show robustness tests without propensity score weighting and excluding various groups of observations.

Before adjusting for T&D costs or transfers, public firms are estimated to charge residential consumers \$0.019-0.023/kWh, more than private firms. Due to accounting in the EIA database, the unadjusted prices reflect the *total* price that residential consumers supplied by public firms or Texan private firms pay for electricity, while the price excludes charges for transporting electricity for all other private firms. The average transportation-only ('delivery') costs reported in the EIA for all states included in this analysis is \$0.0745/kWh, and the minimum state average is \$0.0476/kWh. Applying this conservative estimate of \$0.0476/kWh to all public firms and Texan firms suggests that private firms charge residential consumers at least \$0.013-0.015/kWh, or roughly 13%, more than public firms, on average. Applying state-specific average T&D costs produces estimates of private firm price premiums above public firms equal to \$0.037-0.040/kWh, or roughly 37%.

Excluding New York increases the unadjusted price level difference to \$-0.031/kWh, the conservative adjusted difference to \$0.002, and the estimated differential to \$0.026. While this difference may be primarily driven by public providers in this area having historic rights to hydroelectric power, it may also be driven by particularly relaxed market regulations and private firms in New York charging particularly high rates. In fact, concerns about customer abuses and overcharging caused the New York regulator to conclude in December 2016 that

[7]Note that, although Franklin D. Roosevelt gave public firms preferential purchasing power of low-cost federally developed or licensed hydroelectric power (Vince and Fogel, 1995), there is very little federally-owned hydroelectric power in the states covered in this analysis (See Appendix B.4).

the retail competition initiative had failed (NYSDPS CASES 15-M-0127, 12-M-0476, and 98-M-1343).

Table 2.5: Price Level Results

	Dependent variable: (Average Retail Price)$_t$ (\$/kWh)							
	(1) 2SLS	(2) OLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS
Private	−0.020***	−0.023***	−0.019***	−0.021***	−0.021***	−0.025***	−0.016***	−0.031***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.003)	(0.002)
Marginal Cost$_t$	0.633	2.492***	0.052	0.230	0.317	5.367	1.009*	1.986**
	(1.433)	(0.279)	(0.033)	(1.265)	(1.346)	(3.880)	(0.598)	(1.006)
Marginal Cost$_{t-1}$	0.585***	0.290***	0.491***	0.642***	0.612***	0.134	0.540***	0.473***
	(0.164)	(0.053)	(0.057)	(0.148)	(0.158)	(0.310)	(0.108)	(0.125)
Includes StatexYear FEs		x						
Includes State Trends			x					
Weighted	x	x	x		x		x	x
Truncated MCs for Overlap					x			
Includes EIA Short Form Firms	x	x	x	x	x		x	x
Includes PA and IL	x	x	x	x	x	x		x
Includes NY	x	x	x	x	x	x	x	
Observations	7,479	7,479	7,479	7,479	7,377	4,868	5,884	6,473

*p<0.1; **p<0.05; ***p<0.01. All standard errors clustered on supplier-state. All models include year fixed effects. All costs in 2017 $/kWh.

Figures 2.1-2.5 present the distributions of average residential retail prices of municipal and competitive firms. Figures 2.1 and 2.2 use 2SLS to normalize prices for predicted marginal costs, predicted lag marginal costs, and state and year fixed effects. Figures 2.4 and 2.5 use OLS to normalize prices for state by year fixed effects and potentially endogenous marginal costs and lagged marginal costs.

I present three sets of results for price distribution comparisons: 1) unadjusted prices; 2) prices excluding embedded T&D costs, estimated by state as the average delivery costs of delivery-only within-state electricity suppliers; 3) prices excluding a conservative estimate of T&D costs of \$0.0476/kWh.[8]

The unadjusted price distributions for municipal utilities and competitive suppliers are similar despite the fact that the government-owned suppliers' prices include T&D costs and most of the competitive suppliers' prices do not. After adjusting for even conservative T&D costs, the estimated cumulative distribution of prices is higher for competitive suppliers than that of public suppliers under the conservative T&D costs at any price level. A Kolmogorov-Smirnov test fails to reject the null of first-order stochastic dominance of the competitive supplier price CDF over the public supplier price CDF in either the 2SLS or OLS specification (p-values > 0.9999). Another Kolmogorov-Smirnov test rejects the null of first-order stochastic dominance of the public supplier price CDF over the competitive supplier price CDF at the $\alpha = .0001$ significance level under the 2SLS and OLS specifications.

[8] Form EIA-861 does not report any delivery-only service in Texas. The second results include imputed Texas delivery charges equal to \$0.074/kWh, i.e. the average delivery charge in the other 12 states.

Table 2.6: First Stage Results: Main Price Level and Pass Through Specifications

	Dependent variable:					
	MC_t	MC_{t-1}	ΔMC_{t-1}	ΔMC_t	Private × Δ MC_t	Private × ΔMC_{t-1}
	(1)	(2)	(3)	(4)	(5)	(6)
(Wholesale Gas Price)$_t$	−0.001***	−0.003***				
	(0.0001)	(0.0003)				
(Wholesale Gas Price)$_{t-1}$	0.0003***	0.004***				
	(0.0001)	(0.0002)				
Private			0.001**	0.0001	−0.001***	−0.00004
			(0.0005)	(0.0005)	(0.0004)	(0.0004)
Δ(Wholesale Gas Price)$_{t-1}$			0.005***	−0.0005***	0.0003***	−0.001***
			(0.0003)	(0.0002)	(0.0001)	(0.0002)
Δ(Wholesale Gas Price)$_t$			−0.001***	0.004***	−0.001***	−0.001***
			(0.0002)	(0.0004)	(0.0002)	(0.0001)
Private×Δ(Wholesale Gas Price)$_{t-1}$			−0.001*	0.001**	0.0001	0.005***
			(0.0004)	(0.0002)	(0.0002)	(0.0003)
Private×Δ(Wholesale Gas Price)$_t$			0.001***	−0.001**	0.005***	0.001***
			(0.0003)	(0.0004)	(0.0003)	(0.0003)
F	22	250	128	110	55	78
Observations	7,479	7,479	6,905	6,905	6,905	6,905

All models include state and year fixed effects. All regressions weighted by propensity score.
All dependent variables in 2017 \$/kWh. All other costs in \$/MCF.

To explore estimated private firm markups relative to price levels, I create a modified Lerner Index. This metric equals (P-MC)/P where P denotes average bill and MC captures costs associated with serving a marginal customer with fixed electricity usage equal to the firm's mean usage per customer. Since consumers respond to average costs (Ito, 2014), it is appropriate to analyze average price per customer as opposed to marginal price. The commensurate cost is the marginal cost of serving a marginal customer. This includes the cost associated with supplying a marginal kWh of electricity to an existing customer as well as any additional customer service and other administrative costs associated with serving a marginal customer.

I estimate the marginal cost of serving an additional customer using Massachusetts public firm financial data. Since public firms may be less efficient than private firms, this may serve as a conservative estimate of marginal administrative costs. I regress administrative costs on number of residential and non-residential customers using various fixed effect specifications. I test an analysis of levels as well as first-differences. While no specification rejects the null of zero marginal costs, the largest estimate is \$170/customer. Using this conservative estimate and a uniform 15% transmission and distribution loss factor, I estimate modified Lerner Indexes. I exclude Texas from these calculations because their retail prices embed an unknown level of T&D costs.

Figure 2.7 displays the distribution of estimated modified Lerner Indexes. The mass near zero is suggestive that the error in the cost estimates is small. There appears to be substantial market power in the retail electricity markets. Estimates suggest bills exceed marginal costs by about 50% for the median firm-year, with 16% of firm-years having estimated markups over 100%.

Price Volatility and Marginal Cost Pass Through

Column 2 of Table 2.7 presents 2SLS estimates of a first differences version of Equation 2.1. An increase in marginal costs of \$0.01/kWh is associated with a \$0.00264/kWh greater same-year increase in residential retail prices for competitive firms relative to public firms. This implies that a \$0.05/kWh marginal cost increase would increase the annual electricity bill for a typical household that uses 10,000 kWh per year by \$132 more under a competitive supplier than under a public supplier. The estimates do not show a significant difference in the effect of electricity supplier ownership on retail prices the following year. These results suggests that, as argued in Section 2.3, retail price variance is higher under competition than government provision.

As shown in Table 2.7, the result that private firm electricity bills are relatively more sensitive to marginal wholesale costs is robust to a number of specifications and to excluding observations for which one may be particularly concerned about measurement error or endogenous location.

The OLS (Column 1) point estimate on the interaction term between ownership and contemporaneous marginal cost change is significantly lower than the 2SLS estimate. This may suggest attenuation or reverse causation bias in the OLS estimate. This result could

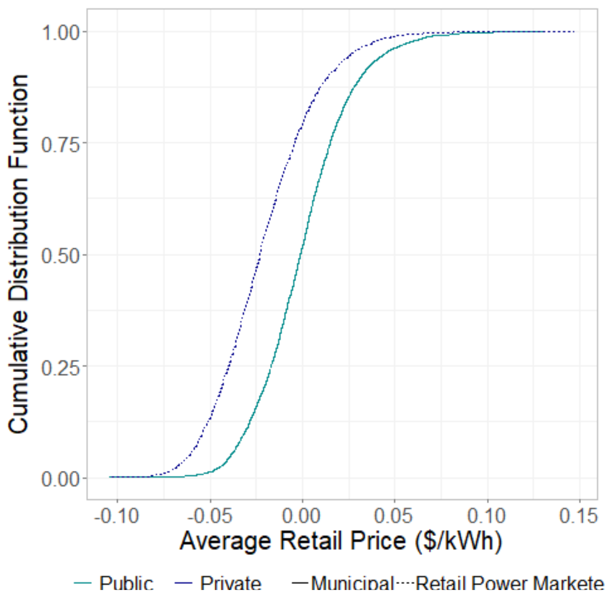


Figure 2.1: 2SLS Normalized Price Distributions

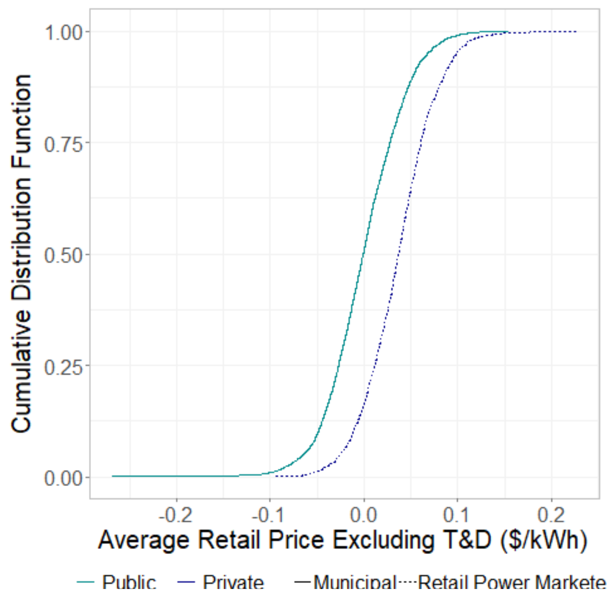


Figure 2.2: 2SLS Estimated Normalized Price Distributions

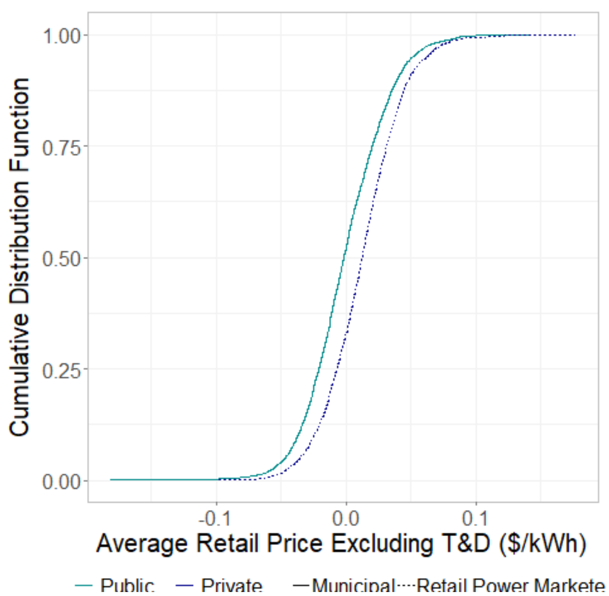


Figure 2.3: 2SLS Price Distributions under Conservative T&D Costs

Notes: Figures of average residential retail price normalized by marginal costs, lag marginal costs, and state and year fixed effects using a 2SLS regression. The top right figure is adjusted for state average delivery charges from Form EIA-861 and the bottom figure is adjusted for T&D costs equal to the lowest state average delivery charge from Form EIA-861 in the 13 analyzed states.

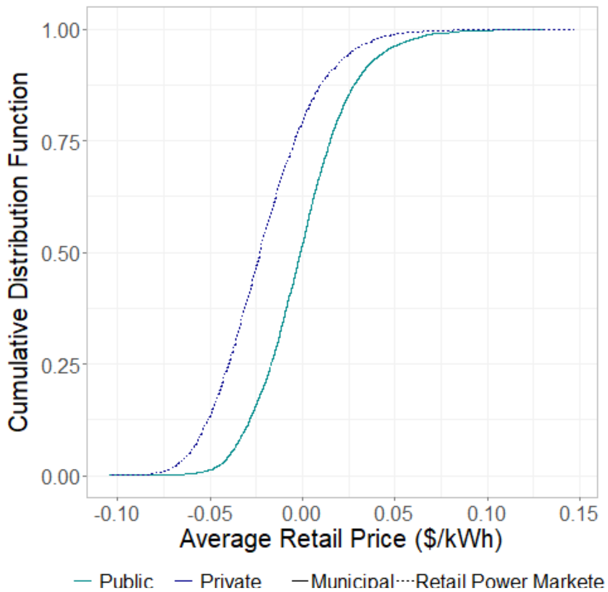


Figure 2.4: OLS Normalized Price Distributions

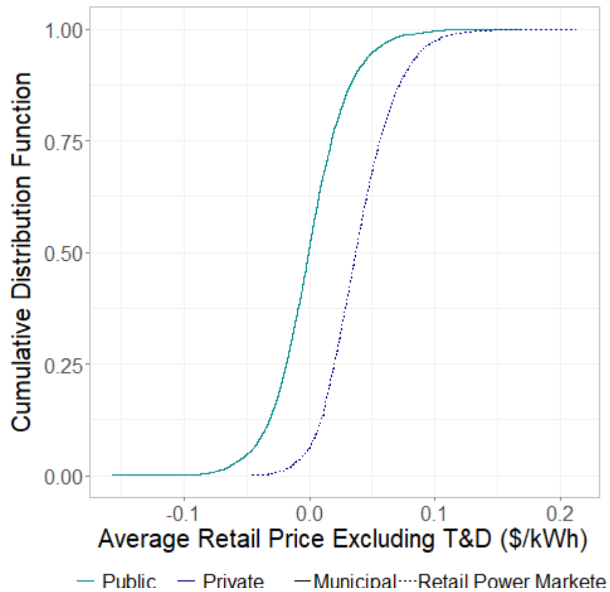


Figure 2.5: OLS Estimated Normalized Price Distributions

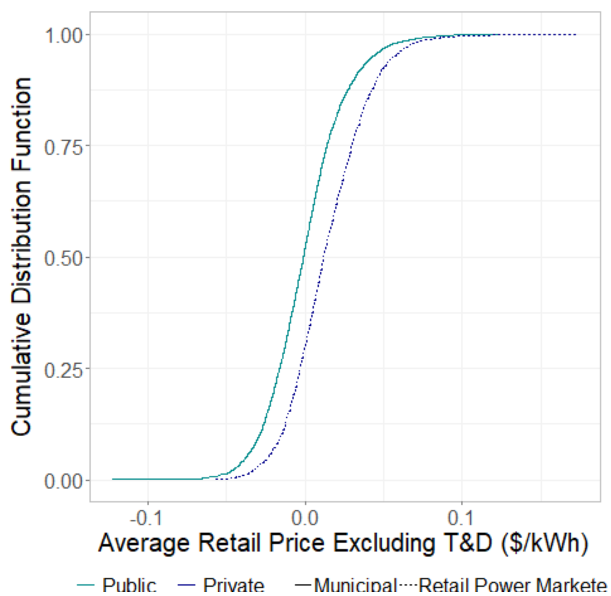


Figure 2.6: OLS Normalized Price Distributions

Notes: Figures of average residential retail price normalized by marginal costs, lag marginal costs, and state by year fixed effects using an OLS regression. The top right figure is adjusted for state average delivery charges from Form EIA-861 and the bottom figure is adjusted for T&D costs equal to the lowest state average delivery charge from Form EIA-861 in the 13 analyzed states.

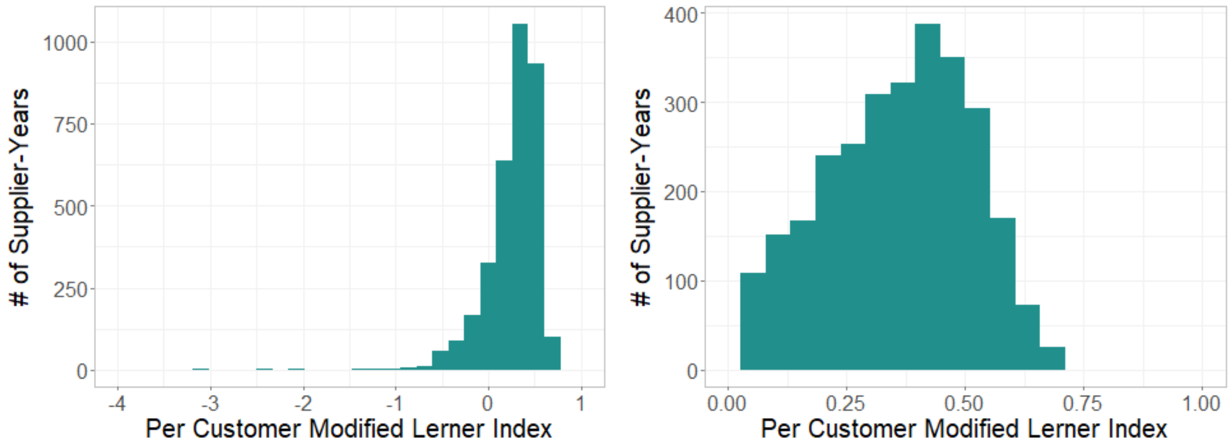


Figure 2.7: Modified Per-customer Lerner Index Distribution for Private Supplier Firm-Years, Full Distribution (left) and Truncated Distribution (right)

also be explained, however, by a larger local average treatment effect (LATE) than average treatment effect. The LATE captures the difference in pass through only when natural gas is the marginal fuel for electricity generation, which tends to occur in hours of moderate to high demand. This explanation is consistent with the fact that many municipal financial reports indicate ownership of generators for arbitraging electricity spot prices during peak demand hours.

Table 2.7: Pass Through Results

	Dependent variable:							
	ΔRetail$_t$ (\$/kWh)							
	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS
β_1: Private	-0.001^{***}	-0.0004	-0.0005	-0.0004	-0.0005	-0.001^{**}	-0.001	-0.0003
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
β_2: ΔMC$_{t-1}$	0.082^{***}	0.028	0.063^{*}	0.028	0.020	0.056	0.038	0.005
	(0.019)	(0.039)	(0.037)	(0.041)	(0.039)	(0.039)	(0.045)	(0.041)
β_3: ΔMC$_t$	0.038^{*}	-0.103^{**}	-0.049	-0.106^{**}	-0.103^{**}	-0.019	-0.092^{*}	-0.076
	(0.023)	(0.046)	(0.044)	(0.049)	(0.046)	(0.047)	(0.054)	(0.047)
β_4: Private $\times$ ΔMC$_{t-1}$	0.027	0.042	0.008	0.041	0.051	0.022	0.032	0.060
	(0.027)	(0.044)	(0.044)	(0.045)	(0.045)	(0.046)	(0.049)	(0.047)
β_5: Private $\times$ ΔMC$_t$	0.170^{***}	0.264^{***}	0.258^{***}	0.263^{***}	0.266^{***}	0.197^{***}	0.281^{***}	0.165^{***}
	(0.039)	(0.052)	(0.052)	(0.053)	(0.053)	(0.057)	(0.057)	(0.050)
Weighted	x	x	x		x	x	x	x
Includes State Trends			x					
Truncated MCs for Overlap					x			
Includes EIA Short Form Firms	x	x	x	x	x		x	x
Includes PA and IL	x	x	x	x	x	x		x
Includes NY	x	x	x	x	x	x	x	
F Test Statistics:								
$\beta_4 + \beta_5 = 0$	13	15	12	14	16	7	13	7
$\beta_2 + \beta_3 + \beta_4 + \beta_5 = 1$	312	249	176	244	248	253	169	275
$\beta_3 + \beta_5 = 1$	836	659	479	662	658	681	436	827
Observations	6,905	6,905	6,905	6,905	6,805	4,512	5,417	5,989

*p<0.1; **p<0.05; ***p<0.01. All standard errors clustered on supplier-state. All models include year fixed effects. All costs in 2017 \$/kWh.

Table 2.6 presents the first stage results for the main 2SLS specification. The instruments are jointly significant for all endogenous variables. Note that the estimated marginal cost pass through for competitive firms is 16%, which provides further evidence that the private markets are not perfectly competitive.

Discussion

These results suggest substantial market power exists in retail electricity markets. There is some reason to believe that market power will be even higher going forward because these estimates include some years with price regulations. Moreover, the difference between public and competitive firms may also become larger going forward because marginal costs were likely lower than anticipated during this period, causing many past hedging decisions by public firms to increase costs above marginal costs. While it is possible that fear of future regulation could put downward pressure on retail prices, there may be a need for additional regulation and information diffusion in competitive retail markets to improve consumer welfare. Following the theoretical work by Epple and Romano (1996), enabling public and private provision in the same markets may also further increase consumer welfare.

However, market power does not necessarily imply that private firms are earning exorbitant profits. A large markup above costs may be necessary for a functioning retail electricity market to cover fixed marketing and customer acquisition costs, which seem to be large (Joskow, 2008). In addition, to the extent that the municipal utility cost advantage comes from getting resource rents from pre-existing rights to a scarce resource, hydropower, external validity may be limited.

I end this discussion with two important caveats about the welfare analysis. One caveat is that this paper only analyzed consumer welfare as it relates to pricing. A full consumer welfare analysis would consider any differences in quality of service. Another caveat is that this analysis only analyzes consumer welfare, as a key motivation of both public and competitive provision of residential electricity is consumer well-being. However, consumer welfare may not be well aligned with total social welfare. The efficiency implications of the empirical results depend largely on whether prices lie above or below marginal costs (Borenstein and Bushnell, 2022a).

2.7 Conclusion and Next Steps

This paper finds evidence that consumer welfare was higher under government electricity provision than competitive retail provision in thirteen states in the U.S. over the period 2005-2017. Under conservative assumptions about uncertain costs, I show that retail electricity prices are higher under competition than government provision under any rational consumer preferences. Relaxing these assumptions, I find that the variance of retail prices are larger under competition.

The difference in price levels appears to be driven by market power in the retail markets. Using a modified Lerner Index analysis, I demonstrate substantial market power in the U.S. competitive retail markets.

The retail price variance analysis focuses on pass through of volatile marginal costs. While pass through may have efficiency gains and increase overall welfare, it decreases consumer welfare under the assumption of risk averse consumers.

These results highlight the need for future research in this area. Incorporating financial data on T&D costs from government-owned electricity suppliers would reduce bias and measurement error and, thereby, improve the key empirical estimates in this paper. Further exploring mechanisms could also further our understanding of the external validity of these results. It may be particularly fruitful to analyze how private firms exert market power and the role played by hydroelectric power generation rights in the retail prices offered by municipal utilities.

Chapter 3

Does Timing Matter? Impact of Time-based Rates on Energy Efficiency, Rooftop Solar, and Building Electrification

Note: Andrew Satchwell and Chandler Miller are coauthors on this chapter.

3.1 Introduction

Energy efficiency (EE), solar PV (PV), and building electrification are critical to meeting U.S. decarbonization goals (Williams et al., 2012, Nadel and Ungar, 2019, Langevin et al., 2022, US OSTP et al. 2023). Under current electricity rate designs and declining capital cost trends, the country has seen substantial and growing adoption of EE and PV (Consortium for Energy Efficiency, 2021; Barbose et al., 2022; Davis, 2022) and growing policy interest in electrification (e.g., Inflation Reduction Act 2022). At the same time, there is increasing regulatory support for time-varying electricity rate designs to better reflect system costs and encourage more economically efficient consumption (Satchwell et al., 2019). Under time-based rates, consumers pay different prices depending on the day or time-of-day. Since the social cost of providing electricity varies considerably across the hours of a year, time-varying rates can provide consumers with more efficient short-run price signals than conventional time-unvarying rates.

However, time-varying rates do not necessarily provide more economically efficient *long-run* price signals for consumers choosing whether to invest in EE upgrades, install PV, or switch from fossil fuel-based heating to electric heating. The transition to time-based rates has the potential to incidentally reduce bill savings from these investments, which could impact consumer incentives to adopt these critical GHG-reducing technologies and reduce social welfare. Policymakers may need to adjust non-rate incentives for these investments or risk undermining climate goals.

To exacerbate the potential issue, prospective adopters of these GHG-reducing technologies may also be limited in their ability to increase their bill savings by shifting the timing of their energy savings. The energy savings from many of these investments are highly price inelastic once installed. For example, consumers cannot shift the timing of their PV generation across days or hours of the day, and they have little to no incentive to curtail this generation.[1] Even for investments that facilitate price-responsive behavior, such as programmable thermostats, the majority of consumers either do not use the programming feature or keep the thermostats in manual mode (Pritoni et al., 2015).

This paper asks three questions about rate design and GHG-reducing technologies. First, how does electrification impact consumers' total energy bills? Second, how do consumers' incentives to invest in energy efficiency, rooftop solar, and electrification change as electricity rates become more time-varying? Third, does moving from flat rates to time-based rates result in more economically efficient investment decisions? Put differently, we first analyze a baseline of bill savings under current, non-time-varying rate designs. While EE and PV should consistently lead to bill savings, electrification could increase or decrease bills. We then compare these results to bill savings under time-based rates. An increase in bill savings could lead to more customer technology adoption, and a decrease in bill savings could reduce adoption. Next, by comparing bill savings to societal benefits, we assess whether customer technologies are over- or under-incentivized. Across all three questions, we explore heterogeneity across rate design characteristics, geographies, and investment types.

To answer these questions, we calculate residential bill savings and long-run social marginal costs from six different types of inelastic, GHG-reducing investments under 14 actual utility price schedules in four utility service areas. We use the National Renewable Energy Lab's ResStock simulations to capture the heterogeneity in these results across households due to differences in age, size, construction practices, installed equipment, appliances, climate, and resident behavior. In particular, we consider six different GHG-reducing ResStock investment packages: electrification, building envelope upgrades, lighting efficiency upgrades, general equipment efficiency upgrades, and PV. To capture a variety of climates and power system conditions, we analyze these upgrades in four utility service areas: Ameren in Illinois, Arizona Public Service (APS) in Arizona, Green Mountain Power (GMP) in Vermont, and Oklahoma Gas and Electric (OG&E) in Oklahoma.

We analyze a range of residential rate designs offered by these four utilities. They can be loosely classified into five categories: 1) "flat" rates that are time-invariant or vary only by season, 2) time-of-use (TOU) \$/kilowatt-hour (kWh) rates that vary systematically by season, hour of day, and whether the day is a non-holiday weekday, 3) rates with coincident \$/kilowatt (kW) demand charges where consumers pay each month based on their maximum kW demand during certain hours of the day, 4) event-based rates that have higher prices during a small number of hours of the year when there is especially high system demand, and 5) real-time prices that change dynamically based on day-ahead market conditions.

[1] Consumers can use storage to shift the timing of their electricity exports to the grid.

We estimate the societal benefits of each investment. These include all utility system costs avoided due to reductions in the quantity of electricity generated and delivered, the generating capacity reserved for grid balancing, the renewable generation procured to meet policy standards, and investments in new generation, transmission, or distribution capacity. We also include reductions in the external costs associated with carbon emissions and criteria pollutants from electricity generation. These avoided cost calculations closely follow Borenstein and Bushnell (2022a) for short-run marginal cost components and the 2019 Energy and Environmental Economics, Inc. (E3) 2019 Avoided Cost Calculator (ACC)[2] for additional long-run marginal cost components.

We find that electrification reduces many customer bills, and electrification paired with energy efficiency reduces average customer bills across all rate designs. Although electricity rates are high relative to natural gas and fuel oil, reductions in the energy consumed due to improved energy efficiency outweigh the cost increase from higher prices. This result suggests that there may be opportunities for programs to electrify households without burdening these households with higher bills.

We estimate that the impact of time-based rates on bill savings is typically small, but we also uncover large heterogeneity. The change in bill savings from moving from a flat rate to a time-based rate is less than 10% for most people and investments. Average bill savings decrease in about half of the cases we modeled and increase in the other half. We find particularly large percentage increases in bill savings with time-varying rates for building envelope upgrades in hot areas. Looking across rates, we find the largest percentage reduction in bill savings from the two demand charge rates we modeled.

Regardless of the direction of the change in private investment incentives, we find that implementing time-varying rate designs has the potential to improve or worsen the economic efficiency of investment decisions. There are two primary determinants of whether these rate designs improve economic efficiency: how average rate levels compare to average social marginal costs and the timing of the energy savings from the investment relative to the time-varying price schedule. We show that average rate levels and their relationship to social marginal costs have a larger impact on whether incentives are too high or too low than the rate design itself.

Our findings may help policymakers and utilities avoid unintended consequences of retail rate reforms on EE, PV, and building electrification adoption, potentially by adjusting other incentives for these investments accordingly. It is important to note that this analysis does not consider other market inefficiencies in EE or PV markets, such as the potential for under-adoption of EE and PV investments that are privately profitable (Gillingham and Palmer, 2014; De Groote and Verboven, 2019; Allcott and Greenstone, 2012). To the extent that policymakers have been relying on effective subsidies from older electricity rate designs to counteract these and other distortions in energy efficiency and solar panel markets, this research can be used in conjunction with other research on adoption behavior to determine appropriate incentive levels.

[2]Available at: https://www.ethree.com/public_proceedings/energy-efficiency-calculator/

This paper arguably provides the most comprehensive analysis to date of the impact of time-based rate designs on households' incentives to adopt GHG-reducing technologies. There is a small existing body of literature in this area. However, most of the case studies are restricted to one location and technology and analyze only one or two time-varying rates. Liang et al. (2021) compare bill savings from air conditioning in Arizona under a TOU rate and an increasing block rate. Borenstein (2007) similarly compares bill savings from PV under a TOU rate and an increasing block rate. Sergici et al. (2023) consider two types of TOU rates and analyze bill savings from heat pumps for 80 customers in an unnamed utility service territory. In contrast, we consider 12 different energy efficiency technologies, six building envelope efficiency upgrades, three PV orientations, four electrification measures, and 14 different rate designs for 39,526 households in four different geographies. The richness of these data allows us to uncover patterns and important drivers of heterogeneity.[3]

In addition, we employ cutting-edge social marginal cost estimation methods to explore implications for economic efficiency. Of the aforementioned rate design studies, only Liang et al. (2021) compare bill savings to marginal social avoided costs. We improve on these estimates in a few ways. We leverage Borenstein and Bushnell (2022a) to calculate marginal external damage estimates that better reflect the type of generation displaced in each hour and location. We also use marginal estimates of distribution losses and deferred distribution capacity costs as opposed to average estimates, and we use long-run estimates for deferred generation capacity costs as opposed to short-run estimates. We also consider state renewable energy policies in the avoided cost calculations. With these changes, our estimates better reflect the variation in social marginal costs over hours of the year, with relatively higher costs during periods of high demand.

This paper also advances the literature on the impacts of electrification on household bills by analyzing the role of energy efficiency improvements. Our findings depart from existing research, which estimates that average bills will increase from electrification (e.g., Davis, 2022). A key distinction is that Davis (2022) focuses on the electrification of new buildings and assumes electric and natural gas heating efficiencies both match efficiencies of the current housing stock. In contrast, this paper analyzes retrofits and considers energy efficiency differences between retired and new appliances.

This paper proceeds as follows. Section 2 outlines our analytical approach. Section 3 presents the results of our analyses. Section 4 discusses policy implications and concludes.

[3]Other studies have looked at the impact of non-time-varying rate design components, such as fixed charges and inclining block rates (Novan and Smith, 2018; Darghouth et al., 2016). There are also related literatures on the social marginal costs of energy efficiency investments (Boomhower and Davis, 2020) and on the correlations between time-of-use rates, event-based rates, and real-time-prices (Hogan, 2014; Schittekatte et al., 2022; Sallee et al., 2023).

3.2 Analytical Approach

Determining energy saving from EE, PV, and electrification

We use NREL's September 2022 release of the ResStock database to estimate hourly baseline electricity usage under the current housing and appliance stock as well as hourly savings from energy efficiency and electrification. These hourly usage and saving shapes come from physics-based simulation models. NREL created the ResStock data set with funding from the U.S. Department of Energy (DOE) to estimate the energy use and energy-saving potential of the national U.S. residential building stock and the building stock of each U.S. locality. The NREL researchers aimed to create a representative sample of buildings with a realistic diversity of building types, vintages, sizes, construction practices, installed equipment, appliances, occupant behavior, and climate zones. The researchers calibrated and validated the model results using empirical data on actual energy use in buildings, including metered utility data from more than 2.3 million customers throughout the country and circuit-level sub-metered data (Pigman et al., 2022; Wilson et al., 2022).

NREL researchers combine the ResStock information about the existing appliances and building characteristics with known energy efficient and electric alternatives to model feasible energy efficiency upgrade packages. We select four of these packages for our analysis:

- Electrification: The electrification package replaces non-electric space and water heating with electric alternatives, including heat pump water heaters and air-source or multi-source heat pumps for space heating. The package also includes improved ducting and energy efficiency upgrades of electric or non-electric appliances, including clothes dryers and cooking ranges.

- Equipment: The equipment package replaces existing electric air conditioning, space heating, water heating, refrigerators, clothes washers and dryers, and cooking ranges with more efficient alternatives.

- Envelope: The envelope package improves attic and exterior wall insulation and adds exterior storm windows.

- Lighting: The lighting package replaces all existing light bulbs with light-emitting diodes (LEDs).

See Appendix C.3 for detailed information on the specific upgrades embedded in each of these upgrade packages.

Using engineering-based estimates of energy efficiency savings has its limitations. Researchers have shown that realized energy efficiency savings are sometimes much lower than predicted savings from engineering estimates (Davis et al., 2014; Levinson, 2016; Allcott and Greenstone, 2017; Fowlie et al., 2018; Christensen et al., 2021). However, our key results focus on the shape of energy efficiency savings as opposed to the absolute level of savings. Our results will still be accurate if prediction error in savings is proportional to actual realized savings.

For PV generation shapes, we use residential rooftop generation data from NREL's System Advisor Model (SAM). We consider three potential PV orientations: south-facing, southwest-facing, and west-facing. Regardless of orientation, we assume all households size their PV systems to offset their annual electricity usage, so the implied system capacity varies with orientation. We select one PV generation shape for each utility service area and PV system orientation.

All energy usage and generation shapes reflect 2019 weather patterns.

Calculating Social Marginal Avoided Costs

This section summarizes how we calculate the long-run social marginal costs of a change in residential electricity usage due to energy efficiency or behind-the-meter solar PV. These social marginal cost calculations closely follow Borenstein and Bushnell (2022a) for short-run marginal cost components and the Energy and Environmental Economics, Inc. (E3) 2019 Avoided Cost Calculator (ACC) for additional long-run marginal cost components. Short-run marginal cost components capture incremental costs of a residential customer using one additional kilowatt-hour (kWh) of electricity, assuming that the level and composition of generation, transmission line, and distribution line capacity are fixed. We estimate long-run marginal costs, which reflect the incremental costs of one additional kWh of residential electricity usage when we allow for generator entry, exit, and distribution capacity expansion.

We estimate the marginal costs to society, which include all private costs and external costs that are not transfer payments between people. Importantly, these marginal costs are independent of rate level or rate design since electricity bills are transfer payments from consumers to the utility. Private marginal costs are monetary costs included in a utility's revenue requirement and ultimately borne by electricity consumers, i.e., ratepayers. External costs capture all other indirect costs borne by people globally, including costs related to health, agricultural output, materials, recreation, and climate change.

Specifically, we model eight private marginal cost components: energy, transmission congestion, transmission losses, distribution losses, ancillary services, Renewable Portfolio Standard (RPS) policy compliance, and distribution system and generation capacity expansion. Generation capacity costs encompass both thermal generation capacity expansion in the absence of a RPS and incremental generating capacity costs due to RPS compliance. In addition to these private costs, we estimate the external costs associated with carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrous oxides (NO_X, $PM_{2.5}$), and fine particulate matter ($PM_{2.5}$) emissions from electric generation.

There is some debate about what cost components vary with a 1 kWh change in electricity usage and should, therefore, be included in social marginal costs. In addition, there are vastly different perspectives on the most appropriate magnitudes of some cost component inputs, such as the social cost of carbon (Rennert et al., 2021). Our approach in this paper is to include these cost components and present results broken down by social marginal cost category so that readers can understand the impact of excluding or modifying specific marginal cost components on the results.

We consider an annual snapshot of social marginal costs in 2019. This snapshot approach does not take into account any future changes to the generation resource mix or any anticipated changes in the marginal value of energy efficiency and distributed PV with larger penetrations of energy efficiency and distributed generation. This approach is appropriate for comparing social marginal costs and 2019 retail rates.

Table 3.1 summarizes the cost components we include in the analysis and the data sources we use to estimate each component. See Appendix C.2 for a more detailed discussion of social marginal cost calculations, the rationales behind the chosen methods, and a summary of the resulting estimates.

Selecting Time-based Rate Designs

We focus the analysis on a diverse set of existing and historical utility rate schedules to capture variation in outcomes under realistic implementations of time-based rates. Although the shift to time-based rates primarily aims to make rates better reflect temporal variation in costs, designing any utility rates involves balancing many competing objectives and considering the perspectives of many different stakeholders. As a result, time-based rates may differ substantially from social marginal costs in practice and may vary considerably across utilities.

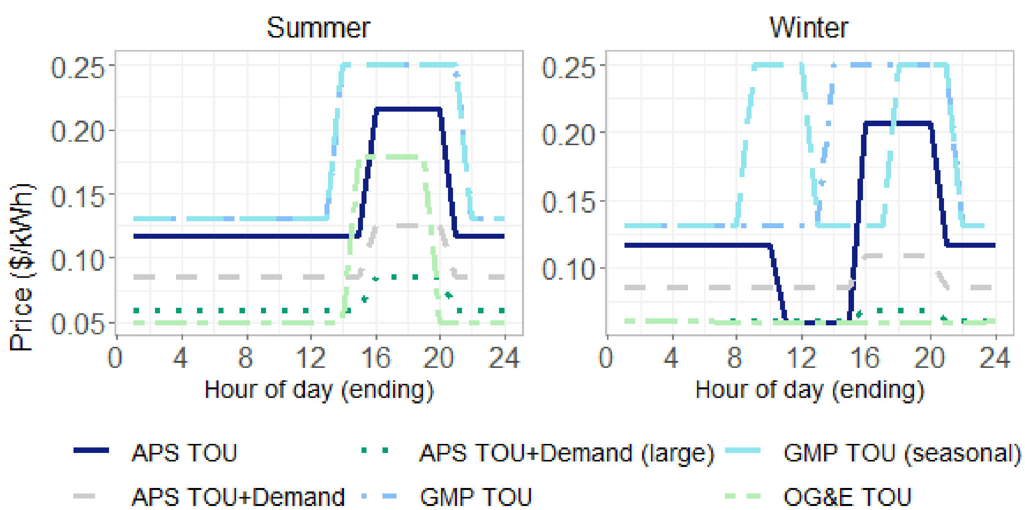
Our ten selected time-based rates come from four utility service areas and include a variety of rate components. This variety enables us to capture heterogeneity in time-based rate impacts due to real-world differences in rate design perspectives and climates. From Ameren, we consider a real-time-price (RTP) rate, known as "Power Smart Pricing", that dynamically updates each day based on forecasted hourly costs. From Arizona Public Service (APS), we select three time-based rates. The first is a time-of-use (TOU) rate with a higher $/kWh rate in the late afternoon and early evening "on-peak" period than the rest of the day and an especially low $/kWh rate midday in the winter. The other two APS rates have $/kWh TOU components and coincident $/kW demand charges. Each month, households pay a demand charge based on their highest kW usage during the on-peak period. The two demand charge rates differ in the magnitude of the demand charge. We model four time-based rates for Green Mountain Power (GMP). A TOU rate has relatively high prices in the afternoon and evening. An Event rate has a very high price for up to ten days a year during the afternoon and evening. GMP also has a TOU+Event rate with both TOU and event pricing components. The fourth rate is a seasonal TOU rate with a relatively high price in the afternoon and evening during the summer and in both the morning and evening during the winter. Finally, we model a TOU and an Event rate for Oklahoma Gas and Electric (OG&E). The TOU rate has a relatively high price on Summer afternoons and early evenings. The event rate uses the same on-peak period, but OG&E sets the on-peak price dynamically to equal the average day-ahead predicted wholesale electricity price during those hours. In the winter, the OG&E TOU and event rate have declining-block schedules

Table 3.1: Marginal Avoided Cost Component Data Sources

Cost component	Description	Data sources
Energy (including transmission congestion & losses)	The location-specific cost of generating a marginal kWh of electricity and transporting it to a given location in the transmission network	FERC Form 714, SNL Financial, Ventyx, ISONE, MISO, SPP, Borenstein and Bushnell (2022a)
Ancillary services	The incremental cost of balancing electricity demand and supply	2019 E3 Avoided Cost Calculator
Distribution losses	The additional cost of electricity that enters the distribution network but is not delivered to consumers	Borenstein and Bushnell (2022a), FERC Form 714, Ventyx
Generation capacity	For markets in need of new capacity, the marginal cost of attracting a new combustion turbine (or the benefits of deferring an investment). For markets with excess electricity supply, the capacity payment needed for the marginal generator to commit to being available during high-demand hours	2019 E3 Avoided Cost Calculator, ISONE, EIA, Borenstein and Bushnell (2022a), NOAA
Distribution capacity	The cost of adding additional capacity on distribution wires (or the benefits of deferring such an upgrade)	The Mendota Group LLC (2014), ResStock
RPS compliance	The net incremental cost of providing renewable generation to comply with a Renewable Portfolio Standard	2016 E3 Avoided Cost Calculator, Luckow et al. (2015), NREL, DSIRE, Gorman et al. (2019)
Carbon	The social cost of CO_2 emitted due to the incremental output of the marginal generator	Borenstein and Bushnell (2022a)
Other environmental damages	The costs of SO_2, NO_X, and $PM_{2.5}$ emitted due to the incremental output of the marginal generator	Borenstein and Bushnell (2022a)

where the marginal price decreases after a customer uses 600 kWh in a month. Figure 3.1 plots the hourly summer and winter rates for the six price schedules with TOU components and no event-based components, and Figure 3.2 shows average prices under each event and dynamic rate by hour of day for four sample months.

Figure 3.1: Time-of-Use Rates



For comparison, we also use the default rate schedules for each utility. All of these default rates are two-part tariffs with fixed monthly charges and variable \$/kWh charges. In APS and GMP, the default rate schedule has one \$/kWh price that is constant throughout the year. In Ameren, there are two distinct \$/kWh prices: one for the summer months (June-September) and another for the other (i.e., "winter") months. In OG&E, the default rate schedule has a declining block design in the winter and an inclining block design in the summer. In the summer, a customer's marginal price increases after they use 1,400 kWh in a month. For simplicity, we refer to all of these rates as "flat" since they do not vary by time of day.[4]

Table 3.2 presents summary statistics of all the rate schedules used in the analysis. The right column presents the correlation between the hourly \$/kWh rates and estimated hourly social marginal costs described in Section 3.2. Notably, the correlation between the RTP rate and social marginal costs is only 0.23 due to rate design despite using the same wholesale electricity prices to calculate prices and social marginal costs.

[4]All together, we use the 2019 versions of the following residential rate schedules: Ameren Basic Generation Service, Ameren Power Smart Pricing, APS TOU-E, APS R-1, APS R-2, APS R-3, GMP R-1, GMP R-9, GMP R-11, GMP R-24, GMP R-22, OG&E R-1, OG&E R-TOU, and OG&E R-VPP. To learn more about these rate schedules, visit the Ameren, APS, GMP, and OG&E websites.

Figure 3.2: Average Prices by Hour and Month for Event and Dynamic Rates

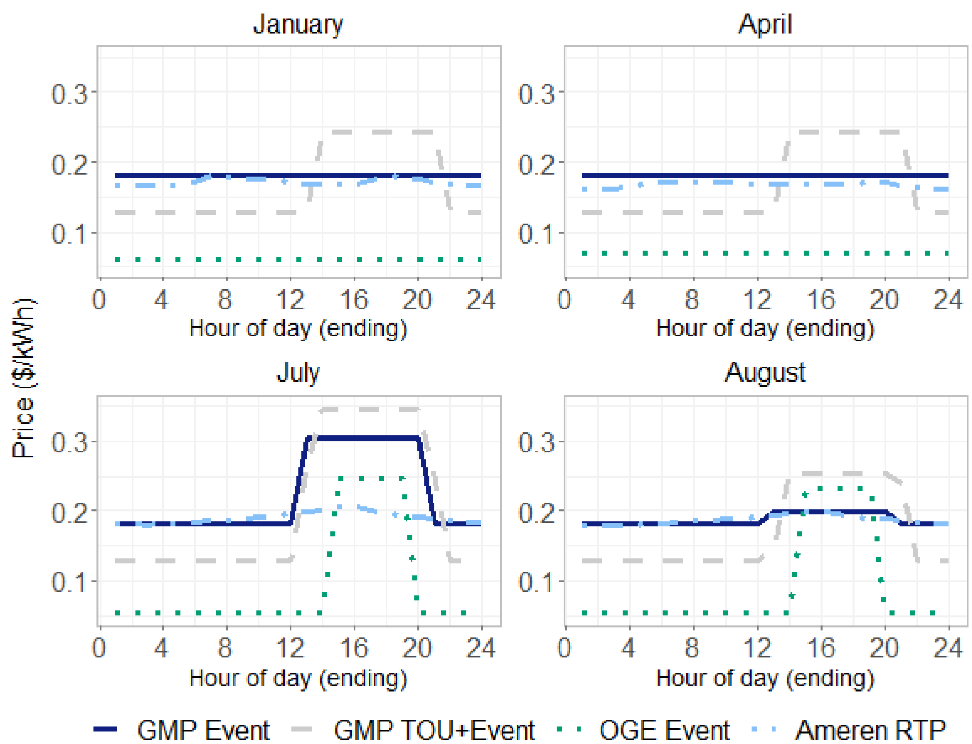


Table 3.2: Rate Summary Statistics

Utility	Rate Name	Fixed Charge ($/mo)	Demand Charge Max $/kW	Variable Price ($/kWh) Min	Med	75th	95th	Max	SD	r
Ameren	Flat	13.98	0.00	0.18	0.18	0.21	0.21	0.21	0.01	0.08
	RTP	16.23	0.15	0.14	0.17	0.18	0.20	0.29	0.01	0.23
APS	Flat	17.56	0.00	0.13	0.13	0.13	0.13	0.13	0.00	0.00
	TOU	15.55	0.00	0.04	0.12	0.12	0.25	0.25	0.05	0.13
	TOU+Demand	15.55	8.40	0.09	0.09	0.09	0.14	0.14	0.02	0.16
	TOU+Demand (large)	15.55	17.44	0.06	0.06	0.06	0.09	0.09	0.01	0.18
GMP	Flat	15.26	0.00	0.19	0.19	0.19	0.19	0.19	0.00	0.00
	Event	15.26	0.00	0.18	0.18	0.18	0.18	0.73	0.05	0.11
	TOU	20.34	0.00	0.13	0.13	0.13	0.29	0.29	0.07	0.14
	TOU+Event	20.34	0.00	0.13	0.13	0.13	0.28	0.73	0.09	0.16
	TOU (seasonal)	20.34	0.00	0.13	0.13	0.13	0.29	0.29	0.07	0.16
OGE	Flat	13.00	0.00	0.05	0.08	0.09	0.09	0.09	0.02	0.06
	TOU	13.00	0.00	0.05	0.05	0.09	0.09	0.22	0.04	0.27
	Event	13.00	0.00	0.05	0.05	0.09	0.15	0.28	0.05	0.31

Note: Summary statistics of the rates used in the analysis. The fixed charge is in $ per month. In order, the subheadings under variable price stand for minimum, median, 75th percentile, 95th percentile, maximum, standard deviation, and the Pearson correlation coefficient of correlation between the hourly $/kWh rates and estimated hourly social marginal costs.

Economic Efficiency

Is it beneficial to society to increase or decrease the bill savings from investing in EE or PV? We compare investment incentives to their economically efficient levels to answer this question. Quantifying welfare changes with rate design changes would require strong assumptions about consumer behavior. Instead, we primarily focus on a key component of economic efficiency: the deviation of bill savings from avoided societal costs, or the size of the investment externality per kWh. Our primary metric for charts is the ratio of annual bill savings from an investment to the annual avoided social costs from the investment. We refer to this ratio as the *incentive ratio*. With rational consumers and perfect information, an incentive ratio above one indicates over-investment, while an incentive ratio below one indicates under-investment. The further the incentive ratio is from one in either direction, the larger the deadweight loss is due to inefficient investments.

Many rate components change across tariffs, including the size of a fixed \$/month charge. Since energy efficiency and PV cannot avoid fixed charges, larger fixed charges will mechanically lead to lower bill savings. To focus on the impact of the time-varying component of rates, we normalize utility rates to their fixed charge under the basic rate. The thought exercise is to estimate the incentive ratio if the only changes to the rate were changes in the timing of \$/kWh and \$/kW charges. We achieve this by shifting all \$/kWh hourly rates by the weighted average basic rate less the weighted average \$/kWh rate and average demand charges per kWh, as shown in the following equation:

$$
\begin{aligned}
&(\$/kWh\ Rate\ Normalized)_h = \qquad (1)\\
&\quad (\$/kWh\ Rate)_h + \frac{\sum_h (Basic\ \$/kWh\ Rate)_h (\times Class\ kWh\ Usage)_h}{\sum_h (Class\ kWh\ Usage)_h}\\
&\quad - \frac{\sum_h (\$/kWh\ Rate)_h \times (Class\ kWh\ Usage)_h}{\sum_h (Class\ kWh\ Usage)_h} - \frac{Class\ Demand\ Charges\ (\$)}{\sum_h (Class\ kWh\ Usage)_h}
\end{aligned}
$$

We report mean usage-weighted incentive ratios and 95% confidence intervals. We bootstrap standard errors to calculate these confidence intervals. Specifically, we take 1,000 different customer samples and calculate the mean usage-weighted incentive ratios for each sample. We do not bootstrap standard errors for PV since we use the same PV generation shape for all households in a utility service area. Bootstrapping incentive ratios using these data would suggest false precision.

We also analyze the relative welfare impacts of rate design and average variable rate level. Average variable electricity rates frequently differ from average social marginal costs, which can contribute to over- or under-investment of GHG-reducing technologies (Borenstein and Bushnell, 2022b; Novan and Smith, 2018). We estimate these deviations of average variable basic rates from social marginal costs. We also consider four aspects of a rate design: the variance in price over hours of the year, the correlation between hourly \$/kWh price and social marginal costs, the correlation between \$/kWh price and energy savings from each investment, and the \$/kW demand charge. Specifically, we compare the importance of rate design relative to variable rate levels for economic efficiency under time-based rates by estimating the following models:

$$\begin{aligned}(Overinvest)_{ijur} =&\beta_1(Avg\ Flat\ Rate)_u + \beta_2(Fixed\ Charge)_{ur}\\&+ \beta_3(\$/kWh\ variance)_{ur} + \beta_4 cor(p_{ur}, (kWh)_{ijur})\\&+ \beta_5 cor(p_{ur}, (AC)_{iju}) + \beta_6(Max\ \$/kW\ Charge)_{ur} + \varepsilon_{ijur}\end{aligned} \tag{2}$$

and

$$\begin{aligned}|(Savings)_{ijur} - AC_{iju}| =&\beta_1|(Avg\ Flat\ Rate)_u - AC_{iju}| + \beta_2(Fixed\ Charge)_{ur}\\&+ \beta_3(\$/kWh\ variance)_{ur} + \beta_4 cor(p_{ur}, (kWh\ savings)_{ijur})\\&+ \beta_5 cor(p_{ur}, (AC)_{iju}) + \beta_6(Max\ \$/kW\ Charge)_{ur} + \epsilon_{ijur}\end{aligned} \tag{3}$$

where $(Savings)_{ijur}$ is the per-kWh bill savings for consumer i in utility u from making investment type j under time-based rate schedule r, AC_{iju} is the associated per-kWh societal avoided costs, $(Overinvest)_{ijur}$ equals one if $(Savings)_{ijur} > AC_{iju}$ and zero otherwise, $(Fixed\ Charge)_{ur}$ is the annual fixed charge under the rate schedule, $(\$/kWh\ variance)_{ur}$ is the variance in \$/kWh price over the hours of the year, $cor(p_{ur}, (kWh)_{ijur})$ is the Pearson correlation coefficient of this hourly price and the consumer's hourly energy usage, $(Max\ \$/kW\ Charge)_{ur}$ is the maximum monthly \$/kW demand charge under the rate schedule, and ε_{ijur} and ϵ_{ijur} are normally-distributed error terms. We cluster standard errors at the investment-utility-rate level. For the PV analysis, we drop the consumer subscripts to more accurately reflect the variation in our energy savings data. To reduce the influence of outlier households in the EE analysis, we exclude observations with values of bill savings less avoided costs above the 99th percentile and below the 1st percentile.

We estimate each of these two models in three ways: without constraints, fixing $\beta_1 = \beta_2 = 0$, and fixing $\beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$. We compare the adjusted R^2 across specifications to determine which of average variable rate levels and time-based components of rate design have larger explanatory power on whether there is over- or under-investment and the deviation between bill savings and avoided costs.

We use this analysis, theory, and mean incentive ratios by rate, investment, and utility to draw additional conclusions. We discuss the key drivers of variation in incentive ratios across investments and geographies. We also explore the impact of time-based rates on the variance of deadweight loss from investment decisions.

3.3 Results

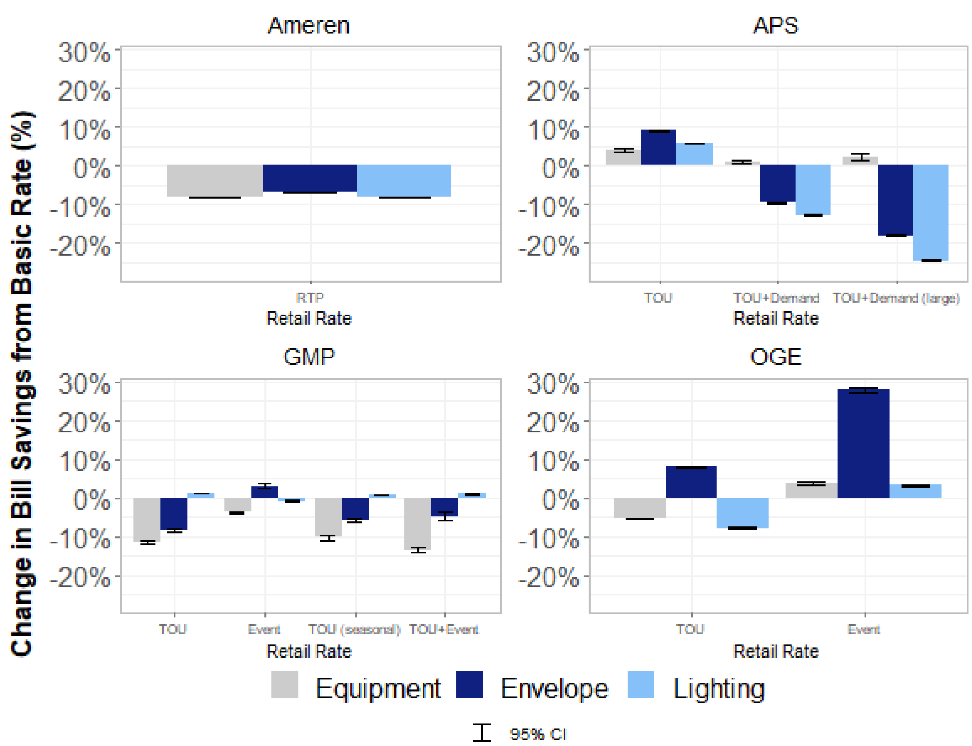
Bill Savings

Energy Efficiency

Energy and bill savings are highly correlated under basic rates, and time-based rates only slightly reduce this correlation. For APS and GMP, energy and bill savings are perfectly correlated under the basic rate. Even with the seasonality of Ameren and OG&E's basic rates and OG&E's declining block rate structure, the Pearson correlation coefficients of energy and bill savings under these basic rates are over 0.99. With time-based rates, these correlations decrease slightly across all utilities and rate schedules. As a result, time-based rates increase the variance of bill savings from energy efficiency investments. However, customer bill savings are still largely driven by energy savings. Within-utility Pearson correlation coefficients between total energy and total bill savings are over 0.96. We, therefore, focus the rest of our discussion using two metrics: 1) bill savings per kWh of energy savings and 2) percentage change in bill savings from an investment relative to a utility's basic rate.

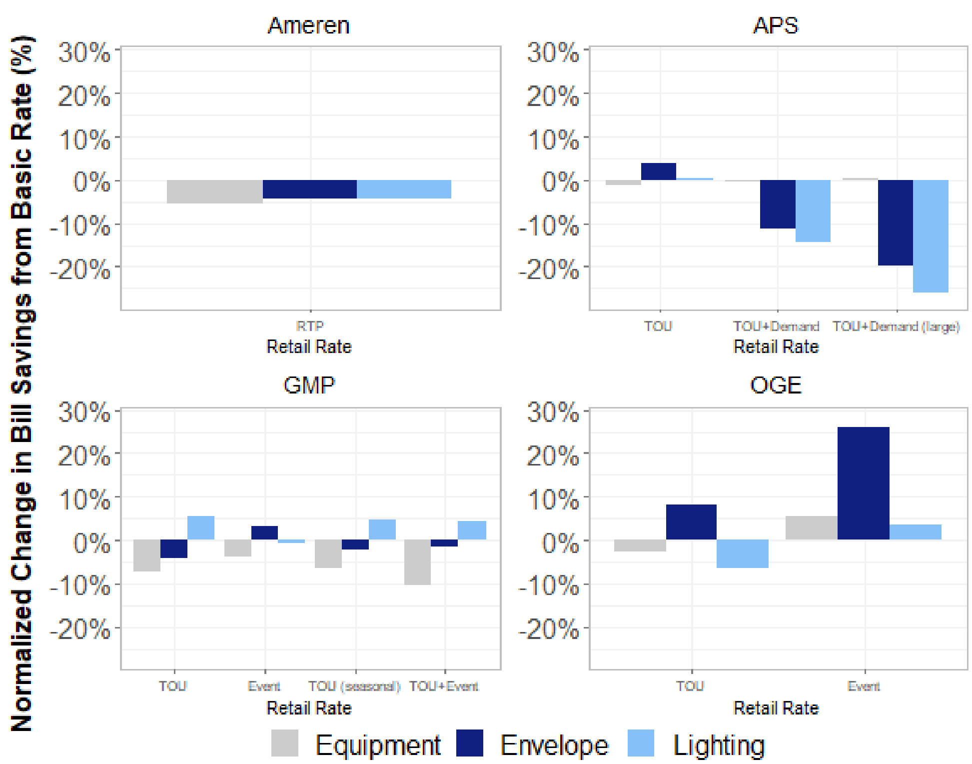
Figure 3.3 shows mean percentage changes in bill savings from moving from a flat to a time-based rate (i.e., a TOU, event, or RTP rate) by rate schedule and energy efficiency upgrade type. The average impact on bill savings is less than 10% in most cases. For about 40% of investments and rates, the mean percentage bill savings change is less than 5%. We can attribute some of these bill impact to differences in fixed charges. If fixed charges stayed constant across rate designs, we estimate that the mean change in bill savings would be less than 5% for the majority of investments and rates, as shown in Figure 3.4.

Figure 3.3: Change in Bill Savings: Energy Efficiency



However, there is large heterogeneity in the impact of time-varying rate designs on bill savings across energy efficiency upgrades, rates, and geographies. We observe particularly

Figure 3.4: Normalized Change in Bill Savings: Energy Efficiency



large percentage increases in bill savings with OG&E's variable peak pricing plan for building envelope upgrades, likely because envelope upgrades save more energy during periods of high system cooling demand when wholesale electricity prices are especially high. At the other extreme, the rates with demand charges lead to the largest average percentage reductions in bill savings from lighting and envelope upgrades. Under these rates, a large percentage of a customer's bill comes from usage in one hour of the month, so energy savings have to be very large during this one hour to offset the lower price in all other hours. These savings may also need to be sustained for multiple hours to reduce demand charges substantially. In addition, the peak period in the APS demand charge rates includes many daylight hours in the summer, when lighting demand is low.

These findings illustrate some patterns that may be more generalizable. For example, time-based rates seem to reduce bill savings from efficient lighting in areas with peak demand in the summer and increase these savings in winter-peaking areas, although this result is not significant with utility by rate by investment clusters since we only have four utilities. The pattern may be due to differences in the coincidence of lighting demand with heating and cooling demand. Households use lighting most at night and in the winter, when heating demand may be high and cooling demand may be low.

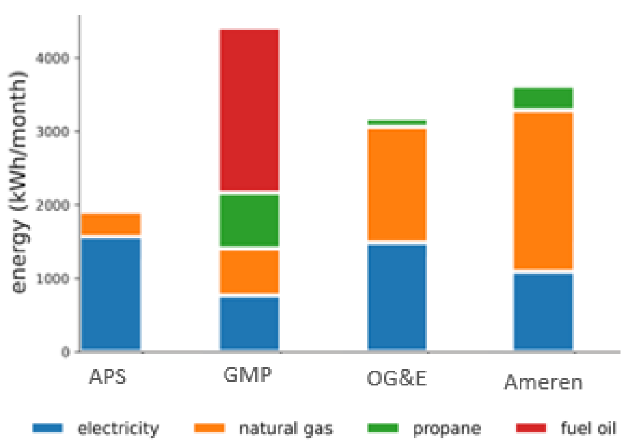
We also find substantial heterogeneity in the bill-saving impacts of time-based rates across households. Overall, the standard deviation in the percentage change in bill savings is 28 percentage points, with the 90% confidence interval ranging from a bill savings reduction of 25% to a bill savings increase of 34%. We observe especially large variations in savings under the APS demand charge rates, the OG&E variable peak pricing rates, and the APS TOU rate. This result may be driven be the especially short peak periods in these rate schedules.

Fuel Switching

While bill savings for energy efficiency and PV upgrades are only impacted by changes in the level and shape of electricity consumption, bill savings for fuel switching depend on the change in electricity consumption, the change in consumption of other fuels, and the differences in the volumetric energy costs for non-electric fuels and electricity. Non-electric fuels in the baseline building stock include natural gas, propane, and fuel oil. All utilities have households that use natural gas for heating, and all utilities except for APS have homes that use propane. Some households in GMP also use fuel oil.

Figure 3.5 shows the shares of non-electric fuels in the baseline building stock for fuel switching. Table 3.3 shows average fuel costs for each fuel converted to cents/kWh based on heat content. The volumetric rates of non-electric fuels are lower than electricity rates in nearly all cases.

Figure 3.5: Source of Energy in Baseline Building Stock



While the current general perception is that fuel switching always leads to energy bill increases because of this differential in electricity rates (e.g., Davis, 2022), we find many instances of energy bill reductions. We compare the total energy costs from water and space heating for households that electrified these end uses under the basic rates. On average, consumers in APS and OG&E save money, while consumers in Ameren and GMP spend more. Recall that APS and OG&E have lower average electricity rates than Ameren and GMP.

Table 3.3: Average Fuel Prices in cents/kWh

	Ameren	APS	GMP	OG&E
Electricity (basic rate)	19.1	13.2	18.8	8.5
Natural Gas	2.3	5.4	4.7	1.5
Propane	11.3	7.0	11.3	11.3
Fuel Oil	-	-	6.3	-

When we bundle electrification with additional energy efficiency investments, we find a much higher prevalence of bill savings and ubiquitous reductions in total energy consumption. Ninety percent of households experience at least a 20% decrease in energy consumption when they receive the ResStock electrification and energy efficiency bundles. For some households, the lower consumption outweighs the higher energy rate and leads to net reductions in energy bills. In fact, for APS and OG&E, all households experience net bill reductions under the basic rate with average bill savings greater than 25%. For GMP and Ameren, average bill savings under the basic rate are approximately centered around zero. These differences across utilities are partially due to price differences and partially due to the lower heating load in the APS and OG&E areas.

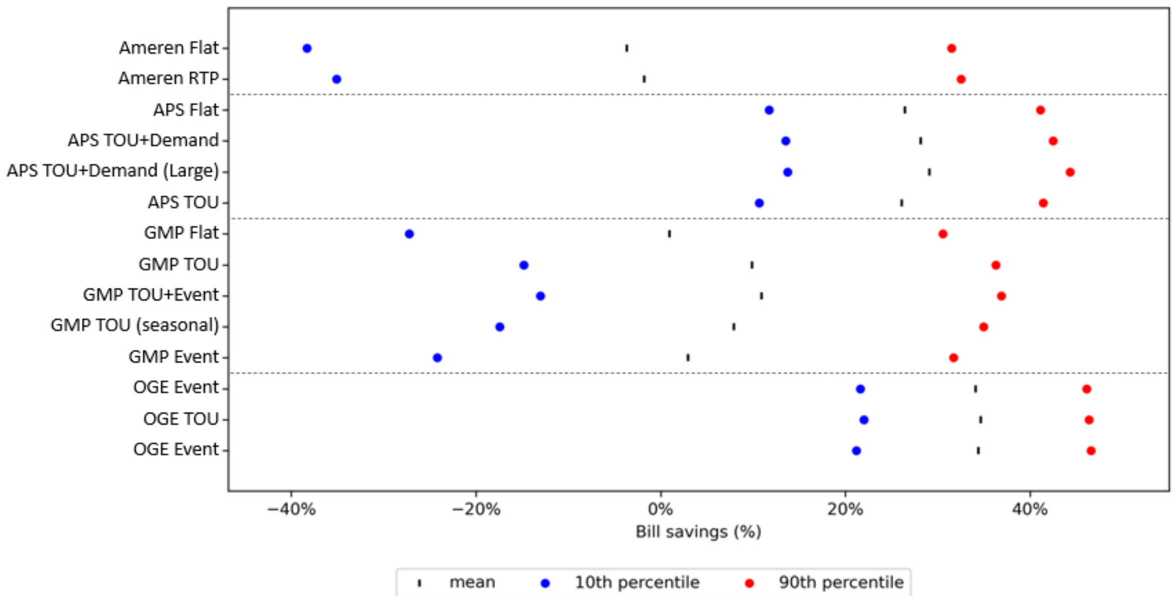
We also find considerable heterogeneity in bill savings from the electrification and energy efficiency bundle across households within a utility service area. For example, in Ameren's service territory, ten percent of households experience bill savings of more than 25% under the basic rate, while another ten percent of households experience bill increases of at least 40%. Figure 3.6 shows the bill savings distribution for each utility. The variance in electrification-induced bill impacts is larger than the variance in energy efficiency bill impacts. Across all households, rates, utilities, and technologies, the standard deviation in percentage bill savings is 16 percentage points for electrification compared to 10 percentage points for energy efficiency.

Moving from basic to time-based rates generally increases incentives to invest in electrification and energy efficiency bundles. Similar to the results for energy efficiency alone in Section 3.3, the change in bill savings tends to be small. Figure 3.6 shows each rate schedule's mean, 10th percentile, and 90th percentile bill savings. Within a utility, most rates shift the distribution of savings right. All but one of the time-based rates increase average bill savings.

Solar PV

The impacts of time-based rates on bill savings from PV can be larger than those of EE, and these impacts vary considerably across utilities, rates, and PV orientations. Unlike EE, PV generation is limited to daytime hours, which may make savings more sensitive to temporal price variation. Figure 3.7 shows the percent change in bill savings per kWh generated relative to the basic rate by PV orientation and rate. Figure 3.8 presents the same

Figure 3.6: Bill Savings from Fuel Switching by Rate



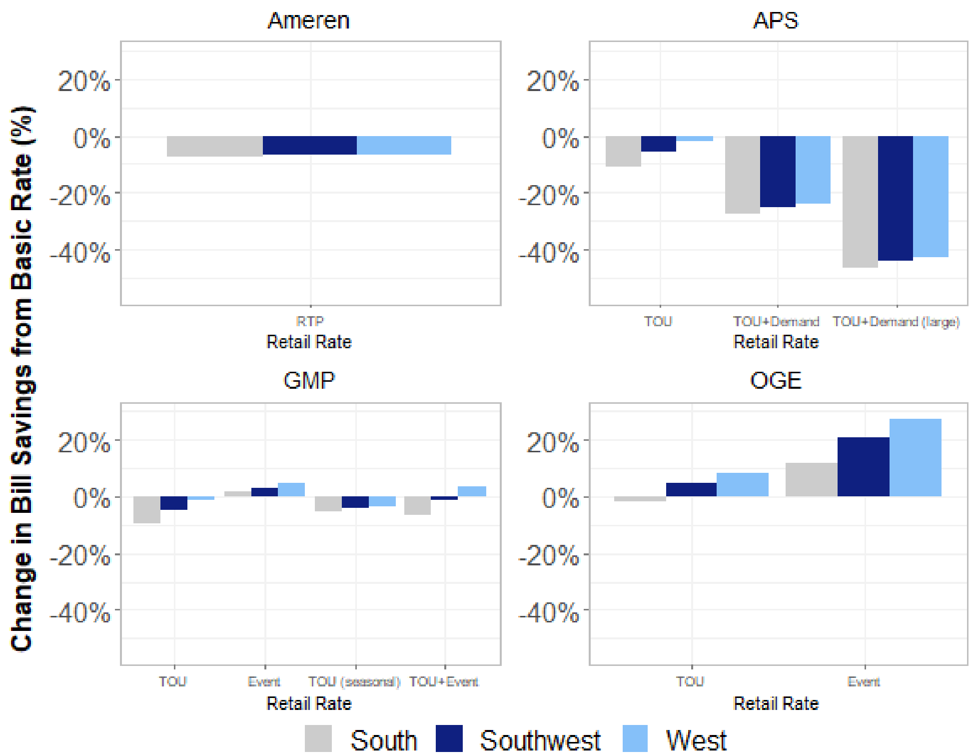
results after normalizing the fixed charges to equal the fixed charge in the relevant utility's basic rate. Recall that this isolates the effect of the time-varying component of rates.

Time-varying rates consistently increase bill savings more — or decrease savings less — for west-facing systems than south-facing systems. Under flat rates, bill savings per kWh do not depend on PV orientation. As shown in Figure 3.7, west-facing systems receive the largest savings per kWh, and south-facing systems receive the smallest savings per kWh for every time-varying rate modeled.

The impact of time-based rates on bill savings from PV varies substantially across the utilities and rates studied. In APS, time-based rates reduce bill savings across all rates and orientations, with one rate cutting savings by about half. In OG&E, time-based rates increase bill savings in most cases, with saving increases up to 27%. The APS demand charges largely drive these bill savings differences, although small differences in the on-peak hours and the APS TOU rate's winter midday super off-peak period also contribute. In this small sample of rate designs, households that install PV receive relatively high bill savings under event rates and relatively low savings under rates with demand charges. To avoid demand charges, the PV system must generate during households' peak monthly demand, which is frequently around 6 PM in APS.

Comparing Figures 3.7 and 3.8 shows the importance of fixed charges for bill savings. For example, households see bill reductions around 7% under Ameren's RTP rate, but the increase in the fixed charge entirely drives this result. Isolating the change in variable rates, we observe bill savings increases of less than 0.3% from the RTP rate. Similarly, many GMP rates that reduce PV bill savings relative to the basic rate would lead to higher

Figure 3.7: Change in Bill Savings: Solar PV



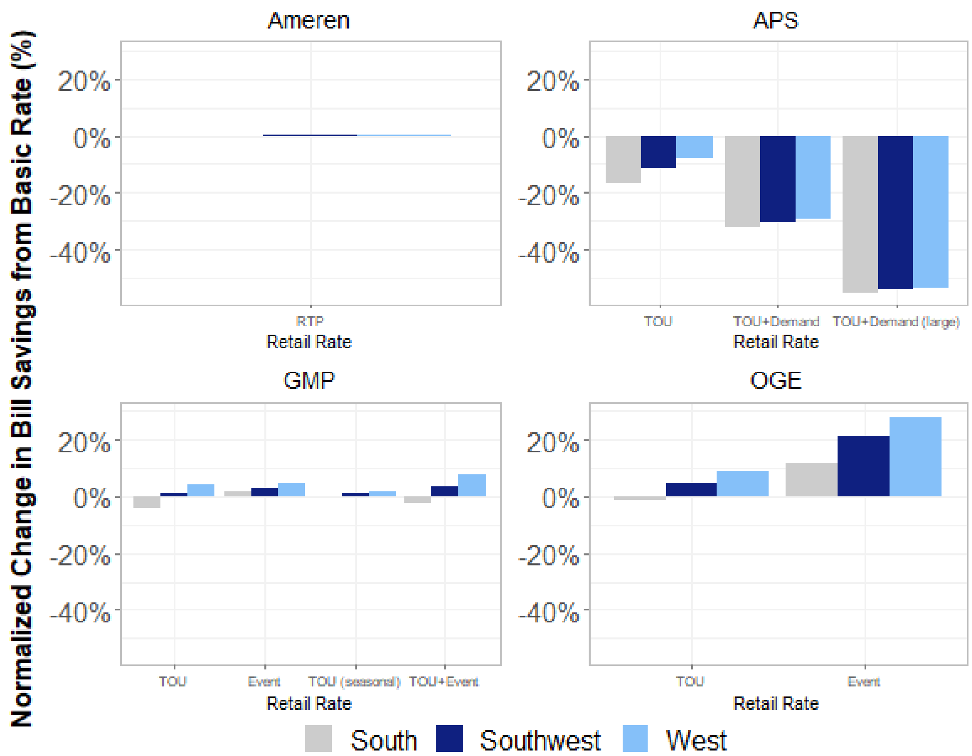
savings without the fixed charge changes. In the opposite direction, we observe that APS bill reductions would be even larger if not for the fixed charge reductions.

Economic Efficiency

Moving from flat to time-based rates also impacts the economic efficiency of investment decisions by changing the alignment of the adopter's bill savings with the investment's societal benefits. Figures 3.9 and 3.10 present mean incentive ratios by retail rate for each energy efficiency technology and PV orientation. Figures 3.11 and 3.12 show the estimated incentive ratios if all rate designs had the fixed charge in the basic rate. The rates are ordered from left to right by a measure of how much the rates vary with time: the sum of the variance of \$/kWh charges over hours of the year and the variance of \$/kW coincident demand charges over hours of the year. Recall that any deviation from an incentive ratio of one suggests that some economic inefficiency exists, with overinvestment for ratios above one and underinvestment for ratios below one. As the time variation of rates increases, some incentive ratios move closer to one, and others move farther away. This section analyzes the key drivers of heterogeneity in these changes.

Figures 3.9 through 3.12 suggest that average rate level has a larger impact on whether

Figure 3.8: Normalized Change in Bill Savings: Solar PV

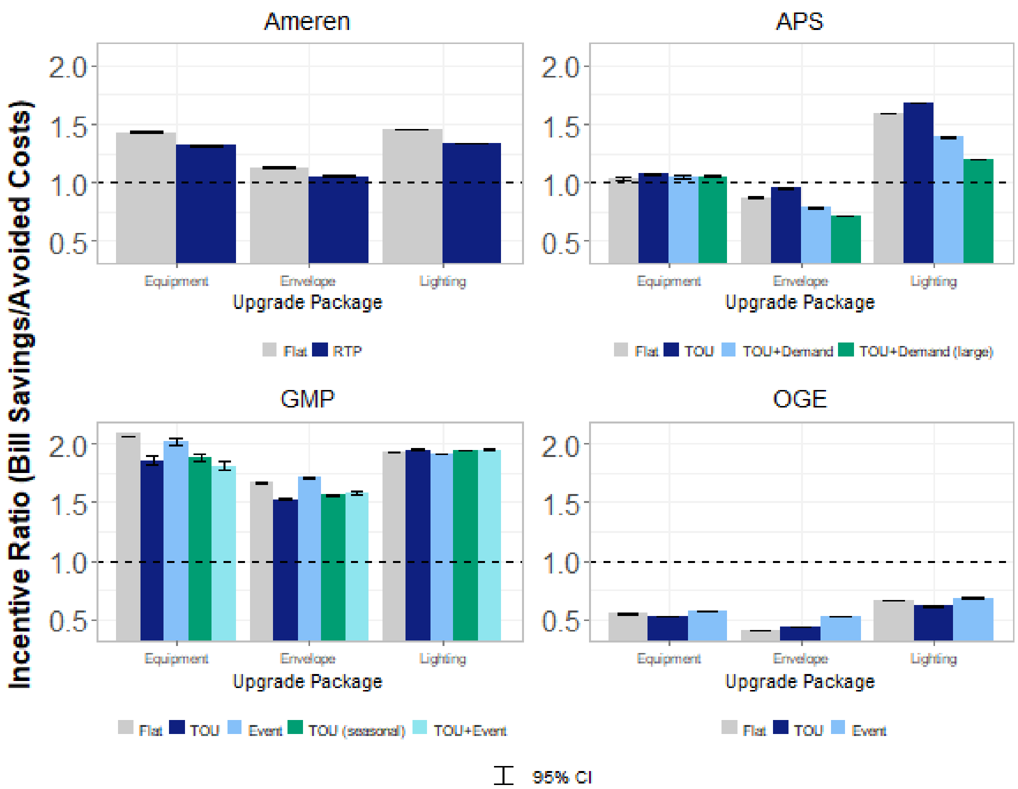


EE and PV incentives are too high or too low than rate design. Figure 3.13 displays average price less social marginal under the basic rate and total estimated residential usage for each utility. For the two utilities with the highest flat rates, Ameren and GMP, we estimate over-investment across all rate designs, technologies, and orientations. For the utility with the lowest flat rate, OG&E, we estimate under-investment across all rate designs, technologies, and orientations. Only the utility with average rates close to marginal cost, APS, displays an impact of rate design on whether investment incentives are too high or too low.

Estimating the model outlined in Equation 2 confirms this result. Column 1 in Table A1 displays estimates of the linear probability model of whether there is over-investment, and Columns 2 and 3 display estimates from the same model, restricting the coefficient on price to zero and restricting the coefficients on all four rate design variables to zero, respectively. Comparing the adjusted R^2 values from these models confirms that average \$/kWh price under the basic rate is a stronger predictor of over-investment than all four rate design variables combined. Average price can explain about 29% of the variation in whether an individual household over-invests in energy efficiency, while the rate design components together can only explain 2% of this variation. Utility-level estimates for PV, shown in Columns 4-6, suggest that these results translate to PV.

Average rate level also has a larger impact than rate design on a key component of

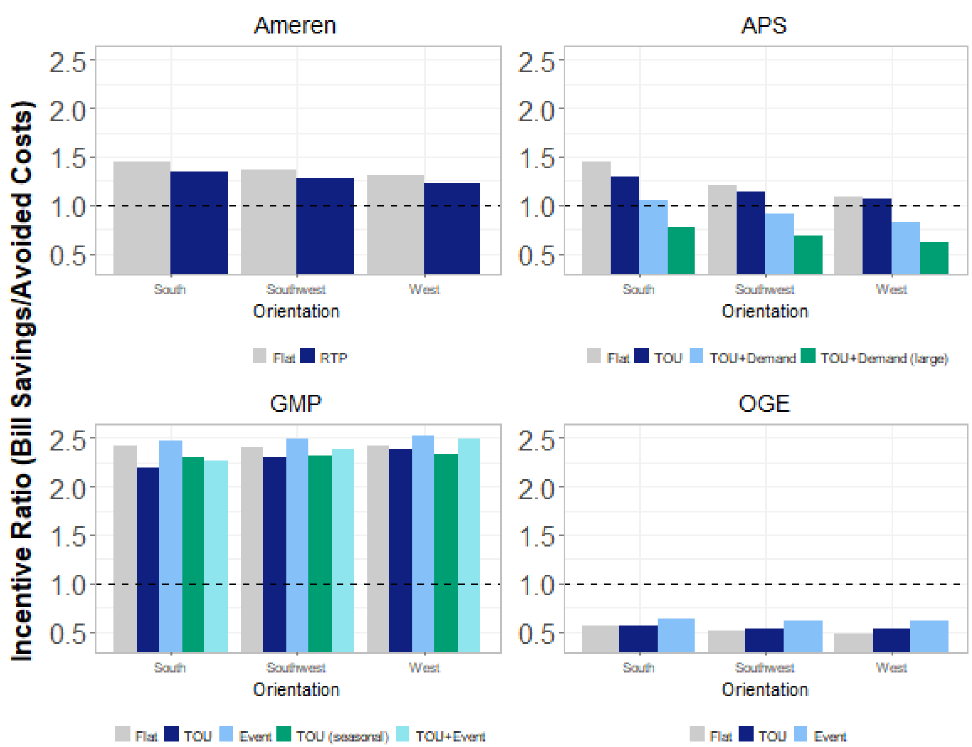
Figure 3.9: Mean Incentive Ratios: Energy Efficiency



economic inefficiency: deviation of bill savings from avoided costs ("incentive deviation"). Column 1 in Table A2 displays estimates of the model outlined in Equation 3. Columns 1-3 show that the distance between the average rate and avoided costs is a stronger predictor of investment economic inefficiency than all four of the rate design variables combined. Columns 4-6 suggest this result translates to PV too.

This result suggests that we can make decent predictions about whether economic efficiency will increase or decrease from only knowing average rates and whether energy savings are more correlated with the time-based rate than the baseline residential usage shape used to set the rates. Since the change in bill savings due to time-based rates will not change whether there is over- or under-investment in most cases, the economic efficiency of investment decisions will likely improve with a rate design change if average rates are lower than social marginal costs and the correlation is especially good. In contrast, if average rates are higher than social marginal costs, time-based rates will generally improve the economic efficiency of investment decisions for technologies with poor correlations and increase deadweight loss for technologies with good correlations. This suggests that the bill savings heterogeneity analysis has clear interpretations for economic efficiency. For example, if a rate design increases bill savings for a given investment in a given geography (e.g., lighting in a winter-peaking

Figure 3.10: Mean Incentive Ratios: Solar PV

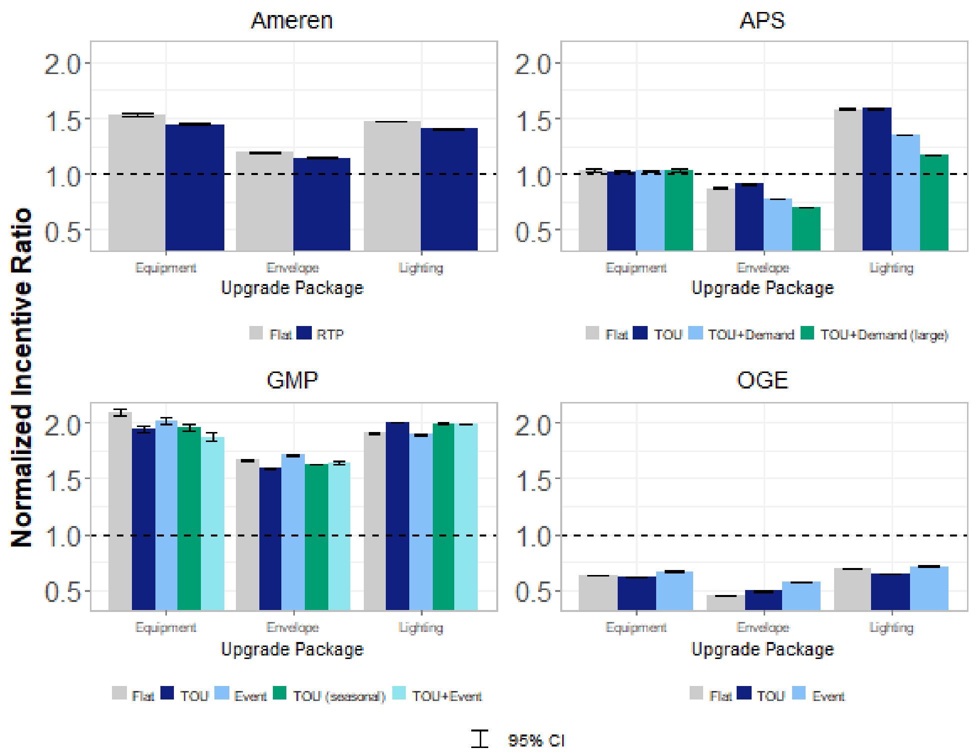


area), this will increase economic inefficiencies if average rates are well above social marginal costs (e.g., in GMP) and improve economic efficiency if average rates are relatively low.

Figure 3.11 also highlights the role of avoided costs in determining the impact of time-based rates on economic efficiency. Investments with savings that are coincident with high system costs will have relatively low incentive ratios under basic rates. For example, Figure 3.11 shows that incentive ratios are significantly lower for envelope upgrades than for all other modeled investments. This result is due to avoided costs of envelope upgrades being particularly large per kWh avoided. Envelope upgrades save energy when system-wide demand for electricity (e.g., for heating or cooling) is high.

Regression results suggest that we can also make decent predictions about the magnitude of the externality, i.e., per-kWh bill savings less avoided costs, and the change in this externality with time-based rates with only a small amount of information. This exercise may be useful for designing non-rate investment incentives. As shown in Column 1 of Table A3, knowing only average variable rates and utility system average social marginal costs can explain 60% of the household-level variation in bill savings less avoided costs. If the practitioner also has a good guess about how well savings are correlated with the time-based rate, Column 2 of Table A3 shows that this variable alone can explain over half of the variation in the change in the externality relative to a flat rate.

Figure 3.11: Normalized Mean Incentive Ratios: Energy Efficiency



States and utilities are particularly grappling with the impact of time-based rates on PV adoption since the bill savings impacts can be large. The competing objectives of advancing climate change mitigation and advancing equity in who pays for climate change mitigation makes these rate design trade-offs especially sensitive. Motivated by this debate, we illustrate the potential impact of these time-based rate designs on PV adoption and welfare. As customer PV adoption is its own area of intense debate and consideration, we intend for this exercise to be only illustrative, not exhaustive.

Specifically, we estimate changes in south-facing PV adoption and welfare under simple assumptions about capital costs, discount rates, and consumer behavior. In contrast to the rest of the estimates of economic efficiency and incentive ratios in this paper, we base our estimates on realized historical adoption patterns and allow for a gap between rational consumers' adoption decisions and observed adoption. Specifically, we use state-level estimates of installed PV costs from LBNL's Tracking the Sun 2022 public data (Barbose et al., 2022),[5] capacity factors from NREL's Annual Technology Baseline, and PV adoption probabilities as a function of the payback period from Dong and Sigrin (2019). To determine optimal adoption, we assume a real discount rate of 2% and a PV system lifetime of 25 years. For

[5]The report does not include cost estimates for every state. We use Wisconsin values for Illinois, Texas values for Oklahoma, and New Hampshire values for Vermont.

Figure 3.12: Normalized Mean Incentive Ratios: Solar PV

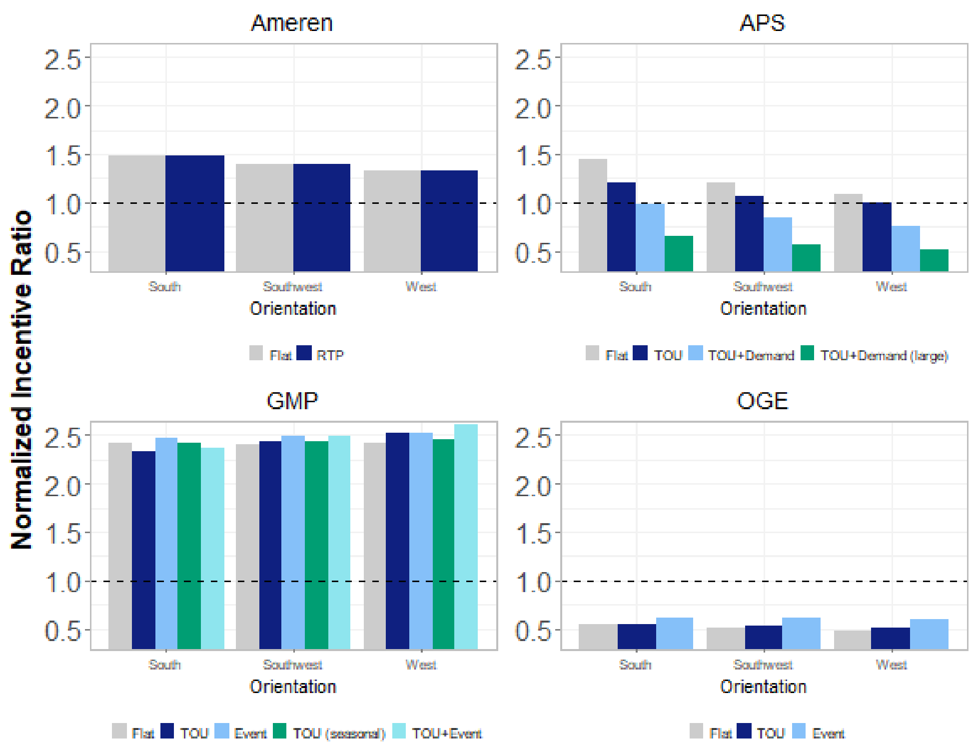
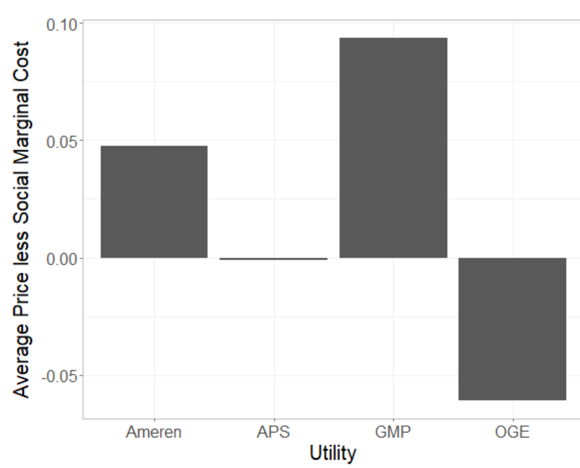


Figure 3.13: Average Price Less Social Marginal Cost



simplicity, we assume that the 2019 social marginal costs persist in real terms throughout the lifetime of the PV system. When estimating realized adoption, we similarly assume that consumers expect 2019 bill savings to continue throughout the lifetime of the PV system.

Our simplified approximation suggests that these rate design changes can have meaningful impacts on PV adoption. Focusing on south-facing systems, we estimate a ten percentage point reduction in PV adoption under the APS large demand charge rate. Despite the large \$/kWh bill saving increases under the OG&E event rate, we estimate that PV adoption in OG&E increases by only a fifth of a percentage point since bill savings are still small relative to capital costs. Adoption changes in GMP and Ameren range from 1.0 to 4.6 percentage points, depending on the rate.

We estimate that, on average, the time-varying rates increase the economic efficiency of south-facing PV investment decisions, primarily by reducing over-investment. Looking across rates, the median welfare effect of switching all customers to a time-based rate is an increase in welfare of \$435 per capita. Rate-specific estimates range from a welfare reduction of \$222 per capita under GMP's event rate to an increase of \$1,676 per capita under the APS large demand charge rate.

3.4 Discussion and Conclusion

While time-based rates can improve the economic efficiency of short-run consumption decisions, they can also have unintended consequences on consumers' incentives to make long-run investments in GHG-reducing technologies. This paper quantified the impacts of time-based rates on EE, PV, and electrification investment incentives for a diverse set of investments and households. We also assessed the implications of these compensation changes for economic efficiency.

Our analysis broadly shows that the average rate level matters more for bill savings and economically efficient investment signals than the rate design. The impacts of time-based rates on bill savings from EE and PV investments are small relative to existing variation in average rate levels, and average variable electricity rates are far from social marginal costs in three out of the four analyzed utility service areas. For electrification, bill savings also depend heavily on the natural gas and heating fuel prices. While we did not explore the welfare impacts of time-based rate on electrification in detail, a translation of our EE and PV results suggests that getting natural gas and fuel heating prices close to their social marginal costs may also have a first-order impact on the efficiency of electrification investment signals. The implication is that regulators and policymakers can improve short-term economic efficiencies through time-based rates without harming long-term efficiency or climate goals by also focusing on the alignment of average variable rates and societal costs. Strategies to achieve more efficient variable rate levels may include adding lump-sum bill refunds or modifying fixed charges, potentially in a way that limits the costs borne by low-income households (Borenstein et al., 2021).

We also find that time-based rates have highly heterogeneous effects on bill savings. Not all energy efficiency and electrification measures will fare better or worse under a particular rate design, and the impact may differ across geographic areas. In general, bill savings will increase if energy savings coincide with high-rate periods. We also document increased heterogeneity of bill impacts from the same investment across households, which may complicate consumers' investment decisions. Rates with demand charges and a high price variance lead to especially heterogeneous bill impacts. Policymakers and utilities that want to limit consumers' uncertainty may prefer simpler time-based rates.

If it is not feasible to set average variable rates to social marginal costs or if non-rate adoption barriers exist, additional targeted incentives could improve welfare. In areas where prices are well above social marginal costs, additional incentives for electrification may be needed. In contrast, additional incentives for energy efficiency may increase welfare in areas where prices are below social marginal costs. Even with prices at social marginal costs, additional incentives may be beneficial. To the extent that non-rate market distortions reduce the adoption of energy efficiency, PV, and electrification, there may not be an average electricity rate level that can provide efficient investment signals for all of these investment types. Prices below social marginal costs may be second-best optimal for energy efficiency, while prices above social marginal costs may be second-best optimal for electrification. Price reform and targeted incentives together could achieve the efficient solution. We hope policymakers and utility regulators can use these results and the patterns we uncovered to inform coupled changes in rate design and other EE, PV, and electrification policies.

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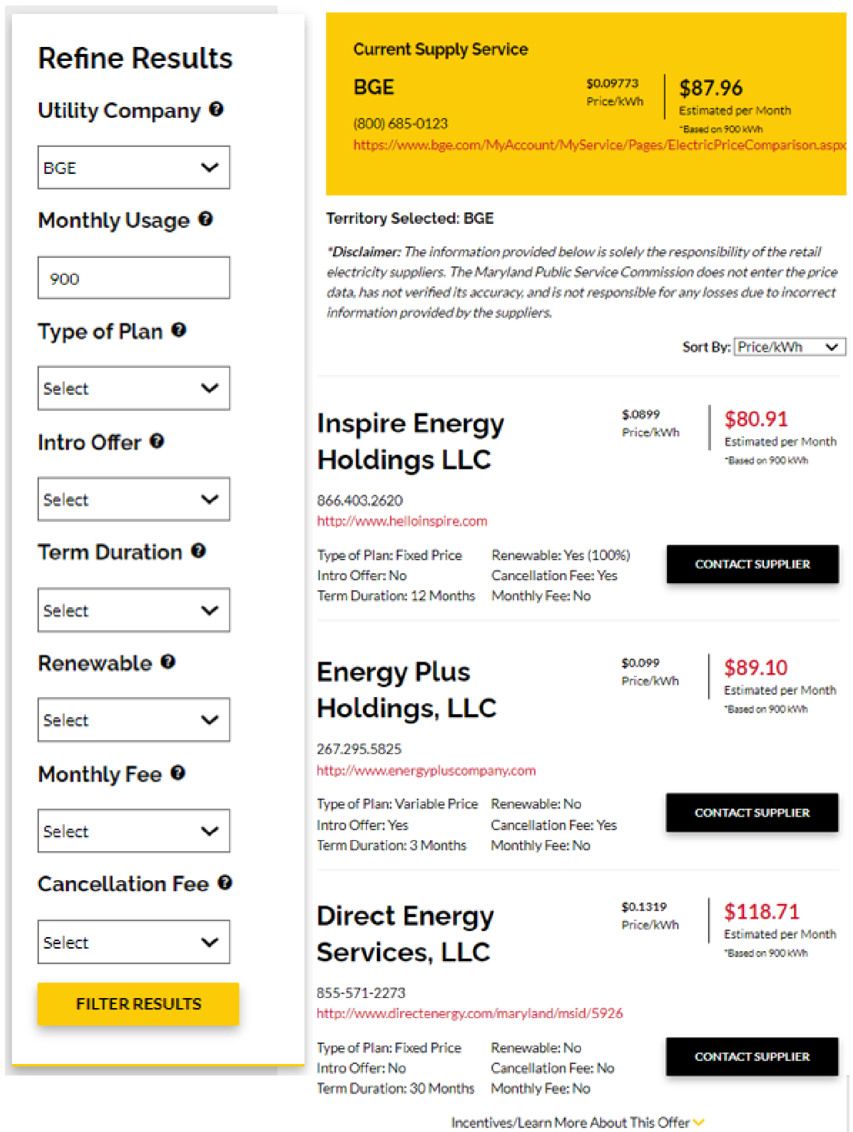
Appendix A

Appendix for *Competing for (In)attention: Price Discrimination in Residential Electricity Markets*

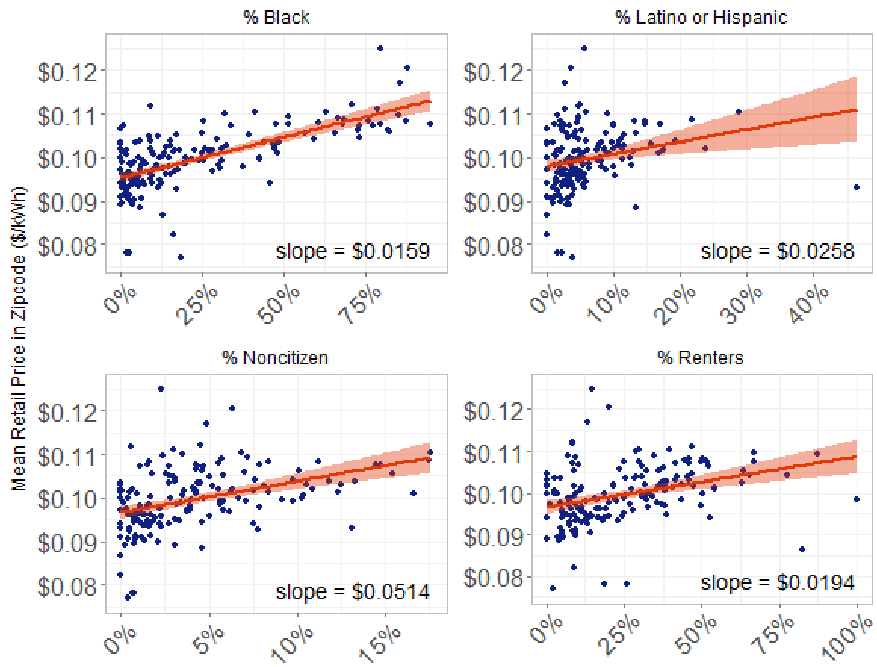
A.1 Additional Tables and Charts

Figure A1: Screenshot from MDElectricChoice.gov



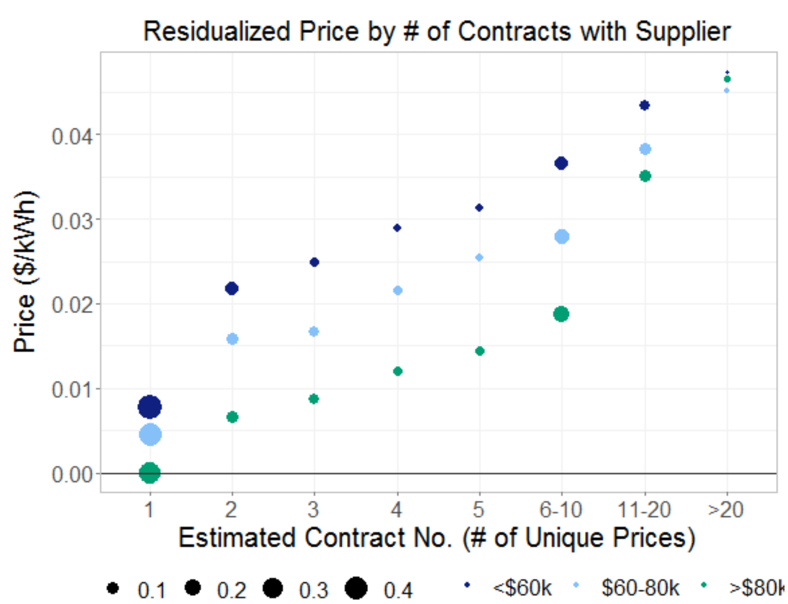
Accessed October 2022.

Figure A2: Scatterplots of Price and Key Zip Code Demographics: September 2019



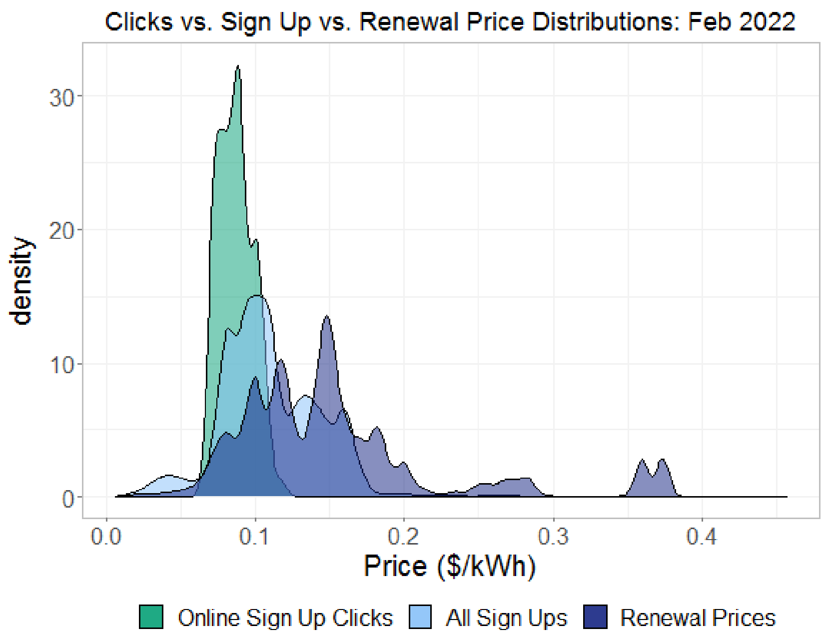
Generation supply prices for residential retail choice customers in Baltimore Gas and Electric Company service area in September 2019. Zip code tabulation area (ZCTA) demographics from the 2019 American Community Survey. A dot represents one ZCTA. Best linear fit line and 95% confidence intervals in red.

Figure A3: Comparison Website Click vs. New Contract vs. Renewal Contract Prices



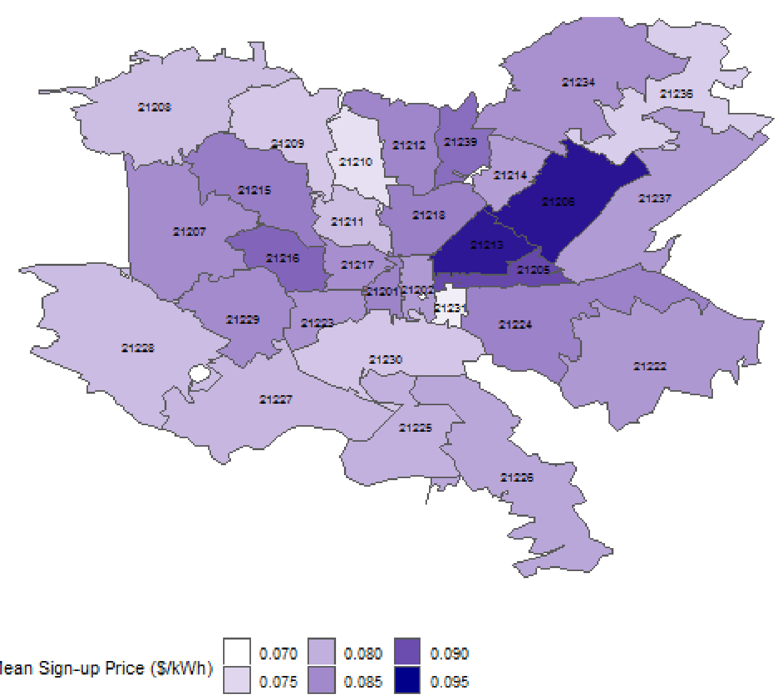
Estimates from a regression of electricity supply price on time fixed effects, number of unique prices a consumer has faced since last switching suppliers, and income group. Excludes standard offer service prices. Only includes linear tariffs that are not time-differentiated. Sizes reflect the share of the income group on that renewal number. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

Figure A4: Comparison Website Click vs. New Contract vs. Renewal Contract Prices



In green, probability density of prices associated with plan-specific clicks on the MDElectricChoice.gov website in February 2022 in the Baltimore Gas and Electric Company (BGE) service area. Excludes standard offer service prices. In yellow, probability density of sign-up prices for all consumers who switched electricity suppliers in February 2022 in the BGE service area. In blue, probability density of prices for all consumers who did not switch suppliers in February 2022 and experienced a price change between January and February 2022. Only includes prices for consumers on linear tariffs that are not time-differentiated.

Figure A5: Sign-up Price Map of Baltimore City: September 2019



Mean sign-up prices billed to consumers who switched electricity suppliers in September 2019 by

Table A1: Difference in Differences Results

	Switch	
	(1)	(2)
Marketing x Shelter	-0.027^{***}	-0.026^{***}
	(0.0004)	(0.0005)
Marketing	0.011^{***}	0.035^{***}
	(0.0002)	(0.0001)
Shelter	-0.006^{***}	-0.008^{***}
	(0.0002)	(0.0003)
Supplier Fixed Effects	x	
Observations	8,977,071	8,977,071
Adjusted R^2	0.047	0.009

*p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by consumer.

Table A2: Regression Discontinuity of Lifting Restrictions on Non-essential Businesses

	Dependent variable:	
	Switch	
	(Search)	(Marketing)
After Event (x100)	0.02	0.54^{***}
	(0.1)	(0.1)
Days Since Event (x100)	-0.01^{***}	-0.05^{***}
	(0.002)	(0.003)
After Event x Days Since Event (x100)	0.02^{***}	0.09^{***}
	(0.003)	(0.004)
Observations	349,307	226,524
Adjusted R^2	0.085	0.074
Supplier Fixed Effects	x	x

*p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by consumer.

Table A3: Results from Regressions of Marketing Presence on Income Metrics

	Number of Suppliers Door-to-door Marketing							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median Income ($1000s)	-0.094^{***}	-0.027^{***}						
	(0.012)	(0.008)						
Median Income >$60k			-8.702^{***}	-1.368				
			(1.365)	(0.934)				
Median Income >$80k					-7.617^{***}	-2.425^{***}		
					(0.935)	(0.632)		
Poverty (%)							42.856^{***}	11.426^{***}
							(5.787)	(4.281)
Total Population		0.0002^{***}		0.0002^{***}		0.0002^{***}		0.0002^{***}
		(0.00002)		(0.00002)		(0.00002)		(0.00002)
Population Density		0.001^{***}		0.001^{***}		0.001^{***}		0.001^{***}
		(0.0001)		(0.0001)		(0.0001)		(0.0001)
Constant	x	x	x	x	x	x	x	x
Observations	151	150	151	150	151	150	154	152
Adjusted R^2	0.304	0.774	0.209	0.759	0.304	0.778	0.260	0.770

*p<0.1; **p<0.05; ***p<0.01. OLS standard errors in parentheses.

A.2 Theory: Dynamic Model

Now, consider the representative firm's dynamic problem if consumers are inertial. A firms' customers only differ by search type. Let p_{r1} be the firm's renewal price for searchers, and let p_{r2} be the renewal price for non-searchers. We will still use p_o and p_m to denote the perfectly competitive online offer price and the marketing offer price. It is also useful to define the respective probabilities that a searcher and non-searcher switches given a price- or marketing-driven attention shock, and a choice set X as $prob_1(switch|X)$ and $prob_2(switch|X)$.

The firm's value function of having a searcher is:

$$\begin{aligned} V_1 = \max_{p_{r1}} &(p_{r1} - c + \beta V_1)(1-\zeta)((1 - \pi_M prob_1(switch|p_{r1}, p_o, p_m))\mathbb{1}\{p_{r1} \leq \bar{p}\} \\ &+ (1 - prob_1(switch|p_{r1}, p_o))\mathbb{1}\{p_{r1} > \bar{p}\}) \end{aligned}$$

where β is the firm's discount factor. The firm's value function of having a non-searcher is:

$$\begin{aligned} V_2 = \max_{p_{r2}} &(p_{r2} - c + \beta V_2)(1-\zeta)((1 - \pi_M prob_2(switch|p_{r2}, p_o, p_m))\mathbb{1}\{p_{r2} \leq \bar{p}\} \\ &+ (1 - prob_2(switch|p_{r2}, p_o))\mathbb{1}\{p_{r2} > \bar{p}\}) \end{aligned}$$

In this dynamic model, the previously perfectly competitive marketplace is no longer perfectly competitive. The equilibrium price is no longer $p_o = c$ because this would imply positive profit from new entry as long as $\beta V_1 > 0$. The free entry and exit conditions require the equilibrium price to satisfy $p_o = c - \beta V_1$. The firm's marketing problem similarly incorporates this continuation value.

Under these assumptions, we can show that renewal prices are greater than initial offer prices for both consumer types.

Proposition 2. *$p^*_{r1} > p_o$ and $p^*_{r2} > p_m$.*

Proof. See Appendix A.3. □

The final proposition requires an additional assumption on the relationship between $\bar{p}$, π_m, and the shape of the reservation price distribution.
Assumption 1: $\pi_M < F(\bar{p})$ and $f(p_{r2})/(1 - F(p_{r2})) > 1/(p - c + \beta V)\ \forall p > \bar{p}$.

We can think of this condition as putting a lower bound on $\bar{p}$. The inattention threshold must be sufficiently high relative to the distribution of reservation prices so that the firm is not incentivized to provide an attention shock. The first condition also requires that there is an increase in switching probability when price crosses the $\bar{p}$ threshold. At this threshold, the probability of an attention shock jumps from π_M to one. This assumption is sufficient, but not necessary, for the remaining propositions to hold.

Under Assumption 1, we can show $p^*_{r2} = \bar{p}$. It follows that renewal prices are increasing in this inattention threshold. The optimal renewal price also allows us to prove that the probability of switching is decreasing in marketing costs since a reduction in marketing also reduces the frequency of attention shocks. Proposition 3 formalizes these results and states that all of the single-period results also translate to the dynamic case under Assumption 1. Here, we interpret the single-period equilibrium value average price p as the average sign-up price.

Proposition 3. *Under Assumption 1, $\frac{\partial p_{r1}}{\partial \bar{p}}, \frac{\partial p_{r2}}{\partial \bar{p}} > 0$, the probability of switching decreases with λ, and Proposition 1 holds under the dynamic model assumptions.*

Proof. See Appendix A.3. □

Note that the average sign-up price comparative static result is not necessarily robust to relaxing Assumption 1 and introducing heterogeneous inertia. The key condition for this assumption to hold is that $p^*_m > p_o$ or, equivalently, $p_m - c - \beta(V_2 - V_1) > 0$. In the structural model, we will also allow for persuasive marketing, modeled as decision error with a non-zero mean, which makes this condition more likely to hold. The other two key drivers embedded in this expression are inattention thresholds, $\bar{p}_1$ and $\bar{p}_2$, and switching probabilities. The expression is decreasing in $\bar{p}_2 - \bar{p}_1$. Search frictions and inattention being positively correlated would tend to decrease the probability that the inequality holds. The probability of switching given an attention shock may also vary across consumer types, but these probabilities are both likely to be very close to one given $\bar{p} >> c$ and modest preferences and decision error. If we take a step back from the assumption of a single market, we notice there may be a fourth consideration. Proposition 1 tells us that marketing level decreases with α, and the proof of Proposition 3 shows that switching increases with the level of marketing. If α varies across markets, we would expect switching to decrease with α. Hence, the effect of a higher α in one market than another on mean sign-up prices is ambiguous. If inattention levels are similar across the two markets, we would still expect lower sign-up prices in the market with a higher portion of searchers.

By similar logic, the signs of the effects of λ and α on overall billed prices are ambiguous. More marketing increases average sign-up prices, but it also increases switching and, thereby, reduces the probability that a consumer will pay the renewal premium in any given period. The overall impact on average billed prices depends on the relative strengths of these two opposing effects. This suggests that if search frictions or marketing level *and* inattention are higher in one area than another, the difference in the average prices in these two areas will be smaller than that of sign-up prices and renewal prices.

A.3 Proofs

Proposition 1. *Let R^* be the equilibrium proportion of non-searchers who are active in the market, and let p^* be the average price in the market. The following comparative statics hold:* $\frac{\partial M^*}{\partial \lambda}, \frac{\partial M^*}{\partial \alpha}, \frac{\partial R^*}{\partial \lambda}, \frac{\partial p^*}{\partial \lambda}, \frac{\partial p^*}{\partial \alpha} < 0$.

Proof. We begin with the marketing level comparative statics. Differentiating the marketing level first-order condition with respect to λ produces:

$$0 = C'(M^*(\lambda)) + \lambda C''(M^*(\lambda))\frac{\partial M^*(\lambda)}{\partial \lambda}$$

Rearrange and simplify this expression to get:

$$\frac{\partial M_i^*}{\partial \lambda} = -\frac{C'(M_i)}{\lambda C''(M_i)} < 0$$

by convexity of the marketing costs and the second order condition of the marketing level problem.

Now, differentiate the marketing level first order condition with respect to α:

$$-(p_m^* - c)D(p_m^*) = \lambda C''(M^*(\alpha))\frac{\partial M^*(\alpha)}{\partial \alpha}$$

which we an rearrange to find:

$$\frac{\partial M^*}{\partial \alpha} = \frac{(p_m^* - c)D(p_m^*)}{\lambda C''(M^*)} < 0$$

since $p_m^* > c$ and $D(p_m) > 0 \; \forall p_m$.

Next, we turn to market participation. First, observe that the number of searchers in the market does not change with λ. The percent of non-searchers consumers who switch to the outside option is ζ. The percent of non-searchers on the outside option who enter the market is $D(p_m)\pi_M$. In equilibrium, the probability that a non-searcher is in the market is, therefore, $R^* = \frac{D(p_m)\pi_M}{\zeta+D(p_m)\pi_M}$. Differentiating with respect to λ produces:

$$\frac{R^*}{\partial\lambda} = \frac{D(p_m)\frac{\partial\pi_M}{\partial\lambda}(\zeta + D(p_m)\pi_M) - D(p_m)\frac{\partial\pi_M}{\partial\lambda}D(p_m)\pi_M}{(\zeta + D(p_m)\pi_M)^2} = \frac{D(p_m)\zeta\frac{\partial\pi_M}{\partial\lambda}}{(\zeta + D(p_m)\pi_M)^2} < 0$$

since $\frac{\partial M}{\partial\lambda} < 0$ implies $\frac{\partial\pi_M}{\partial\lambda} < 0$. Because the number of non-searchers is decreasing in λ and the number of searchers is constant in λ, the ratio of non-searchers to searchers and, therefore, the percent of all consumers in the market who are non-searchers, is decreasing in λ.

Turning to α, the ratio of non-searchers to searchers in the market is:

$$\frac{(1-\alpha)\frac{D(p_m)\pi_M}{\zeta+D(p_m)\pi_M}}{\alpha(1-F(c))}$$

We differentiate this expression with respect to α:

$$\frac{\partial\frac{(1-\alpha)\frac{D(p_m)\pi_M}{\zeta+D(p_m)\pi_M}}{\alpha(1-F(c))}}{\partial\alpha} = \frac{\frac{D(p_m)\pi_M}{\zeta+D(p_m)\pi_M}(1-F(c))}{(\alpha(1-F(c)))^2} < 0$$

Finally, we turn to average price in the market, which we can write as

$$p = c + (p_m^* - c)\frac{(1-\alpha)\frac{D(p_m)\pi_M}{\zeta+D(p_m)\pi_M}}{(1-\alpha)\frac{D(p_m)\pi_M}{\zeta+D(p_m)\pi_M} + \alpha(1-F(c))}$$

Let $t2 = \frac{D(p_m)\pi_M}{\zeta+D(p_m)\pi_M}$ and $u = -\frac{D(p_m)\pi_M}{\zeta+D(p_m)\pi_M} + (1-\alpha)\frac{D(p_m)\zeta}{(\zeta+D(p_m)\pi_M)^2}\frac{\partial\pi_M}{\partial\alpha}$. Then

$$\begin{aligned}\frac{\partial p}{\partial\alpha} &= (p_m^* - c)\frac{u \times ((1-\alpha)t_2 + \alpha(1-F(c))) - (u + (1-F(c)))((1-\alpha)t_2)}{((1-\alpha)t_2 + \alpha(1-F(c)))^2} \\ &= (p_m^* - c)\frac{u\alpha(1-F(c)) - (1-F(c))(1-\alpha)t_2}{((1-\alpha)t_2 + \alpha(1-F(c)))^2} < 0\end{aligned}$$

To see the last inequality, notice that the denominator is positive and the numerator is negative since $\frac{\partial M}{\partial\alpha} < 0$ implies $\frac{\partial\pi_M}{\partial\alpha} < 0$ and, therefore, $\frac{\partial u}{\partial\alpha} < 0$.

Similarly, let $v = (1-\alpha)\frac{D(p_m)\zeta}{(\zeta+D(p_m)\pi_M)^2}\frac{\partial\pi_M}{\partial\lambda}$. Then

$$\begin{aligned}\frac{\partial p}{\partial\lambda} &= (p_m^* - c)\frac{v \times ((1-\alpha)t_2 + \alpha(1-F(c))) - v((1-\alpha)t_2)}{((1-\alpha)t_2 + \alpha(1-F(c)))^2} \\ &= (p_m^* - c)\frac{v\alpha(1-F(c))}{((1-\alpha)D(p_m)\pi_M + \alpha(1-F(c)))^2} < 0\end{aligned}$$

since $\frac{\partial M}{\partial\lambda} < 0$ implies $\frac{\partial\pi_M}{\partial\lambda} < 0$. $\square$

Proposition 2. *$p^*_{r1} > p$ and $p^*_{r2} > p_m$.*

Proof. Note that searchers must prefer p to the outside option by revealed preference. Suppose $p^*_{r1} \leq p_o$. Then $p^*_{r1} \leq c$. To see this, $p^*_{r1} > c$ would imply $V_1 > 0$, which would imply $p_o < c$, which is a contradiction to $p^*_{r1} \leq p_o$. Free exit excludes the case where $p^*_{r1} < c$, since this would cause the firm to have a negative renewal value. This implies $p^*_{r1} = p = c$ and $V_1 = 0$. In this case, the partial derivative of the firm's renewal problem with respect to p^*_{r1} is

$$\begin{aligned}(1-\zeta)(1-\pi_M prob_1(switch|p_{r1}, c)) - (c-c)(1-\zeta)\pi_M \frac{\partial prob_1(switch|p_{r1}, c)}{\partial p_{r1}} \\ = (1-\zeta)(1-\pi_M prob_1(switch|p_{r1}, c)) > 0\end{aligned}$$

since $\pi_M \leq 1$ and the probability of switching is less than one if the consumer is indifferent between the two plans. This is a contradiction to $p^*_{r1} = c$ being the optimal renewal price. Thus, $p^*_{r1} > p$.

For non-searchers, if $p^*_{r2} \geq \bar{p}$, then the claim holds trivially. If $p^*_{r2} < \bar{p}$, then p^*_{r2} must satisfy the first order condition:

$$(1-\pi_M prob_2(switch|p^*_{r2}, p_m, p_o)) - (p^*_{r2} - c + \beta V_2)\pi_M \frac{\partial prob_2(switch|p^*_{r2}, p_m, p_o)}{\partial p_{r2}} = 0$$

Dividing by π_M and rearranging produces:

$$prob_2(switch|p^*_{r2}, p_m, p_o)) + (p^*_{r2} - c + \beta V_2)\frac{\partial prob_2(switch|p^*_{r2}, p_m, , p_o)}{\partial p^*_{r2}} = 1/\pi_M$$

We can write the marketing price first order condition in a similar format:

$$\pi'_M(p^*_m) = prob_2(switch|p_{r2}, p^*_m, p_o)) + (p^*_m - c + \beta V_2)\frac{\partial prob_2(switch|p_{r2}, p^*_m, p_o)}{\partial p^*_m, p_o} = 0$$

Together, these two equations imply $\pi'_M(p^*_{r2}) < 0$. By concavity of the profit function, this implies $p^*_{r2} > p^*_m$. □

Proposition 3. *Under Assumption 1, $\frac{\partial p_{r1}}{\partial \bar{p}}, \frac{\partial p_{r2}}{\partial \bar{p}} > 0$, the probability of switching decreases with λ, and Proposition 1 holds under the dynamic model assumptions.*

Proof. Given Proposition 2, the probability that a searcher switches given any attention shock is one. The firm's renewal pricing problem for non-searchers is, therefore,

$$\max_{p_{r1}} (p_{r1} - c + \beta V_1)(1-\zeta)(1-\pi_M)\mathbb{1}\{p_{r1} \leq \bar{p}\}$$

This expression is increasing in p_{r1} through $\bar{p}$. At $\bar{p}$, net present value profit is positive since $p_{r1} > c - \beta V_1$ by Proposition 2 and $\pi_M < 1$ by Assumption 1. For $p_{r1} \geq \bar{p}$, net present value profit is zero. Thus, $p^*_{r1} = \bar{p}$.

Similarly, Proposition 2 implies that the probability that a non-searcher switches given a marketing attention is one, so the firm's renewal pricing problem for non-searchers is

$$\max_{p_{r2}}(p_{r2} - c + \beta V_2)(1-\zeta)((1-\pi_M)\mathbb{1}\{p_{r2} \leq \bar{p}\} + (1 - prob_2(switch|p_{r2}))\mathbb{1}\{p_{r2} > \bar{p}\})$$

For $p_{r2} \leq \bar{p}$, this expression is increasing in p_{r2}. By Assumption 1, the net present value profit for $p_{r2} > \bar{p}$ is less than for the case where $p_{r2} = \bar{p}$. Thus, $p^*_{r2} = \bar{p}$.

It follows that $\frac{\partial p_{r1}}{\partial \bar{p}}, \frac{\partial p_{r2}}{\partial \bar{p}} > 0$.

Given this result, the equilibrium weighted average probability across types of a consumer switching in a given period is

$$1 - ((1 - \pi_M prob_1(switch|p^*_{r1}, p_o, p_m))\alpha + (1-\zeta)(1 - \pi_M prob_2(switch|p^*_{r1}, p_m))(1-\alpha))$$

The partial derivative with respect to λ is

$$(prob_1(switch|p^*_{r1}, p)\alpha + (1-\zeta)prob_2(switch|p^*_{r1}, p)(1-\alpha))\frac{\partial \pi_M}{\lambda} < 0$$

since $\frac{\partial \pi_M}{\lambda}$ must have the same sign as $\frac{\partial M}{\lambda}$. Hence, switching probability decreases with λ.

Turning to the comparative statics in Proposition 1, the proofs of $\frac{\partial M_i^*}{\partial \lambda} < 0$ and $\frac{\partial M^*}{\partial \alpha} < 0$ are analogous to the proofs in Proposition 1 and skipped here.

The expression for the equilibrium ratio of non-searchers to searchers in the market and the resulting proof remains unchanged. By revealed preference, searchers and non-searchers in the market have reservation values below p_o and p^*_m, respectively. Hence, the probability of switching to the outside option conditional on being in the market is still ζ, and the probability of switching to the market conditional on being on the outside option is zero for a searcher and $D(p_m)\pi_M$ for a non-searcher.

To prove $\frac{\partial p}{\partial \alpha}, \frac{\partial p}{\partial \lambda} < 0$, first notice that Proposition 2 and $p^*_{r1} = p^*_{r2} = \bar{p}$ imply $V_1 = V_2 \equiv V$. We have already shown that $p_o = c - \beta V$. Free disposal requires $p^*_m > c - \beta V$ since otherwise marketing would reduce net present value profit. Thus, we still have $p^*_m > p_o$ in this dynamic setting. Combining this fact with the fact that the market consumer type weights have not changed, the single-period proof can be easily altered to include a continuation value without changing the comparative static results.

Thus, Proposition 1 translates to the dynamic case. □

A.4 Alternative Theories

Underpayment Risk

Low-income consumers may be particularly likely to underpay their bills. In many industries, firms may need to charge these high-risk consumers higher prices than low-risk consumers to get the same level of expected profit or risk-adjusted utility. In the Maryland retail electricity choice markets, however, suppliers do not directly bear the risk of their consumers' underpayment. Through a program known as "Purchase of Receivables" (POR), the PSC requires Baltimore Gas and Electric Company to purchase suppliers' receivables at a regulated industry-wide percentage discount. This discount was zero during the analysis timeframe. Whether or not a consumer paid, BGE paid their supplier exactly the amount the supplier charged.

The PSC updates the POR discount periodically. Between updates, a supplier's own consumers' underpayment will not affect its revenues at all. In the long run, some or all of the historical underpayment may get collected from all suppliers in the form of a higher POR discount. Since the PSC sets one discount for all suppliers in the BGE territory, a supplier that is small relative to the market bears a negligible reduction in profits due to its own consumers' underpayment.

Quantity- and Time-differentiated Rate Designs

Some suppliers charge consumers quantity-differentiated rates, such as two-part tariffs or rates that differ by time of day or day of week. If differences in electricity usage cause low-income consumers to benefit relatively less from these types of rate designs, they may face relatively high bills despite having identical prices. However, in the BGE service area, very few consumers are on quantity- or time-differentiated rates.[1] During the analysis timeframe, an average of 95% of consumers faced linear per-kWh rates, 5.0% had plans with fixed charges, and 0.006% were on time-differentiated rates.[2]

I restrict the analysis to consumer-months where consumers faced a flat per-kWh rate. I also drop about 3.9% of consumer-months who are on budget billing since their BGE bills may differ from the amount they owe.[3] This applies to all results presented in other sections of this paper, so quantity- and time-differentiated rates cannot explain the income-price gap pr other price heterogeneity demonstrated in Section 1.4.

Cost to Serve

Geographic-driven Variation in Cost to Serve

A hypothesized explanation for the income-price gap in other markets is that the price gap reflects real differences in marginal costs across geographic areas as opposed to differences in markups. However, per-kWh marginal electricity costs do not differ much across geographic locations within the BGE service area. The entire BGE service area is located within the

[1] The low incidence of quantity- or time-differentiated rates may be partly due to the billing arrangement between the suppliers and BGE. These type of rate designs appear more common in the Texas retail electricity market.

[2] Estimates based on a subset of 94.4% of consumer-months for which I observe the full rate structure.

[3] Budget billing is an attempt to reduce the month-to-month variability in bill amounts by smoothing an expected annual bill over months of the year. While budget billing for transmission and distribution service is mandatory for BGE customers receiving low-income subsidies, there is not a similar mandate for electricity supply.

same transmission zone and locational deliverability area within the PJM market, so there is no variation in capacity costs and limited variation in transmission-related costs within the BGE service area.

Geographic variation in marginal costs primarily comes from transmission constraints, congestion, and losses, but this variation is small. To explore geographic variation in transmission-related costs, I analyzed locational marginal prices (LMPs). These are market-clearing prices that reflect the cost of energy, transmission losses, and transmission congestion. I used SNL Financial to identify locations and prices of nodes. There were 278 nodes available on SNL Financial in July 2022 with hourly data for the full analysis timeframe that appeared to lie within the BGE service area. Of these nodes, the mean locational marginal price had a standard deviation of \$0.001/kWh and a range of \$0.007/kWh. Excluding points near the border of the BGE service area, this range reduces to \$0.003/kWh. Within the Baltimore Metropolitan region, this range is only \$0.001/kWh. Thus, marginal cost variation is very small and not sufficient for explaining price differences.

The electricity tax in Baltimore City also causes differences in post-tax marginal costs within and outside of Baltimore City. The income-price gap persists within Baltimore City itself.

Consumption-driven Variation in Cost to Serve

Per-kWh marginal costs do not vary with a consumer's consumption *level* in a given time period, but they may vary with the *timing* of a consumer's electricity consumption. A supplier's marginal costs differ by time of a day and day of year. Consumers with usage that is relatively more coincident with the aggregate system electricity usage should be relatively more costly to serve. I do not have data on consumers' sub-monthly electricity usage. Literature and external data sources suggest that, if anything, low-income consumers use relatively less of their electricity during high-cost hours.

The highest cost hours in the PJM wholesale electricity market typically occur on hot summer days with especially high levels of air conditioning. We may, therefore, expect consumers who use a lot of electricity for air conditioning relative to other uses to be particularly costly to serve. According to data from the U.S. Energy Information Administration's 2015 Residential Energy Consumption Survey, air conditioning usage comprised 8.0% and 9.5% of household annual electricity, on average, for households with median household income below and above \$60,000, respectively. In the South region, these shares are 15.4% and 16.6%, respectively. More generally, Zethmayr and Makhija (2019) study differences in electricity usage patterns across income groups in Illinois. They find that low-income consumers in urban areas have particularly flat electricity usage patterns that are particularly non-coincident with aggregate system electricity usage and costs.

Although *marginal* costs do not vary with a consumer's consumption level in a given time period, it is possible that *average* costs of serving a customer do. Suppliers may face ongoing fixed costs after a customer signs up, such as administrative and customer service costs. If suppliers recover some or all of these fixed costs in a variable price,[4] they would need to charger relatively higher prices to lower-usage customers to recover the same fixed costs. Specifically, we would expect the average incremental cost to serve a marginal customer to be the sum of the supplier's marginal cost and average fixed costs. Average price may be higher than this average incremental per-customer cost due to marketing costs and other fixed costs that do not vary with number of customers. This suggests that we can recover an estimate of the fixed cost to serve a customer from the following two-stage least squares model:

$$P_{ijt} = \beta_0 + \beta_1 MC_t + \beta_2 (1/(\widehat{Usage})_{ijt})$$

where P_{ijt} is the average price in \$/kWh for consumer i with supplier j in time period t, MC_t is estimated marginal cost in period t (see Section 1.3 and Appendix A.7 for estimation details), β_0 is a constant that aims to capture all other fixed costs per kWh, and $(\widehat{Usage})_{ijt}$ is predicted electricity usage in kWh. Our coefficient of interest is β_2. I estimate the model using one-year lagged electricity usage as an instrument for current usage to address potential simultaneity that would otherwise if consumers are not perfectly price inelastic. I also estimate a version of this model controlling for supplier fixed effects.

Using this model and the BGE billing data, I estimate incremental fixed costs per customer to be $0.16 per customer-month. To put the number in the context of the price gap, if there were no relevant differences across households in low- and high-income areas except for electricity usage level, we would expect to see a price gap of less than one hundredth of a cent per kWh. Fixed costs per customer may be especially small in this industry since BGE handles billing. Survey results also suggest that many consumers do not know the name of their supplier (see Appendix A.9), which may reduce customer service costs.

I find additional evidence that fixed costs are not driving the income-price gap. First, the correlation between residualized prices and customer-specific usage after controlling for time fixed effects is small (r =-0.089). Second, the variable price income gap persists in the restricted subset of consumers on two-part tariffs. Third, the average cost explanation is inconsistent with the finding of more direct marketing in low-income areas since suppliers should find these consumers relatively less profitable.

Preferences for Premium Attributes

Electricity is often considered a homogeneous good. However, retail electricity suppliers can differentiate their products by the way they charge consumers for this electricity or by bundling the electricity with other goods and services. Most commonly, suppliers bundle electricity with renewable energy certificates or financial products.

One possible explanation for the price gap is that low-income households have a higher willingness to pay (WTP) for certain bundled products than high-income households. To explore this theory, I analyze clicks on the MDElectricChoice comparison website. Analysis

[4]The term "variable price" in this context refers to the charges that vary with a consumer's electricity usage. The term does not take the industry meaning of a price that may change each month.

results will translate to the more general retail choice market if the preferences of consumers who use the comparison website are representative of other consumers who live in similar areas and are active in the retail choice market. Overall, households in low-income areas click on *lower*-priced plans, on average, than do consumers in high- and moderate-income areas ($t = 2.2$). The mean price difference is \$0.0038/kWh.

To further explore differences in WTP for bundled products, I perform a conditional logit analysis separately for consumers with IP addresses that map to zip codes with annual median household income below and above \$60,000. For this exercise, I consider the market to only include people who clicked on a plan on the website during the six-month period I analyze. I estimate the models with and without supplier fixed effects. Specifically, I assume the following latent utility model:

$$u_{ijt} = \alpha_g p_{jt} + \beta_g X_{jt} + \delta_j + \epsilon_{ijt}$$

where u_{ijt} is consumer i's latent utility for plan j in time t, g denotes income group, p_{jt} is plan price, X_{jt} is a matrix of plan characteristics, δ_j are supplier fixed effects (when included), and ϵ_{ijt} are independent and identically distributed Extreme Value 1.

I do not instrument for price. The identifying assumption with supplier fixed effects is that unobservable quality only varies across suppliers, not across plans offered by the same supplier. Without supplier fixed effects, the identifying assumption is that consumers who use the website do not consider any supplier-specific attributes or any plan-related attributes that are not listed.

Whether the preferred specification includes supplier fixed effects or not may vary by attribute. In general, supplier fixed effects control for any systematic differences in quality, such as customer service quality, across suppliers. However, firms also specialize in some attributes, such as being a "green" or "renewable" company. The majority of suppliers offer only non-renewable products or only 100% renewable products. Similarly, only three suppliers offer a plan with and a plan without a financial incentive, so it is difficult to identify WTP for these incentives in a model with supplier fixed effects.

Table A4 displays the implied willingness to pay estimates. Estimates are in cents per kWh. The stars reflect significance levels of the logit coefficients. None of the differences between income groups in WTP for attributes are statistically significant at the 5% level. With Bonferroni multiple hypothesis correction, none of the differences are significant at any conventional level. Point estimates suggest that, if anything, high-income households have larger WTP for almost all attributes. For example, I estimate that high-income households are willing to pay \$0.003-0.007/kWh (44-62%) more than low-income households to get an 100% renewable plan instead of a hypothetical 0% renewable plan.

There is one attribute for which I estimate a higher WTP in low-income areas than in high-income areas. Excluding supplier fixed effects, low-income consumers seem to have a stronger preference for avoiding fixed charges. This is consistent with low-income households using less electricity, on average, than high-income households. The coefficients imply that a low-income household would be indifferent between a marginal increase in their fixed

Table A4: Estimated Willingness To Pay For Product Attributes by Income Group

Attribute	WTP by Median Household Income (cents/kWh)					
	<\$60k	>\$60k	p-value	<\$60k	>\$60k	p-value
Contract Term (months)	0.050	0.148***	0.08	-0.002	0.017**	0.17
	(0.050)	(0.027)		(0.012)	(0.006)	
Renewable (%)	0.012	0.019***	0.55	0.007***	0.010***	0.17
	(0.011)	(0.005)		(0.002)	(0.001)	
Cancellation Fee {0,1}	-0.820	-0.053	0.53	0.218	0.293**	0.75
	(1.097)	(0.541)		(0.213)	(0.110)	
Introductory Offer (bool)	-0.587	-1.150*	0.63	-1.006***	-1.326***	0.28
	(1.046)	(0.501)		(0.255)	(0.147)	
Financial Incentive (bool)	-33.2	-31.8	1.00	0.446	0.778***	0.34
	(19646)	(4850)		(0.303)	(0.172)	
Monthly Fee (\$/month)	-0.066	0.160**	0.07	-0.125***	-0.080***	0.17
	(0.106)	(0.063)		(0.029)	(0.015)	
Supplier Fixed Effects	Yes	Yes		No	No	

Estimates of β_g/α_g from the specified conditional logit model. Standard errors in parentheses were calculated using the Delta method. "bool" indicates that all observations take on values of zero or one. P-values come from a test of equality of willingness to pay values across income groups. Stars reflect significance of the β_g parameters with significance levels *p<0.1; **p<0.05; ***p<0.01.

and variable charges at a usage of 800 kWh per month. For a moderate- or high-income household, this estimate is 1,247 kWh per month. These estimates are greater than the mean electricity usage for each of these two groups, which suggests that a marginal reduction in fixed charges and a commensurate increase in variable rates should lower expected bills. Hence, aversion to fixed charges should be even larger under rational and risk-neutral preferences.

All together, I do not find much evidence that preferences can explain the income-price gap we observe. If anything, ignoring differences in preferences seems most likely to lead to an underestimate of the consumer welfare gap between low- and high-income households since low-income households appear to be relatively more focused on price than premium attributes. The one potential exception is fixed charges, and I limit the empirical analyses in this paper to plans without fixed charges.

Subsidies

The government offers some low-income consumers electricity bill subsidies. If these subsidies change low-income consumers' price responsiveness and suppliers have some ability to discriminate on this price responsiveness, then subsidies may be able to explain an income-price gap.

However, the electricity bill assistance subsidies in Baltimore are generally lump-sum transfers that do not vary with electricity price.[5] The possible exception is the Arrearage Retirement Assistance Program, which provides subsidies that vary with households' outstanding arrearage, or underpaid amount. Arrearage amount could conceivably vary with price, but grants through this program are capped at \$2,000 over seven years, which is less than the vast majority of households' total electricity bills. Above this limit, a higher price will not translate into a larger subsidy.

The income-price gap persists when I exclude subsidy recipients. Not all eligible households receive the electric subsidies since households have to apply to the programs. In the Baltimore area, I observe whether a household applied for a low-income subsidy program. Excluding these applicants, I estimate a mean income-price gap of \$0.0090/kWh, which is only slightly smaller than the overall \$0.0094/kWh income-price gap.

I find that low-income program applicants who live in low-income areas have significantly lower prices than non-applicants in those areas, while low-income program applicants who live in higher-income areas have significantly higher prices than non-applicants. If I look only at areas with median household income above \$120,000, where few suppliers market in any zip code, the mean price of low-income subsidy applicants and non-applicants do not differ significantly. The point estimate of the difference is less than \$0.0001/kWh. These results are consistent with a story of low-income subsidy applicants being a selected group that is particularly attentive to electricity price or has particularly low search frictions (e.g., a larger α) while also being more likely to live in areas within zip codes that receive a relatively large amount of marketing conditional on income bin. A shown in Figure 1.10, the variance in marketing presence is much greater in the \$80-100k median household income bin than in the under \$60k or over \$120k bins.

These results suggest that low-income subsidies are not a key driver of the income-price gap. This is consistent with the results of Byrne et al. (2022) who find no evidence that suppliers price discriminate based on low-income subsidy recipient status in Australia.

Negotiation

Consumers can negotiate their price with suppliers. If low-income households are less willing to negotiate or have less negotiating power than high-income households, this could explain the income-price gap. I do not find any evidence for this theory. Among survey respondents, there is not a statistically significant difference across low- and high-income households in the probability of having ever negotiated price ($\chi^2 = 0.3$; see Table A14). Recall that negotiation is not very common in the market, with 66% of surveyed retail choice participants reporting that they had never negotiated their electricity price.

[5]Subsidy amounts vary with household income, type of fuel used for heating, and electricity usage.

A.5 Structural Model Pre-processing Steps

This section describes the pre-processing steps outlined in Section 1.8. It covers classification of consumer types and marketing- versus search-related sign ups, estimation of mean willingness to pay for premium product attributes, and estimation of suppliers' net present value profit from each remaining customer at the end of the analysis period.

Marketing Sign Ups, Search Sign Ups, and Consumer Types

In the first pre-processing step, I approximate the distributions of marketing- and search-related sign-up prices and use these to identify the most likely consumer type for each consumer. The key assumptions underlying this approach are that consumer types are fixed and that each of the underlying price distributions are roughly symmetric around their respective modes.

For each month, I first identify the two modes of the sign-up price distribution. For an initial estimate of the marketing and search distributions, I assume all overlap of these distributions occurs between the two modes. In addition, rational expectations implies that each underlying distribution should be symmetric around the mode. I, therefore, assume the distribution of search-related sign ups with prices above the search-related modal price is a reflection of the distribution below the modal price. I similarly assume the distribution of marketing-related sign ups below the marketing model price is a reflection of the distribution above this modal price. I smooth the resulting distributions using a kernel density estimator with a triangular kernel and a bandwidth equal to the maximum Silverman benchmark bandwidth across time periods. I normalize each of these distributions to integrate to one.

For each consumer who signed up with a supplier at least once during the analysis timeframe, I calculate the probability of observing the realized sign-up prices if the consumer were each a searcher and a non-searcher using these assumed probability distributions. Specifically, I estimate:

$$prob(searcher) = \Pi_t f_{st}(p_t)\frac{N_{st}}{N_{st}+N_{mt}}$$

and

$$prob(non-searcher) = \Pi_t f_{mt}(p_t)\frac{N_{mt}}{N_{st}+N_{mt}}$$

where N_{st} and N_{mt} are the total estimated number of search-related and marketing-related sign ups at time t, respectively, and f_{st} and f_{mt} are the respective probability distributions of search-related and marketing-related sign-up prices. These are posterior distributions conditional on sign up method. I assign each consumer to the type (i.e. searcher or non-searcher) with the higher probability.

For consumers who did not sign up with a new supplier during the analysis timeframe, I perform a matching algorithm to estimate consumer type. I match each consumer in this category to a consumer with an assigned type by matching on the observables of price, supplier in the first period of the analysis timeframe. For consumers with one or more exact matches on these two observables, I select the modal type of consumer matches. For consumers without an exact match, I perform nearest-neighbor matching and select the type of the consumer that had the same supplier and closest price in the first period. The implicit assumption is that these consumers initially signed up in a similar setting and timeframe and that any future switching decision differences come from discrepancies in realizations of random marketing or attention shocks. The overlap assumption here is that the probability that a consumer will switch suppliers in the subsequent three years is strictly between zero and one for all consumers in the market at the beginning of the analysis period.

After assigning a Type to each consumer, I revise my estimates of search- and marketing-related sign-up price distributions. For a given month, the final search-related sign-up price distribution is the distribution of sign ups from all searchers in that month. Similarly, the final marketing-related sign-up price distribution in each month is the distribution of sign ups from all non-searchers. These distributions enter into the likelihood function used to estimate the demand primitives in Section 1.8.[6]

Truncated Profit

As a potential solution to selection bias due to truncation at the end of the analysis period, Berry and Pakes (2000) suggest creating a non-parametric estimate of net present continuation value based on the state. I follow this approach and estimate net present value continuation profit for each consumer active on choice in February 2022. To get this estimate, I combine a cross-sectional non-parametric model of continuation profit for consumers active in February 2019 and a time-series non-parametric model of how next-period profit varies with expected marginal costs.

The cross-sectional model estimates the net present value profit of consumers on retail choice in February 2019 over the subsequent three-year period. I aim to estimate this net present value as some function of the consumer observables total February 2019 bill, months since signing up with the supplier, consumer type, and geography. Using zip code for the geography variable would raise concerns about overfitting for zip codes with few consumers on choice in February 2019. At the other extreme, using income group as the geography may aggregate over important heterogeneity within an income group. As an intermediate solution, I use k-means clustering to cluster zip codes into six clusters based on zip code population density, household income, poverty rate, citizenship rate, high school completion rate, centroid latitude and longitude, percent of households who rent their homes, percent of the population who identify as Black, and percent of the population who identify as Latino and Hispanic.

I use Least Absolute Shrinkage and Selection Operator (LASSO) regression to determine the model specification for predicting February 2019 continuation value. I allow for

[6]These are also the distributions used in the regression discontinuity and differences-in-differences analyses in Section 1.4. The results are robust to identifying the saddle point between the two modes and assigning all prices below this price cutoff to search-related sign ups and all prices above this price to marketing-related sign ups.

third-order polynomials and first-order interaction terms. Table A5 presents the final model specification and results. Ninety eight percent of consumers in the excluded cluster live in zip codes with median annual household income below $60,000. Cluster 6 has 14% of consumers in this category, and the other clusters have none. Results suggest that continuation profit is greater for consumers who start with higher bills and live in more privileged areas. The geographic result may be due to a combination of marketing activity and electricity usage differences.

Let V be the discounted net present value of expected profit for three years after the end of the analysis timeframe (T), and let $X = \{Bill, Type, Cluster, Duration\}$. The model presented in Table A5 provides estimates of $E[V|X, c_2]$ where c_2 is the vector of all expected future marginal costs as of February 2019. We are looking for $E[V|X, c_T]$. I use the following approximation:

$$E[V|X, c_T] \approx E[V|X, c_2] + E[V|c_T] - E[V|c_2]$$

This is a decent approximation if the impacts of consumer attributes X and expected marginal costs on net present value profit are predominantly orthogonal.

To estimate $E[V|c_T]$ and $E[V|c_2]$, I estimate the relationships between marginal costs and each of period profits and switching probability using temporal marginal cost variation across the full analysis period. I again use LASSO to determine the functional forms of these relationships, allowing for up to a fifth-order polynomial approximation. I settle on a cubic specification for switching probability and a fourth-order polynomial for period profit. In a longer time series, it may be prudent to also control for month of year fixed effects. I do not add this control given the small sample size of each individual month, but the two relevant periods, 2 and T, fall on the same month of year. I use one-month ahead expected marginal costs to estimate the model and then calculate predicted period profit and switching probabilities for each consumer using expected future marginal costs as of February 2019 and February 2022. I use these predicted values to estimate net present value profit as

$$E[V|c_t] = \sum_{s=t+1}^{t+36} \delta^s (Predicted\ Profit)_s (\sum_{\tau=t}^{s} (1 - (Switch\ Predict)_\tau)^{s-1})$$

where δ is the firm's discount factor, $(Predicted\ Profit)_s$ denotes predicted period profit in time s, and $(Switch\ Predict)_\tau$ is predicted switching probability in time τ. Using this method, I estimate that the predicted continuation value of having a consumer in February 2022 was $183 less than the predicted continuation value of having a consumer in February 2019.

A.6 Results from Other States

This section presents descriptive evidence that some key stylized facts presented in Section 1.4 also hold in several other Northeast U.S. residential electricity markets. Pricing data

Table A5: Prediction Model for 3-year Continuation Profit Post February 2019

	Net Present Value 3-year Continuation Profit
Duration (months)	0.408**
	(0.165)
Supply Bill ($)	1.233***
	(0.059)
Non-searcher	−47.770***
	(6.139)
Cluster 2	35.500**
	(13.870)
Cluster 3	−13.156
	(16.449)
Cluster 4	33.500**
	(13.238)
Cluster 5	45.448***
	(13.962)
Cluster 6	21.040**
	(8.226)
(Supply Bill)x(Cluster 2)	0.719***
	(0.080)
(Supply Bill)x(Cluster 3)	0.577***
	(0.089)
(Supply Bill)x(Cluster 4)	0.272***
	(0.083)
(Supply Bill)x(Cluster 5)	0.019
	(0.096)
(Supply Bill)x(Cluster 6)	0.445***
	(0.065)
Constant	121***
	(9.92)
Observations	46,488
Adjusted R^2	0.222

*p<0.1; **p<0.05; ***p<0.01

for these analyses come from Central Maine Power and from public Eversource data in Connecticut Public Utilities Regulatory Authority dockets 18-06-02, 06-10-22, and 21-11-01, New York Public Service Commission Case 15-M-0127, Rhode Island Public Utilities Commission Docket 5073, the Office of the Attorney General of the Commonwealth of Massachusetts (MA AGO 2018), and the Office of Illinois Attorney General (Satter, 2020).

Data richness vary by location. I have household-level panel billing data for Central Maine Power in Maine from November 2018 through October 2021.[7] Eversource Connecticut data are repeated monthly cross-sections of electricity supply prices that suppliers billed to consumers on retail choice. For many months between October 2018 and March 2019, these data are broken down by whether the consumer signed up with a new supplier that month and whether the consumer is on a low-income program that protects them from power shutoffs ("hardship status"). For two months each year between 2011 and 2018, the pricing data are broken down by zip code. In all other states, I have summary statistics of mean price or retail choice participation rates for various subsets of the population. In New York and Chicago, I have zip code-level statistics. In Massachusetts and Rhode Island, statistics vary by low-income subsidy status.

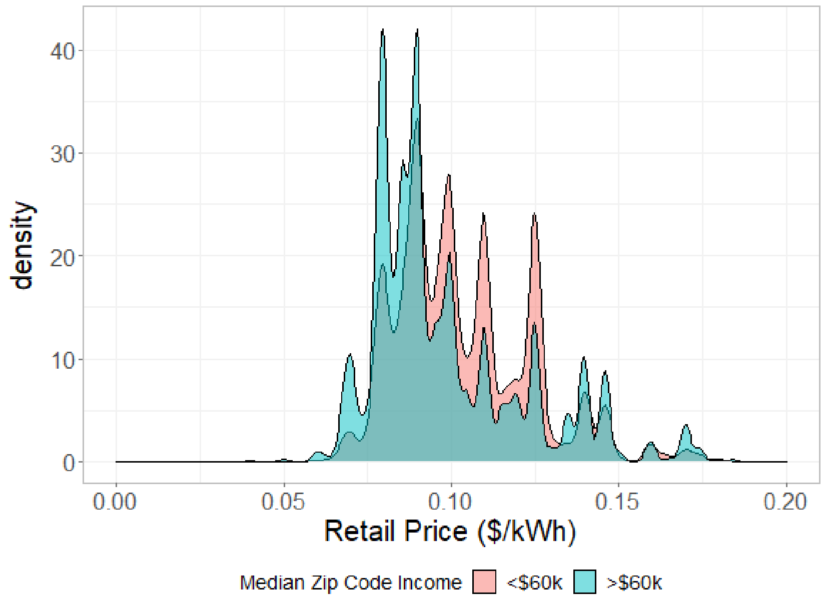
Large price heterogeneity, with relatively high prices in low-income and other marginalized communities

I find evidence that large price heterogeneity exists in Connecticut and Maine. Looking across all months, the standard deviations in residualized prices after controlling for time fixed effects are \$0.027/kWh in Connecticut and \$0.028/kWh in Maine. In Connecticut, a quarter of consumers have prices at least 23% higher than the median price, and 5% of consumers have prices 58% higher than the median price.[8] These percentage price differences are 9% and 38%, respectively, in Maine. Figures A6 and A7 show cross-sections of these price distributions.

[7] Data came in three separate annual panels.

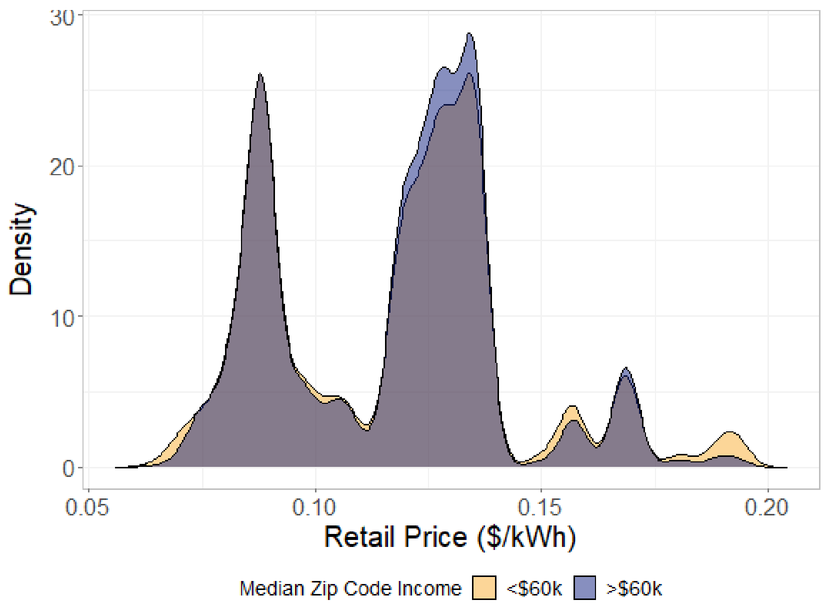
[8] These values reflect the mean and median percentage price differences across months of the analysis timeframe.

Figure A6: Prices by Zip Code Median Household Income (June & Sep 2018): Connecticut



Probability density of generation supply prices for residential retail choice customers in Eversource service territory in Connecticut by 2019 American Community Survey zip code tabulation area median annual household income.

Figure A7: Prices by Zip Code Median Household Income (Sep 2019): Maine

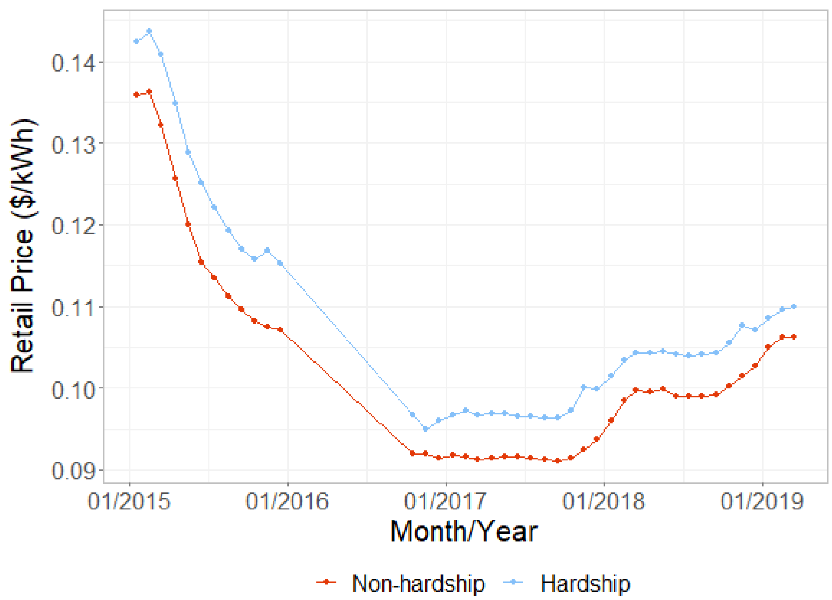


Probability density of generation supply prices for residential retail choice customers in Central Maine Power service territory by 2019 American Community Survey zip code tabulation area median annual household income.

In Connecticut, households with low-income protections, households in low-income areas, and households in other types of marginalized communities pay especially high prices. The average price paid by hardship customers in the retail choice market was consistently higher than that of non-hardship customers, as shown in Figure A8.[9] Looking across zip codes, prices in zip codes with median annual household income below $60,000 were $0.005/kWh higher, on average, than prices in zip codes with median annual household income above $80,000. As shown in Figure A9, this income-price gap is even larger on sign up. The mean sign-up price difference across low- and high-income zip codes is $0.017/kWh. Looking across marginalized communities more broadly, Figure A10 shows coefficients and 95% confidence intervals from regressions of price on median household income bin and other zip code demographics, controlling for time fixed effects and clustering standard errors by supplier. Households pay especially high prices in areas with median zip code household income below $10,000 as well as areas with a large share of non-citizens, residents without high school diplomas, and Black, mixed race, and Latino and Hispanic residents.

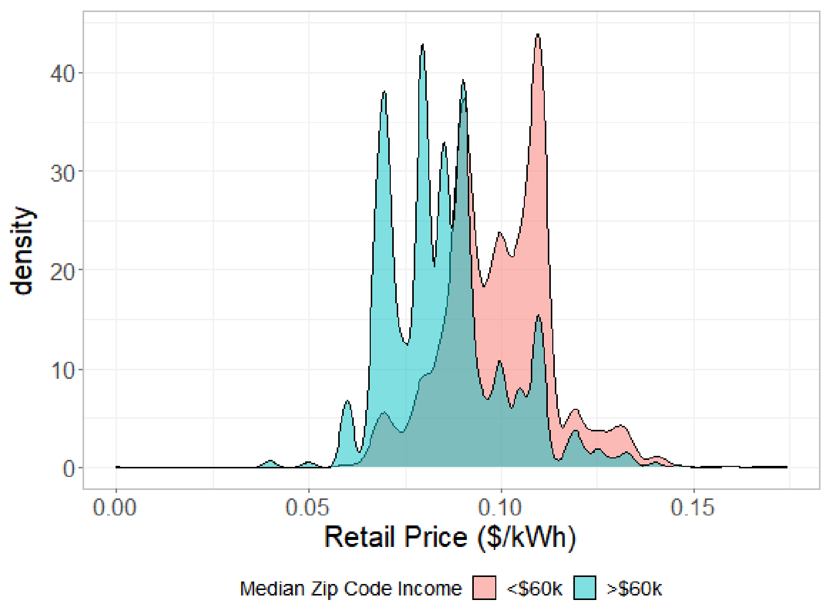
[9]Shortly after this period, hardship customers were banned from the Connecticut retail choice market.

Figure A8: Mean Retail Price by Hardship Status: Connecticut



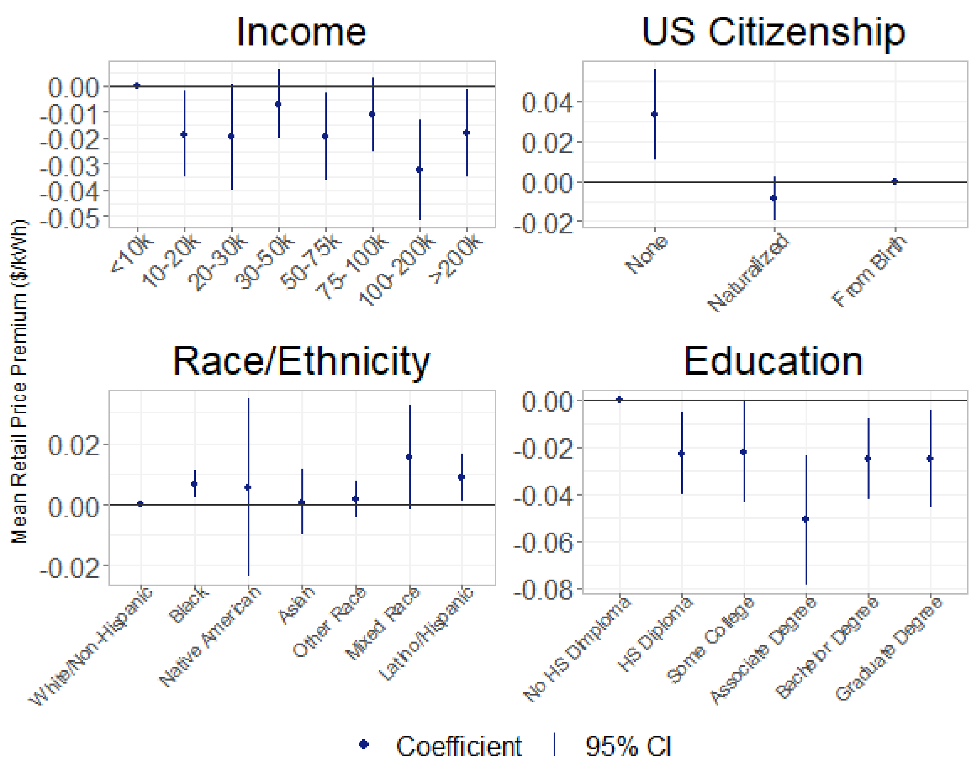
Mean electricity supply prices billed in Eversource's Connecticut service area by month and whether the consumer was awarded hardship status. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

Figure A9: Sign-up Prices by Zip Code Median Household Income (June & Sep 2018): Connecticut



Note: Probability density of generation supply sign-up prices for residential retail choice customers in Eversource's Connecticut service territory for consumers who switched retail suppliers. Distributions by 2019 American Community Survey zip code tabulation area median annual household income.

Figure A10: Coefficient Estimates from Regressions of Price on Key Zip Code Demographics



Coefficients and 95% confidence intervals from regressions of electricity supply price on time fixed effects and zip code tabulation area (ZCTA) demographics from the 2019 American Community Survey. Residential customer accounts on retail choice in Eversource's Connecticut service territory only.

In Maine, average prices are higher in low-income areas than high-income areas conditional on contract number (see Figure A11), but not overall. As shown in Section 1.7, this can be rationalized by the model presented in this paper. Marketing puts downward pressure on average prices by causing more frequent switching in low-income areas.

Summary statistics from Massachusetts, Rhode Island, and New York suggest that low-income households face higher prices, on average, than high-income households in these retail choice markets. In Massachusetts in 2020, low-income subsidy recipients on individual plans with electricity suppliers were billed \$0.0044/kWh more, on average, than consumers who did not receive these subsidies. In Rhode Island, the mean price of households active in the retail choice market was especially high for low-income households, defined as residential accounts in the A-60 rate class, in all months of 2019 and 2020.[10]. In New York in 2016, mean prices of retail choice participants in zip codes with median annual household income less than

[10]The income-price gap did not exist in many months of 2017 and 2018.

$60,000 were greater than those with median annual household income greater than $80,000 in five out of six of the utility service territories. Premiums ranged from $0.001-0.024/kWh.

Greater retail choice participation and more frequent switching in low-income areas

There is evidence that retail choice participation rates are higher in low-income communities than in high-income communities in at least four states. The Office of the Attorney General of the Commonwealth of Massachusetts show that participation rates among low-income subsidy recipients are about double the rate of households who do not receive these subsidies (MA AGO 2018). The Office of Illinois Attorney General finds that retail choice participation rates are highest in low-income zip codes and lowest in high-income zip codes of Chicago (Satter, 2020). I find the same result in Connecticut ($\chi^2 = 1506$) and Maine ($\chi^2 = 75$) comparing participation rates in zip codes with median annual household income below $60,000 and above $80,000.

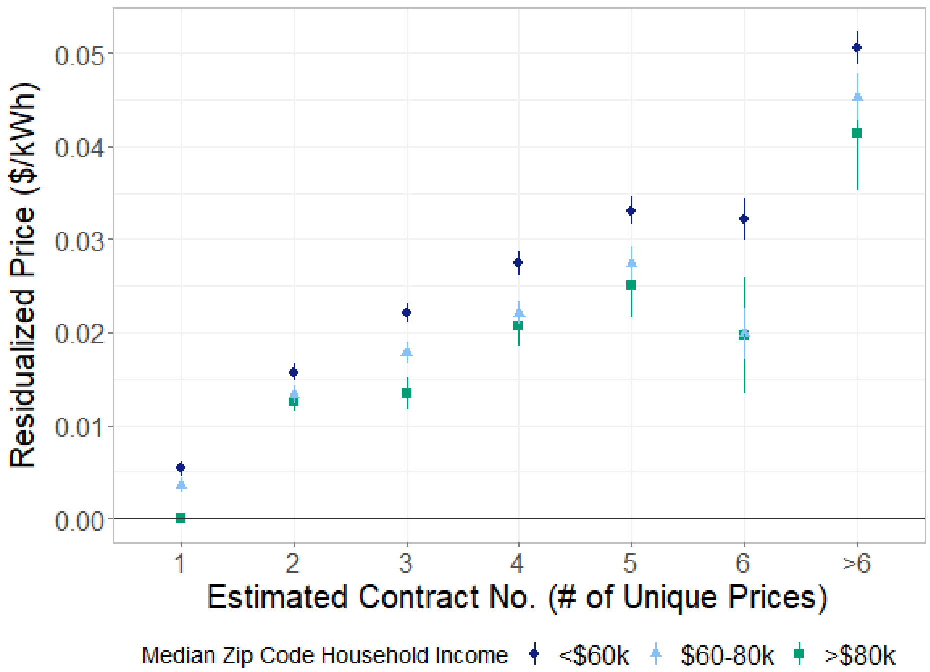
I also observe more frequent switching in low-income communities than high-income communities in Maine ($t = 13$). These estimates come from a regression of whether each consumer signed up with a supplier on income group, controlling for time fixed effects. I restrict the sample to consumers who were active in the retail choice market in each analysis month.[11] In Connecticut, low-income households with hardship status switch with a higher probability in a given month than other retail choice participants ($\chi^2 = 106$).

Prices increase with contract renewals

Panel data in Maine and repeated cross-sectional data in Connecticut provide evidence that prices also increase with contract renewals in these two states. For Connecticut, I restrict the sample to prices that I can identify as sign-up or renewal prices in a given month. I identify renewal prices as non-sign-up prices billed by a supplier in a given month if that price-supplier combination did not exist in the data set in the previous month.

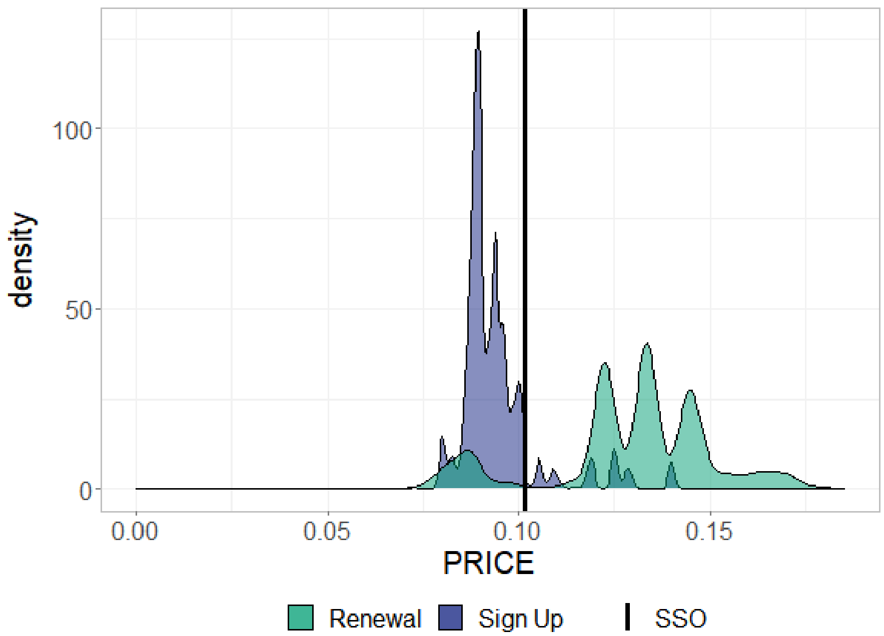
[11] This result is robust to a probit specification.

Figure A11: Residualized Price by Number of Contracts with Supplier: Maine



Estimates from a regression of electricity supply price on time fixed effects, number of unique prices a consumer has faced since last switching suppliers, and income group. Excludes standard offer service prices. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

Figure A12: New and Renewal Price Distributions (March 2019): Connecticut



Note: Probability density of generation supply sign-up prices (purple) and renewal prices (green) for residential retail choice customers in Eversource's Connecticut service territory. Sign-up prices reflect prices of consumers who switched retail suppliers in March 2019. Renewal prices reflect prices for the subset of observable consumers who did not switch suppliers in March 2019 and experienced a price change between February and March 2019.

Households in low-income areas are less likely to sign up through the government comparison website

In addition to regulatory pricing data on first-month sign-up prices in Connecticut, I also have data on aggregate clicks on plans on the plan comparison website run by the Connecticut Public Utilities Regulatory Authority. Comparing these two data sets, 43% of all sign ups are from cities with median income less than $60,000, but only 12% of EnergizeCT comparison website clicks are from those same cities ($\chi^2 = 6357$).

A.7 Marginal Cost Calculation

Table A6 summarizes the data sources by cost component. To estimate suppliers' expected cost of procuring wholesale electricity, I use Platts historical on-peak and off-peak power futures prices, which I access through SNL Financial. I use weighted average prices to calculate expected cost for a given contract length in each starting month. I weight prices by mean per-customer electricity usage[12] in a given month from the BGE billing data and the percentage of usage that occurs in on-peak hours. To estimate this on-peak percentage, I use the North American Electric Reliability Corp definition of on-peak hours in the Eastern Interconnect and public hourly BGE load profiles for residential customers who do not have electric heating and are not on the BGE time-of-use rate. I scale these costs up for transmission and distribution losses using BGE's calculated secondary voltage loss factor of 6.665%.

Table A6: Marginal Cost Data Sources

Cost Component	Data Source
Electricity Futures	SNL Financial On-Peak and Off-Peak BGE Forward Power Indexes, BGE monthly billing data, BGE Hourly Load Profiles Segment R[1]
Distribution Losses	BGE[2]
Capacity Costs	PJM[3], BGE[4], EIA-861
Ancillary Services	Monitoring Analytics (2022)[5]
Renewable Portfolio Standard	SNL Energy Renewable MD Tier I, Tier 2, and Solar REC Indexes, Maryland Code, Public Utilities § 7-703

[1]Available at: https://supplier.bge.com/electric/load/profiles.asp
[2]Available at: https://supplier.bge.com/electric/load/loss-factors.asp
[3]Available at: https://pjm.com/markets-and-operations/rpm.aspx
[4]Available at: https://supplier.bge.com/electric/load/plc-peak-hours.asp
[5]"PJM State of the Market" report. Available at:
https://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2021/2021q1-som-pjm-sec10.pdf

Once a year, BGE updates a supplier's capacity-related cost of serving a marginal customer based on the customer's electricity usage during specific hours of the previous year (i.e. the customer's "Peak Load Contribution") and the results of the Pennsylvania-New Jersey-Maryland (PJM) capacity auction. BGE calculates the cost responsibility for each customer as their Peak Load Contribution multiplied by 365 days in a year and the PJM Final Zonal Net Load Price ($/kW-day) for the BGE deliverability area. BGE charges suppliers for the cost responsibilities of their customers. This cost is constant for each year starting in June. Some customers do not have electricity meters that are able to calculate their Peak Load Contribution. For these customers, BGE assigns a default Peak Load Contribution value. I estimate each supplier's capacity cost responsibility in $/kW-day by mimicking BGE's calculation and using the default Peak Load Contribution value for BGE residential customers without electric heating. I approximate this cost in $/kWh by dividing the annual required payment by the mean annual usage of BGE residential customers, which I calculate from Energy Information Administration Form EIA-861.

[12]Estimates using coefficients from regressions of usage on month of year, consumer fixed effects, and either a time trend or time fixed effects produce very similar weights ($r > 0.999$).

Maryland has a Renewable Portfolio Standard (RPS) that requires all suppliers to meet 50% of their electricity sales from renewable resources by 2030. The law also specifies a path to meet the 2030 standard with less stringent interim standards. For example, in 2019, the total standard was 23.2% of retail sales. To meet this standard, suppliers had to obtain enough RECs to cover 23.2% of their retail sales, where one REC counts as 1,000 kWh of electricity. The law also includes constraints on the portion of the overall standard that can or must be met with certain types of renewable resources. There are separate markets for RECs representing each relevant renewable resource category. To calculate a supplier's marginal RPS cost, I assume suppliers choose the cheapest REC bundle that will meet the requirement.

I also include annual estimates of PJM ancillary service costs per kWh of aggregate electricity usage. These estimates come from quarterly Monitoring Analytics reports on the state of the PJM market.

I assume firms determine prices one month in advance with perfect knowledge of capacity costs and imperfect knowledge of energy and REC prices. For example, the marginal cost used for March 2020 analyses for a one-month contract reflects mean energy and REC future prices for delivery month March 2020 in February 2020 and the March 2020 capacity price.

For convenience, I exclude state and local taxes from the analysis. In BGE, the purchase of receivables discount was zero throughout the analysis timeframe. I also use data from the U.S. Energy Information Administration (EIA) for some small analytical tasks.

A.8 Survey Instruments

Retail Choice Consumer Survey Questions

Section 1: Eligibility

1. What is your 5-digit zip code or postal code?
2. Are you over the age of 18? [Note: information collected automatically for the main survey]
    a. Yes/No
3. Do you pay or make decisions about your [utility] electricity bill?
    a. Yes
    b. No
    c. I make decisions about my monthly electricity bill, but [utility] is not my electric utility
4. [If 4 = c] Please select your electric utility.
    a. Baltimore Gas and Electric (BGE)
    b. Delmarva Power
    c. Eversource / Connecticut Light & Power
    d. Potomac Edison / FirstEnergy / Allegheny Power
    e. Potomac Electric Power Company (Pepco)
    f. Southern Maryland Electric Cooperative (SMECO)
    g. United Illuminating (UI)
    h. Other

Section 2: Self-reported Price, Bill, and Supplier

5. An "**electricity supplier**" purchases electricity for you and chooses what you pay for this electricity. Your electricity supplier is the company named on the "Supply" or "Generation" portion of your [utility] electricity bill. Have you ever chosen an electricity supplier other than [utility] while living in your current home?
    a. Yes/No/Unsure
6. Please write the name of your current electricity supplier. If you are unsure, please state so.
7. Roughly how much do you pay for electricity per month? Please write your answer in US dollars. If you are unsure, please provide your best guess.
8. Roughly how much do you pay for electricity per kilowatt-hour (kWh)? Please write your answer in US dollars per kWh ($/kWh). If you are unsure, please provide your best guess.

Section 3: Reasons for Sign Up

9. [If 5 = Yes] You said that you have signed up with a supplier other than [Utility]. Why did you choose to do that? Please describe the most influential factors in your decision.
10. [If 5 = Yes] How did you find the non-[utility] electricity plan(s)? [Answers shown in random order]
    a. A salesperson/representative came to my door, approached me on the street, or stopped me at a store and told me about it
    b. A salesperson/representative called me on the phone and told me about it
    c. A friend or relative recommended it
    d. I received the offer in the mail
    e. I called the electricity supplier to ask about their available plans
    f. I looked at the electricity supplier's website for available plans

   g. I looked at an online electricity plan comparison website
   h. I looked at the [website name] website run by [Commission]
   i. I saw an advertisement for the offer on TV, radio, an online ad, or a billboard
   j. Other (please write)
11. [If 5 = No, Unsure] What made you choose to sign up for your current electricity plan? Please describe the most influential factors.
12. In the past 5 years, have you paid extra money for any of the following plan characteristics? Please check all that apply. [Answers shown in random order]
   a. Renewable energy / green energy / solar energy / wind energy / renewable energy credits
   b. Gift card
   c. Short contract term
   d. Long contract term
   e. Fixed price
   f. Incentive or rewards program
   g. Low or no cancellation fee
   h. Low or no enrollment fee
   i. Good customer service
   j. Useful website, dashboard, app, newsletter, or personalized reports and suggestions
   k. Trustworthy supplier
   l. Supplier was my local utility
   m. Supplier was not my local electric utility
   n. Other (please write)
13. Have you ever had somebody come to your door, approach you on the street, or talk to you in a store for any of the following reasons?
   a. To help save you money on your [utility] bill
   b. To check if there was an issue on your [utility] bill
   c. To encourage and help you switch to a different electricity supplier
   d. To switch you to a high renewable or green electricity plan
   e. To change your electricity plan in some other way
   f. None of the above
14. This survey will refer to any person described in the previous question as an "**electricity marketer**". The goal of an electricity marketer is to switch your electricity supplier. In the past two years, approximately how many times has an electricity marketer reached out to you **in person**? They may have knocked on your door, approached you on the street, or talked to you in a store.
   a. 1-2 times
   b. 3-5 times
   c. 6-10 times
   d. >10 times
   e. Never
15. Electricity marketers may also call on the phone. In the past two years, approximately how many times has an electricity marketer called you on the phone to switch you to a different electricity plan?

   a. 1-2 times
   b. 3-5 times
   c. 6-10 times
   d. >10 times
   e. Never

16. [If 14 != “Never”] In the past ten years, approximately how many times have you signed up for an electricity plan with an electricity marketer you talked with in person?
   a. Once
   b. Twice
   c. 3-5 times
   d. 6-10 times
   e. >10 times
   f. Never
17. [If 15 != “Never”] In the past ten years, approximately how many times have you signed up for an electricity plan with an electricity marketer who called you on the phone?
   a. Once
   b. Twice
   c. 3-5 times
   d. 6-10 times
   e. >10 times
   f. Never
18. In the past ten years, approximately how many times have you signed up for a non-[utility] electricity plan based on a mail, e-mail, radio, TV, billboard, or internet advertisement? This does not include offers or promotions you looked for online.
   a. Once
   b. Twice
   c. 3-5 times
   d. 6-10 times
   e. >10 times
   f. Never
19. In the past ten years, approximately how many times have you signed up for an electricity plan by calling an electricity supplier or searching online?
   a. Once
   b. Twice
   c. 3-5 times
   d. 6-10 times
   e. >10 times
   f. Never
20. [If 16 != “Never” or 17 != “Never”] Which of the following influenced your decision to sign up for electricity plan(s) through an electricity marketer? Please check all that apply. [Answers shown in random order]
   a. The marketer recommended the plan
   b. The marketer seemed to be well informed

c. I was worried about what the marketer would think about me if I did not follow their suggestion
d. I was worried about what the marketer would do if I did not follow their suggestion
e. I wanted to help the person selling the plan
f. I wanted the marketer to leave
g. I misunderstood the price or terms of the plan
h. I liked the plan's price or believed I would save money
i. I liked the plan's characteristics
j. Other (please write)

Section 4: Search Behavior and Methods

21. [If 16 != “Never” or 17 != “Never”] Last time you signed up for an electricity plan through an electricity marketer, did you first compare the plan to any of the following plans? Please check all that apply.
    a. My current plan at the time
    b. The default [utility] plan, the standard offer service plan, or the price to compare
    c. Plans offered by other electric suppliers
    d. None of the above
22. [If 21 = c] Last time you signed up for an electricity plan through an electricity marketer, roughly how many <u>other</u> electricity suppliers did you consider before choosing a plan?
    a. None
    b. 1
    c. 2-3
    d. 4-6
    e. 7-15
    f. >15
23. [If 21 = c and 5 = no?] How did you find information on the plans offered by other electricity suppliers?
    a. Called electricity suppliers
    b. Looked at electricity supplier websites
    c. Visited an online plan comparison website
    d. Visited the [website name] website run by [Commission]
    e. Asked a friend or family member what they paid for electricity
    f. Other (please write)
24. If an electricity marketer showed up at your door tomorrow saying they could save you money on your [utility] bill, would you sign up?
    a. Yes/No/Unsure
25. If an electricity marketer showed up at your door tomorrow saying they could save you money on your [utility] bill and hand you a $50 gift card to a store of your choice, would you sign up?
    a. Yes/No/Unsure
26. [If 24 = “Unsure” or 25 = “Unsure”] You said you were unsure if you would sign up with an electricity marketer in one of the previous questions. What would your answer depend on or what additional information would you need to make a decision? Please check all that apply:
    a. It would depend on the price the electricity marketer offered

- b. It would depend on what the marketer said or did or who they were
- c. I would review the price of my current plan first
- d. I would review the price of the standard offer service, price to compare, or [utility] plan first
- e. I would review plans offered by other electricity suppliers first
- f. I would look for more information about the electricity supplier first
- g. Other (please write)

27. [If 24 = “No” and 25 = “No”] You said that you would not sign up with an electricity marketer who said they could save you money and give you a $50 gift card. Why wouldn’t you be interested in this offer?
28. [If 27 = e and 21 != c] You indicated that you would review plans offered by other electricity suppliers. Roughly how many electricity suppliers would you consider before making a decision?
    - a. 1
    - b. 2-3
    - c. 4-6
    - d. 7-15
    - e. >15
29. [If 27 = e and 21 != c] How would you find information on the plans offered by other electricity suppliers?
    - a. Call specific electricity suppliers
    - b. Look at specific electricity supplier websites
    - c. Visit an online plan comparison website
    - d. Visit the [website name] website run by [Commission]
    - e. Ask a friend or family member what they were paying
    - f. Other (please write)
30. Have you ever switched electricity suppliers because you noticed a change in your price or bill?
    - a. Yes/No
31. If so, which electricity plans did you consider after seeing the price or bill change?
    - a. The default [utility] plan, the standard offer service plan, and/or the price to compare
    - b. Plans offered by other electric suppliers
    - c. None of the above
    - d. N/A

Section 5: Search Costs

32. What is the minimum amount you would have to save off your next monthly [utility] bill to spend an hour comparing electricity offers? Assume the savings last only one month. Please write the savings in US dollars ($).
33. What is the minimum amount you would have to save off EACH of your next 12 monthly bills to spend an hour comparing electricity offers? Assume the savings last only one year. Please write the savings in US dollars per month ($/month).
34. How much money do you think you could save off of your next monthly [Utility] bill if you spent an hour looking for a cheaper plan that is otherwise similar to your current plan? Please write your answer in US dollars ($/month).

35. [If 34 > 32] You indicated that you expect to be able to save enough money if you searched for other electricity plans to make it worth your time. Why have you not searched for other plans?

Section 6: Availability and Propensity to Engage in Direct Marketing

36. If 10 strangers knocked on your door this year between the hours of 9am and 7pm, approximately how many of them do you think you would talk with?
37. If 10 strangers knocked on your door in 2019 between the hours of 9am and 7pm, approximately how many of them do you think you would talk with?
38. If 10 strangers called you on the phone this year between the hours of 9am and 7pm, approximately how many of them do you think you would talk with?
39. If 10 strangers called you on the phone in 2019 between the hours of 9am and 7pm, approximately how many of them do you think you would talk with?

Section 7: Beliefs about Price Heterogeneity

40. You said you pay about $[X.XXX]kWh for electricity. What do you think is the **highest** price a household in your town or city is charged for electricity? Please write your answer in US $/kWh.
41. You said you pay about $[X.XXX]kWh for electricity. What do you think is the **lowest** price a household in your town or city is charged for electricity? Please write your answer in US $/kWh.

Section 8: Miscellaneous Attention/Behavior:

42. Have you ever negotiated your price with an electricity supplier? Please check all that apply.
    a. Yes, when signing up with a new supplier
    b. Yes, for a renewal price with an existing supplier
    c. No, I never considered it
    d. No, I do not feel comfortable negotiating with my supplier
43. Approximately how frequently do you look at your electricity **bill**?
    e. Once a month
    f. Once every 2-3 months
    g. Once every 4-11 months
    h. Once a year
    i. Less than once a year
    j. Never
44. Approximately how frequently do you look at your electricity **price** or **rate**?
    k. Once a month
    l. Once every 2-3 months
    m. Once every 4-11 months
    n. Once a year
    o. Less than once a year
    p. Never

Information Interventions

- Treatment Arm 1 (search costs):
    - Are you aware that there is a free government-run website where you can compare electric plans offered by different suppliers?

    - Yes/No
  - The [Commission] is a government agency that hosts a free website, [Website], where you can view and compare electricity plans offered by different suppliers. For example, here are some offers listed on the website as of [Date]:

1Select Plans on Offer Comparison Website

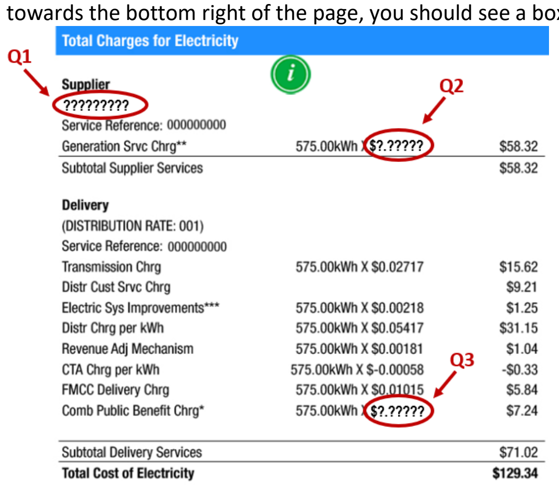
Description	Price ($/kWh)	Typical Total Bill ($/Month)	Price Fixed For:	Electric Supplier	Phone Number	Website Link
Government-regulated plan	[Data]	[Data]	1 month, followed by regulated changes	[Data]	[Data]	[Data]
Cheapest plan	[Data]	[Data]	[Data]	[Data]	[Data]	[Data]
Cheapest plan with a fixed price for at least 1 year	[Data]	[Data]	[Data]	[Data]	[Data]	[Data]
Cheapest plan with 100% renewable energy credits	[Data]	[Data]	[Data]	[Data]	[Data]	[Data]

  You can view other offers at [Website URL].
  - Which of the available plans would you prefer? Please write the phone number of the selected plan below. You may choose one of the plans listed above or another offer on the website.
- Intervention 2 (beliefs about the benefits of searching – all prices):
  - Did you know that the government does not put any limits on the prices retail suppliers can charge and allows electric suppliers to charge customers different prices for the same product?
    - Yes/No
  - You guessed that households' electricity prices in your town or city range from [Q41 Answer] to [Q40 Answer]. In [Month/Year] prices charged by electric suppliers in [Utility or Nearby Utility] territory ranged from a minimum of $[Min Price]/kWh to a maximum of $[Max Price]/kWh kWh. At a typical household monthly electricity usage of [Usage] kWh, this translates to a bill difference of about $[Bill Difference] per month. The average price was $[Mean Price] or about $[Bill at mean price and usage]/month
  - Given this information, how much money do you think you could save off your next monthly [Utility] bill if you spent an hour comparing offers? Assume the plan has the

same characteristics as your current plan. Please write your answer in US dollars ($/month).

Bill Intervention

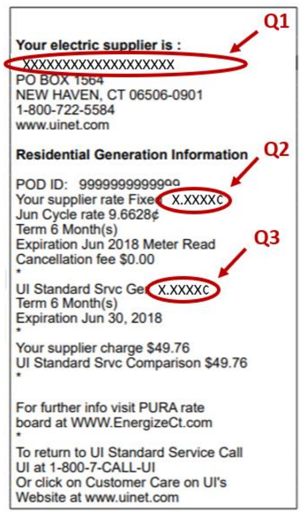
1. This is the last question on the main survey. For another $4, would you be willing to get a recent [utility] bill and answer 3-4 questions about what is on it to verify some information you entered?
    a. Yes, and I am ready to do that right now
    b. Yes, but I would prefer to do that at another time or day
    c. No
    d. Other (please write)
2. [If 1 = Yes and Utility = Eversource] Please find a recent Eversource electricity bill. On Page 2 towards the bottom right of the page, you should see a box that looks like the following:



    Please note that some of the values on your own bill may differ from the values in the picture. The following questions ask about prices and supplier information printed on your own residential electricity bill. The red circles and ?'s in the picture above show where the requested values should be on your bill.
3. [If 1 = Yes and Utility = Eversource] Were you able to find the referenced box on your own residential electricity bill?
    a. Yes
    b. No
    c. Unsure
4. [If 1 = Yes and Utility = Eversource] Q1: What is written on your bill directly under "Supplier" (in circle Q1)?
5. [If 1 = Yes and Utility = Eversource] Q2: What price is written on your bill to the right of "Generation Service Chrg" (circle Q2)? Please include all values to the right of the first dollar sign. For example, if the line reads "Generation Service Chrg** 700 kWh X $0.12345", please enter "0.12345"
6. [If 1 = Yes and Utility = Eversource] Q3: What price is written on your bill to the right of "Comb Public Service Chrg" (circle Q3)? Please include all values to the right of the first dollar sign. For

example, if the line reads "Comb Public Service Chrg* 700 kWh X $0.12345", please enter "0.12345"

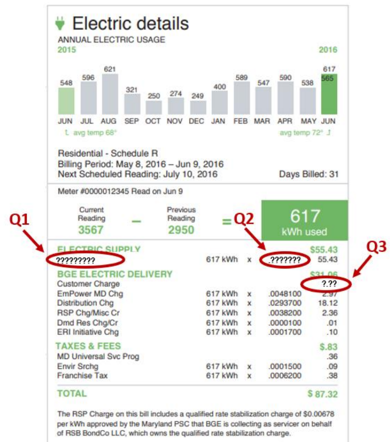
7. [If 1 = Yes and Utility = United Illuminating] Please find a recent United Illuminating electricity bill. On Page 1 towards the bottom right of the page, you should see a box that looks like the following:



Please note that some of the values on your own bill may differ from the values in the picture.

The next three questions ask about prices and supplier information printed on your own residential electricity bill. The red circles and X's in the picture above show where the requested values should be on your bill.

8. [If 1 = Yes and Utility = United Illuminating] Were you able to find the referenced box on your own residential electricity bill?
    a. Yes/No/Unsure
9. [If 1 = Yes and Utility = United Illuminating] Q1) What is written on your bill directly under "Your electricity supplier is:" (in circle Q1)?
10. [If 1 = Yes and Utility = United Illuminating] Q2) What numbers are written on your bill to the right of "Your supplier rate" (in circle Q2)?
11. [If 1 = Yes and Utility = United Illuminating] Q3) What numbers are written on your bill to the right of "UI Standard Srvc Gen:" (in circle Q3)?
12. [If 1 = Yes and Utility = BGE] Please find a recent electricity bill. On Page 2 on the left of the page, you should see a box that looks like the following:



Please note that some of the values on your own bill may differ from the values in the picture.

The following questions ask about prices and supplier information printed on your own residential electricity bill. The red circles and ?'s in the picture above show where the requested values should be on your bill.

13. [If 1 = Yes and Utility = BGE] Were you able to find the referenced box on your own residential electricity bill?
    a. Yes/No/Unsure
14. [If 1 = Yes and Utility = BGE] Q1) What is written on your bill directly under "ELECTRIC SUPPLY" (in circle Q1)?
15. [If 1 = Yes and Utility = BGE] Q2) On the same line as the value you just entered, what is written on your bill to the right of the x? Please include all digits in the number to the right of the x. For example, if the line reads "PEACH 900 kWh x $.12345   55.43", please enter ".12345"
16. [If 1 = Yes and Utility = BGE] Q3) What is written on your bill to the right of "Customer Charge" (circle Q3)? Please include all numbers (e.g. "1.23").

Additional Questions in the Follow-up Survey (note: repeats Baseline Survey questions #7, 8, and 34):

- Have you changed electricity suppliers in the past months?
- In the past month, have you negotiated your price with an electricity supplier? Please check all that apply.
    - Yes, when signing up with a new supplier
    - Yes, for a renewal price with an existing supplier
    - No
- How did the previous survey on electricity suppliers and marketers change your behavior, if at all?
- How did the previous survey on electricity suppliers and marketers change your understanding of the electricity market, if at all?

A.9 Consumer Survey

Design

I conducted a baseline and follow-up consumer survey of 905 consumers in August and September 2022 to gain additional information about consumer behavior, beliefs, and experiences with searching and signing up with electricity suppliers. I partnered with MFour, who administered the survey using their mobile application, and designed the survey in Qualtrics Eligible participants lived in an area of Connecticut, Maryland, or the District of Columbia that is open to retail choice, were over 18 years old, and made decisions about their electricity bill. To facilitate comparison across groups, I undersampled zip codes with median household income between $60,000 and $80,000.

The baseline survey has eight parts excluding verifying eligibility. The first part asks for basic geographic information and verifies the participant's electric utility. The second part asks for self-reported information on electricity supplier, typical monthly bill, and retail price. The third part assesses reasons for sign up, including the number of past sign ups by method, frequency of interactions with electricity marketers, and willingness to pay more money for various supplier and plan attributes. The fourth part asks about historical and hypothetical search behavior and search methods when engaged in a direct marketing interaction and historical search behavior after noticing a price or bill change. The fifth, sixth, and seventh parts assess search costs, propensity to engage in a door-to-door or phone marketing interaction in 2019 and 2021, and beliefs about price heterogeneity in the market, respectively. The final part asks about behavior after initial sign up to better understand attention to bill and price and price negotiation behavior.

Immediately after the baseline survey, treated participants receive a randomized information intervention. I randomly assigned participants to treatment arm one, treatment arm two, or the control group. Treatment arm one aims to reduce search costs by providing information about the participant's electric utility regulator-run offer comparison website and highlighting the lowest-priced plans on the website in a few attribute-based categories. Treatment arm two aims to reduce biases in beliefs about the price heterogeneity in the market and government price protections. The treatment informs participants that, unless they choose the default plan offered by their local utility, the government does not put any limits on the prices electric suppliers can charge and allows electric suppliers to charge customers different prices for the same product. The treatment also provides information about the range of prices in the participant's local market and the approximate associated bill difference. It is important to note that all households in the study receive an information intervention. Even participants in the control groups may receive information about the retail choice market and an attention shock from the baseline survey itself.

I offered consumers who took the survey through August 23 to verify price and supplier information on a recent electricity bill for an additional incentive. This exercise primarily provides more accurate information for research.

The endline survey took place one month after the baseline survey and included 471 of the initial participants.[13] The follow-up survey repeats select questions from the baseline survey. This aims to pick up any changes in self-reported supplier, bill, and price as well as beliefs about the market and propensity to negotiate. The endline survey also asks an open-ended question about any other ways the baseline survey and interventions affected the participants' behavior or beliefs. Appendix A.8 contains copies of all survey instruments.

To inform the survey, I also conducted a one-hour focus group in Baltimore in April 2022. All 15 participants frequented a Baltimore food pantry, GEDCO CARES. The GEDCO CARES program director recruited 12 participants, a GEDCO CARES volunteer recruited two more, and one recruited participant brought a family member.

Results

Summary

The consumer survey supports some key aspects of the theory described in section 1.7. In-person marketing is the most common reported method of sign up. Responses suggest that consumers face large and heterogeneous barriers to search, particularly when engaged with an in-person marketer. I also find evidence of persuasive marketing. While some consumers do value supplier customer service quality and electricity plan attributes, the majority report price or a marketing interaction as the key driver of their sign up decisions. Responses also provide some evidence of inattention to prices, bills, supplier, and market structure.

Comparing responses of consumers in zip codes with median annual household income below $60,000 and above $80,000, the key differences fall into three categories: sign up method, search method, and beliefs about the potential savings available. Respondents in low-income areas report both being approached by in-person marketers and telemarketers more frequently and signing up through direct marketers more frequently. While a roughly proportionate number of consumers actively search across low- and high-income areas, this represents a lower percentage of the consumers active in the choice market in low-income areas. When active search occurs, low-income consumers are relatively less likely to search online and more likely to conduct a phone search in which they call individual suppliers and ask about available plans. I also find a significant difference in beliefs about potential savings, with consumers in low-income areas reporting larger expected savings. I do not find significant differences in preferences for plan attributes or patience across income groups. I also find weak evidence that consumers in low-income areas are especially attentive to prices.

Despite the finding by Byrne et al. (2022) that negotiation can lead to large savings, I find that negotiation is not very common. Byrne et al. (2022) suggest that differences in information going into negotiation may explain the income-price gap, but I find similar and not statistically different negotiation rates across low- and high-income areas.

[13] The survey ended at 471 participants due to budget constraints.

Direct Marketing Prevalence

The most commonly reported method of signing up with an electricity supplier is through an in-person marketing interaction. A significantly larger share of respondents report signing up through an in-person marketer than from actively searching ($\chi^2 = 8$). In total, 43% percent of respondents reported having signed up with an in-person marketer, 27% reported signing up through a telemarketer, 29% reported signing up through other types of marketing, such as mail or online marketing, and 36% reported actively searching for a plan within the past ten years.

The survey confirms that there is more direct marketing in low-income areas. About 77% of respondents in low-income areas reported being approached by an in-person marketer within the past two years. Marketing is significantly lower in high-income areas, where only 57% met an in-person marketer ($\chi^2 = 33$). Low-income households are also more likely to be approached by a telemarketer ($\chi^2 = 18$). This difference in marketing probability translates to more marketing-related sign ups in low-income areas. Fifty seven percent of respondents in low-income areas report signing up through an in-person marketer in the past ten years, compared to 35% in high-income areas ($\chi^2 = 22$). Telemarketing led to 35% and 28% consumers signing up in low- and high-income areas, respectively ($\chi^2 = 2.9$). Respondents in low- and high-income zip codes were roughly equally likely to have signed up through active search. This is evidence in favor of the composition effect discussed in Section 1.7.

Why do consumers sign up with marketers? I find evidence of persuasive marketing. Among consumers who reported signing up through direct marketing, 59% said they signed up to save money, 24.5% selected plan attributes, and 54-61% cited an aspect of the marketing interaction itself. The most commonly cited aspect of the marketing interaction was that the marketer recommended the plan or the marketer seemed well informed (35%). Other reasons were interpersonal, such as fear of what the marketer would think or do otherwise (15%), wanting the marketer to leave (14%), or wanting to help the person selling the plan (10%). The marketing interaction range reflects inclusion or exclusion of misunderstanding the price or terms of the plan, which was selected by 15% of consumers. Some misunderstandings may reflect misleading marketing. Twenty three percent of respondents who had engaged in direct marketing reported that at least one marketer had approached them to check if there was an issue on their bill.

I do not find strong evidence that low-income households are especially easily persuaded by marketing, particularly likely to be marketed higher-priced premium products, or especially likely to engage if a marketer approaches them. Conditional on signing up with a marketer, respondents in low- and high-income areas were roughly equally likely to cite at least one aspect of the marketing interaction as a reason for sign up, but respondents in high-income areas tended to select a greater number of aspects of the marketing interaction ($\chi^2 = 10$). The nature of marketing also differs significantly across geographic areas. Marketers are more likely to pitch saving money ($\chi^2 = 14$) and less likely to pitch high renewable or "green" energy plans ($\chi^2 = 4$) in low-income areas than other areas. I do not find a statistically significant difference across geographic areas in the probability of answering the door if a stranger knocks on it. Point estimates suggest that high-income households may be slightly more likely to answer their doors, while low-income households may be slightly more likely to answer their phones. The difference in 2021 probabilities of answering phones is borderline statistically significant, but this does not survive multiple hypothesis correction.

Search Frictions

Responses suggest that consumers face high search costs. To assess search costs, I asked consumers the minimum amount they would have to save off of their next monthly bill to spend an hour comparing electricity offers, assuming the savings last only one month. Responses were right-skewed with a median of $50 and a mean of $190 with outliers or $107 excluding outliers. If anything, households in low-income areas report requiring a bigger expected reduction in their bill to justify searching, although the difference falls short of significance at conventional levels ($t = 1.4$).

While consumers may be able to do a near-complete search in less than an hour by using a comparison website, many consumers do not know about this option. Only 22% of respondents in high-income areas and 16% of respondents in low-income areas were aware that there was a free government-run website where they could view and compare electric plans offered by different suppliers. The sample size for this question was small (291 participants), so I cannot reject that awareness does not vary across geographic areas. I do find statistically significant evidence of differences in search methods across geographic areas, with more Internet search in high-income areas ($\chi^2 = 5.1$) and more phone search in low-income areas ($\chi^2 = 6.5$).

Respondents also report incomplete search, which could be rational or irrational behavior. Search appears especially limited when signing up through an electricity marketer. Before signing up with an electricity marketer, 48% of respondents compared the offer to their current plan, 39% compared the price to the outside option plan, 13% considered plans from other suppliers, and 19% did not do any comparisons. Note that the outside option may have been the same as the current plan for many consumers. Only 10% of respondents selected both their current plan and the outside option, suggesting that the majority of consumers had only the marketing offer and one other plan in their choice set. Of consumers who did consider plans from other suppliers, 81% considered three or fewer other suppliers. Reported choice sets tended to be larger when consumers searched in response to a price or bill change. When this occurred, 50% of respondents considered the outside option plan, and 63% considered plans offered by other suppliers. I do not find a significant difference in choice sets across income groups in either case.

Attention and Beliefs

Consumers appear somewhat inattentive to their electricity price and bill. About 77% and 51% of respondents reported looking at their bill and price, respectively, every month. Around 6% and 19% of respondents respectively said they looked at their price and bill less than once a year. In addition, 29% reported switching suppliers due to a change in their price or bill. However, when asked for a rough estimate of the electricity price they pay in $/kWh, 82% of respondents provided answers above the highest price charged in Eversource or United Illuminating territories in the month before the survey was conducted, and 21% provided answers over 100 times that value. Bill estimates generally seemed reasonable. Respondents in low-income areas reported looking at price significantly more frequently than consumers in high-income areas ($t = 2$), but this did not translate into more reasonable estimates of own price or more frequent price- or bill-related switching.

Many consumers are also inattentive to their supplier and to market structure. When asked for the name of their current electricity supplier, 31% reported that they were unsure. In addition, only 27% reported ever having a supplier besides their utility at the beginning of the survey. After defining an electricity marketer by their behavior, this number increased to 58%. A small sample of 75 consumers also reported information from a recent electricity bill for additional compensation. Of this selected group, the vast majority were not active in the choice market. Of the eight who were, four had correctly reporter their supplier, two had reported that they were unsure of their supplier, and two had reported their utility as their supplier. In addition, when asked in an open-ended question why they chose their electricity supplier, 33% of respondents either said they did not have a choice (26%) or otherwise indicated they held this belief (e.g., "I needed electricity"). In a smaller sample, only 29% of respondents reported that they knew that the prices non-utility suppliers charged were unregulated and that suppliers could charge customers different prices. Respondents in low-income areas were especially likely to report that they were unsure if they had ever had a non-utility supplier ($t >= 4.3$). I do not find a significant difference across income groups in knowledge of market structure.

Beliefs about the benefits of searching were also right skewed, with respondents in low-income areas reporting higher expected savings. On average, consumers believe they can save $50 off their next monthly bill if they spent an hour looking for a cheaper plan that is otherwise similar to their current plan. The median estimate was $30. I find a large difference across geographic areas. Respondents projected savings of $70 in low-income areas and $40 in high-income areas, on average ($t = 2.5$). The median estimates were $40 and $20, respectively.

Preferences for Non-price Attributes

While respondents did express preferences for plan attributes, price seems to typically be the primary motivator for entering the market. Respondents who self-reported signing up with a supplier also reported why they signed up in an open-response question. Of this group, 62% essentially said to save money, 5% said a renewable energy or a sign up gift (e.g., gift card), 2-3% mentioned a fixed price, low fees, or flat rate design, and 7-9% mentioned liking the supplier or a characteristic of the supplier (e.g., "better service", "reliable", "convenient").

However, consumers do have some willingness to pay for plan attributes. Of respondents who were ever active in the choice market, 64% reported paying extra money for one or more plan or supplier attribute. In terms of plan attributes, 14% reported paying more for renewable or "green" energy, 22% reported paying more to avoid fees, and 42% reported paying more for another financial attribute such as contract length, a price that remains fixed for the entire contract length, or a financial incentive. As for supplier attributes, 20% reported paying more because they like or dislike their utility, and 33% reported paying more for a trustworthy supplier, good customer service, or good information provision. I do not find a significant difference in the proportion of consumers willing to pay a premium for any of these attributes across low- and high-income areas. Comparing respondents in low-income areas to respondents in medium- and high-income areas suggests that these consumers may differ in their dislike of fees ($t = 4.3$) and opinions of their utility ($t = 3.5$).

Respondents tend to heavily discount savings after one month. To assess time preferences, I compare the reported monthly savings required to justify an hour of searching if the savings only last one month and if the savings last one year. The median ratio was 0.83. In the absence of present bias, this implies a discount factor of 0.17. Mean reported ratios did not differ significantly across low- and high-income areas.

Negotiation

Suppliers can further elicit differences in attention and search costs across consumers by negotiating. Byrne et al. (2022) document that consumers can obtain sign-up prices below posted offers by calling and negotiating with suppliers. Suppliers can also price discriminate on inertia by offering consumers a default renewal price and allowing attentive consumers to renegotiate for a lower price.

Of respondents who were ever active in the retail choice market, only 33% reported ever negotiating with a supplier. About 20% reported negotiating on sign up, and 18% reported negotiating on renewal. I do not find a statistically significant difference in negotiation behavior across low- and high-income areas, with 34% and 36% of low-income and high-income households, respectively, reporting having negotiated. Negotiation appears to be positively correlated with attention. Of people who reported signing up with an electricity supplier without any additional prompts, 43% had negotiated on either sign up or renewal.

Response Tables

This section provides survey response summary statistics. All stars reflect statistical significance without corrections for multiple hypothesis testing. The appropriate hypothesis set may vary across purposes.

Table A7: Search Costs (1-month Savings Required to Justify an Hour of Search)

Statistic	<\$60k	>\$80k	Total	t-statistic
Median Search Cost	\$75	\$50	\$50	-
Mean Search Cost	\$114	\$94	\$107	1.2
Expected 1-month Savings from Search	\$39	\$70	\$50	2.5**
Net Cost of Search	\$54	\$55	\$59	0.05
Aware of the MDElectricChoice Website	16%	22%	19%	0.5

*p<0.1; **p<0.05; ***p<0.01

Table A8: Attention to Price and Bill

Plan Type	% of Respondents			χ^2
	<\$60k	>\$80k	Total	LI vs. HI
Has switched suppliers due to a change in price or bill	56%	52%	51%	0.1
Looks at bill every month	79%	76%	77%	0.3
Looks at price every month	61%	53%	53%	1.4
Own price estimate above maximum charged (CT)	83%	85%	84%	0.1

Table A9: Respondents Approached by a Marketer in the Prior Two Years

Marketer Type	% of Respondents			χ^2
	LI	HI	Total	LI vs. HI
In-person Marketer	77%	52%	62%	32.4***
Telemarketer	63%	44%	48%	17.5***

*p<0.1; **p<0.05; ***p<0.01

Table A10: Respondents Who Signed Up For Choice in the Prior Ten Years by Method

Sign-up Method	% of Respondents			χ^2
	LI	HI	Total	LI vs. HI
In-person Marketer	57%	35%	43%	22.3***
Telemarketer	35%	28%	27%	2.9*
Other Advertising	34%	28%	29%	1.2
Independent Search	39%	41%	36%	0.2

*p<0.1; **p<0.05; ***p<0.01

Table A11: Reasons for Signing Up with a Marketer

Sign Up Reasons	% of Respondents			χ^2
	HI	LI	Total	HI vs. LI
Marketer recommended the plan / seemed well informed	36%	36%	35%	0
Misunderstood the price or terms of the plan	15%	13%	15%	0.1
Wanted the marketer to leave	19%	13%	14%	1.6
Interpersonal concerns	13%	9%	10%	0.7
Any of the above	60%	64%	61%	0.3
Any excluding misunderstandings	55%	57%	54%	0.1
Average number of marketing-related selections	0.86	0.68	0.74	9.9***

*p<0.1; **p<0.05; ***p<0.01

Table A12: Open-response Reasons for Retail Choice Participation

	% of Respondents			χ^2
	HI	LI	Total	HI vs. LI
Cost	63%	64%	62%	<.001
Renewable energy or sign-up gift	5%	5%	5%	<.001
Financial attribute	3%	5%	3%	<.001
Supplier quality	15%	5-6%	7-9%	1.6-2.6

Table A13: Have you paid more for any of the following?

Attribute	% of Respondents			t
	HI	LI	Total	HI vs. LI
High renewable or green product	8%	11%	9%	1
Long contract	7%	7%	6%	0
Short contract	4%	2%	3%	1.6
Fixed price	18%	17%	15%	0.1
No or low fees	14%	20%	15%	2.6
Financial incentive	14%	15%	13%	0
Like utility	15%	20%	16%	2.2
Dislike utility	4%	3%	3%	0.8
Supplier quality (e.g., customer service)	24%	24%	24%	0
Other	2%	0%	1%	1.1
None	51%	46%	50%	1.3

Table A14: Have You Ever Negotiated with a Supplier?

Response	% of Respondents			χ^2
	HI	LI	Total	HI vs. LI
No, never considered it	51%	51%	55%	0
No, not comfortable	12%	18%	14%	1
Yes, on sign up	22%	24%	21%	0.1
Yes, on renewal	19%	19%	18%	0
No (Total)	61%	65%	66%	0.3
Yes (Total)	39%	35%	34%	0.3

Table A15: Plans in Reported Choice Sets Prior to Switch

Switch Type	Plan Type	% of Respondents			χ^2
		HI	LI	Total	HI vs. LI
Marketing	Current Plan	46%	46%	48%	<0.01
	Regulated Option	37%	41%	40%	0.4
	Other Suppliers	14%	14%	13%	<0.01
	None	21%	20%	20%	<0.01
Active Search	SOS	50%	48%	50%	<0.01
	Other Suppliers	64%	59%	62%	0.1
	None	3%	6%	4%	0.3

Table A16: Follow-up Survey Outcomes by Treatment Group

Outcome	% of Respondents			χ^2
	Control	Treatment Group 1	Treatment Group 2	Treatment vs. Control
Switched Suppliers	3.2%	2.3%	2.2%	0.1
Negotiated	5.1%	8.3%	11.0%	2.5
Own price estimate >$0.37826[1]	77%	69%	68%	3.2*

[1]Maximum all-in price charged in Connecticut during baseline survey.

*p<0.1; **p<0.05; ***p<0.01

Appendix B

Appendix for *Government vs. Competition: Residential Electricity Pricing and Pass Through*

B.1 Data Appendix

Residential Retail Electricity Revenue, Usage, and Customer Accounts

Annual residential electricity sales in Megawatt-hours (MWh), revenues in thousands of U.S. dollars, and number of residential customers, come from The Energy Information Administration (EIA) Form EIA-861 survey. Form EIA-861 reports sales by utility, state, balancing authority, and delivery type (e.g. bundled, delivery, energy). For delivery-only customers, sales reflect total end-user consumption. Form EIA-861 also reports ownership type, including 'municipal' and 'retail power marketer'. Entities that fall under the former category are government-owned, while the latter category denotes private, competitive entities.

I restrict this analysis to electric load-serving entities (LSEs) that provide energy or bundled service in states that had at least one municipal utility and at least three competitive firms serving residential customers in 2016. Thirteen states fit this description. I further limit the analysis to exclude municipal utilities in Texas that are outside of the Electric Reliability Council of Texas (ERCOT), as those areas are not open to retail competition. I also exclude one municipal utility that switched from delivery only service to bundled service during the analysis timeframe to avoid possible simultaneity or omitted variable bias that could result from including this utility in the analysis. When estimating Equation 2.1, I also truncate the sample to exclude year-competitive firm data with usage per customer greater than that of any of the year-municipal utility data in the sample. I also exclude one outlier competitive firm with an unrealistically low reported number of residential customers which appears to be driven by rounding on Form EIA-861.

In 2012, the EIA altered their reporting system for small utilities. As a result, Form EIA-861 only provides post-2011 data on total sales, revenue, and number of customers across all customer types (e.g. residential, commercial) for many of the municipal utilities. I impute residential-specific data based on the 2011 ratios of residential to total sales. I drop one utility with missing 2011 data. To test this method, I apply the same imputation method to data with known 2017 residential data. The imputations perform well on average. Paired two-sided t-tests do not reject the null hypotheses that the average revenues sales, and number of customers are significantly different at any conventional significance level (t = 0.05, 0.02, and 0.11, respectively). Nonetheless, I perform sensitivity analyses excluding these imputed data to address any remaining measurement error concerns.

I convert all financial data to real 2017 U.S. dollars using the GDP deflator from the US Bureau of Economic Analysis (2019).

Average Residential Retail Electricity Prices

I calculate average residential retail electricity prices in 2017 U.S. dollars per kilowatt-hour (kWh) by dividing residential retail electricity revenue by residential retail electricity sales for each entity. I drop observations with average residential prices greater than five standard deviations above the mean or greater than two standard deviations below the mean. This results in exclusion of three observations that appear to be incorrectly reported. It also drops all observations for one island municipal utility that does not participate in the electricity spot market. Competitive suppliers in Texas and municipal utilities report bundled energy supply and delivery electricity revenues in Form EIA-861.

Table 2.2 displays summary statistics for annual residential retail prices by supplier ownership type.

Marginal Costs

I create annual wholesale electricity prices for each LSE by aggregating publicly-available hourly spot market electricity prices weighted by representative residential load shapes. The five US Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) used in this analysis, the Electric Reliability Corporation Texas (ERCOT), the New England ISO (ISO-NE), the New York ISO (NYISO), the Midcontinent ISO (MISO), and the PJM Interconnection (PJM), provide data on hourly real-time electricity locational marginal prices (LMPs) at tens of thousands of locations in their covered transmission networks. These LMPs incorporate wholesale generation and transmission to the purchase location. For convenience, I downloaded these data from SNL Financial, which provides a centralized database of LMP data ISOs and RTOs.

For tractability, I select 54 LMPs in the thirteen states with near complete data from 2005 though 2017. Whenever possible, I chose aggregated “zonal” LMPs that represent averages of numerous individual nodal prices. In a few instances where substantial data during the analysis timeframe are missing for a key zonal LMP, I selected the closest node with the full time series of data, as measured using Euclidean distance. The load node classification is most appropriate because I use these wholesale costs as measures of LSE input costs. Because LMPs are highly spatially correlated, the selected LMPs should generally reflect the true prices faced by LSEs.

I convert hourly LMP prices to annual values for each node by weighting prices across hours using normalized electricity usage at the same node or at the closest node with available electricity usage data. A drawback of using zonal usage data as a proxy for LSE-specific residential hourly usage data is that this usage embeds electricity usage from non-residential consumers and from some customers served by other suppliers. An alternative approach would be to use simulated residential electricity usage data. I choose zonal usage data as my preferred specification because it reflects actual weather variation, which is a key driver of variation in usage. It also captures heterogeneity in timing of usage across residential consumers, avoiding the issue of unrealistically 'peaky' data (i.e. maximum demand that is unrealistically larger than the average demand across hours) that is common in simulated data.

There are some periods of missing observations in both the LMP and zonal usage data. I impute missing data using data for the closest LMP or usage node, as measured by Euclidean distance. For usage data, I scale the usage data prior to normalization by the ratio of annual usage at the actual node to that of the proxy node to account for average differences in demand in the two locations.

For a sensitivity analysis, I also plan to convert hourly LMP prices to annual values by weighting prices across hours using normalized residential load shapes. The National Renewable Laboratory (NREL) used an engineering model to estimate hourly residential load for a typical household in a typical meteorological year (TMY) for over 900 locations in the U.S. NREL classified each part of the US into five climate categories (e.g. Very Cold/Cold, Hot/Humid) and developed representative housing characteristics, including heating type, foundation, and outside wall construction material, for each climate. The engineering model uses these representative houses and typical weather data by location to estimate electricity usage. I transform each of the NREL TMY3 Building America B10 Benchmark hourly loads to match actual weather years. For each hour and location, I select the hour of TMY load with wet bulb temperature that has the smallest Euclidean distance to actual historical wet bulb temperature. I then normalize load in each location to sum to one. NREL publishes latitude and longitude data for each site. I use these data to map LMP locations to load shapes by identifying the least-cost path based on the Dijkstra (1959) algorithm. This process results in annual LMP prices that reflect the expected cost of providing one additional kWh of load to a residential customer.[1]

I assign an LMP to each municipal utility based on closest Euclidean distance. To do this, I use the Google Geocoding API to extract centroid geographic coordinates for each

[1]Note that this approach implicitly assumes that distribution losses are constant throughout the year. While this is a strong assumption, the impact is likely small.

municipality. Since I do not have data on the precise distribution of competitive providers' customers within a state, I calculate marginal costs for competitive providers in a given state as the average annual LMPs weighted by annual zonal usage associated with each node in the state.

Table 2.2 provides summary statistics on annual wholesale electricity spot prices for the utilities in Figure 1. I convert all spot market prices to \$/kWh to facilitate comparison with retail prices.

B.2 Estimating Reverse Causation Bias in the 2SLS Estimates

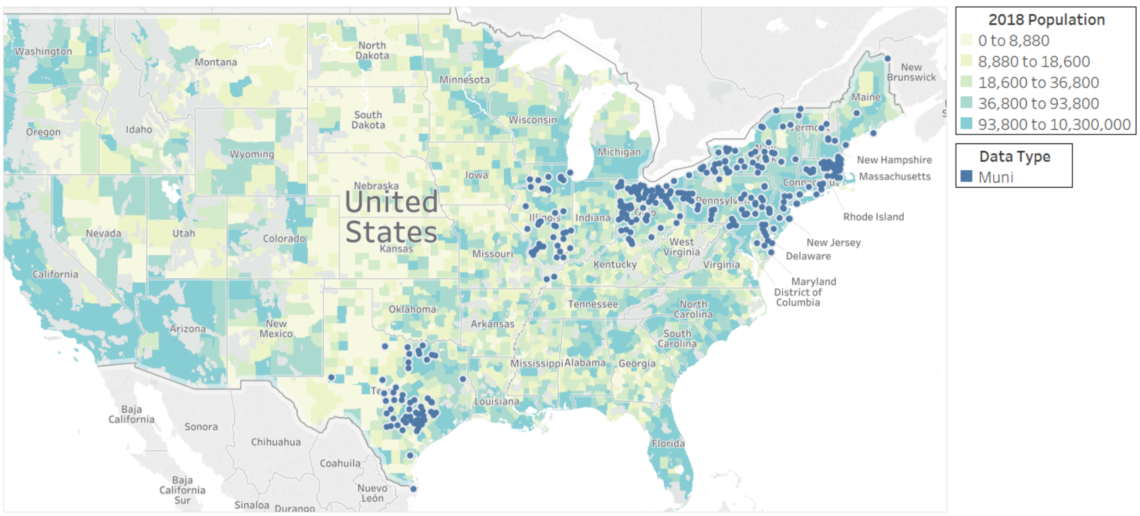
The estimate of the potential bias from reverse causation in the 2SLS estimates use the following assumptions:

- Short-run own-price elasticity of residential electricity demand: -0.35 (Espey and Espey, 2004, mean)
- Conservative estimate of an individual company's residential customer demand as a percentage of total state consumption: 5.08%
- Conservative estimate of the percentage of gas demand from electricity generation: 50%
- Average natural gas price: \$6/MCF

I combine these assumptions with the empirical estimates. The sum of the relevant second stage coefficients is 0.3, and the first-stage coefficient is 0.005. This implies that a \$1/kWh increase in predicted marginal costs leads to a 30% increase in average retail price, which in turn leads to a 0.27% decrease in natural gas demand. Conservatively assuming that natural gas prices also decrease by 0.27%, this implies a \$0.0001/kWh change in predicted marginal costs due to violation of the exclusion restriction.

B.3 Location of Municipal Electric Utilities

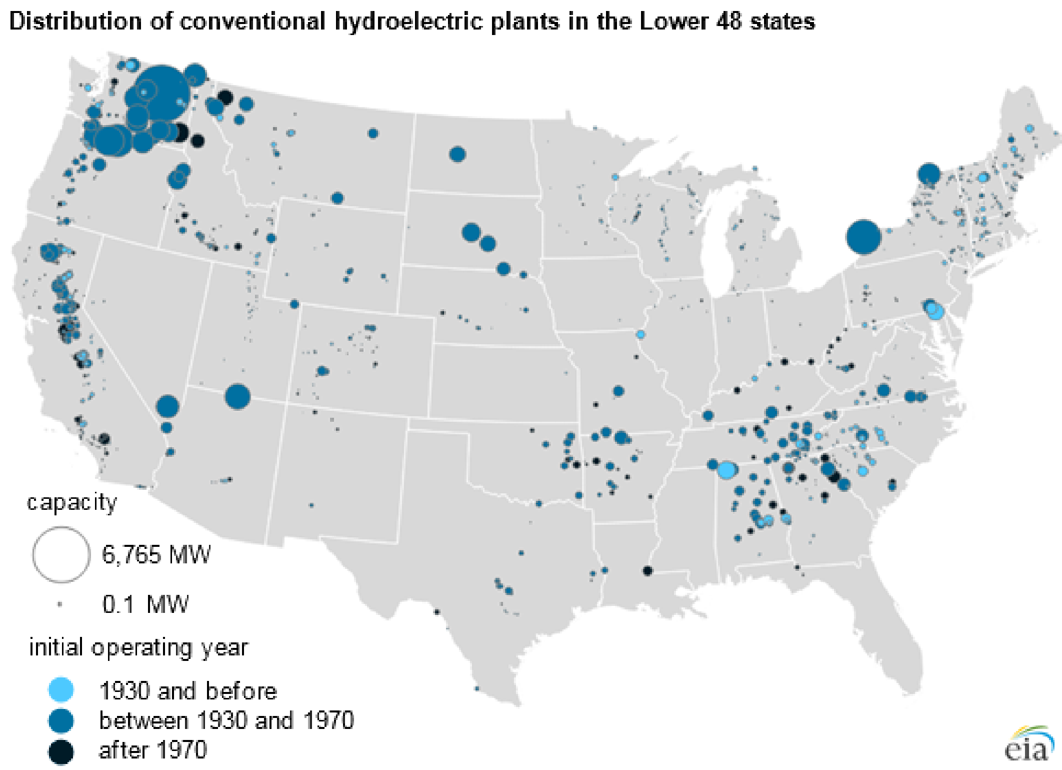
Figure A1: Location of Municipal Electric Utilities included in Analysis



This figure displays the locations of municipal electric utilities included in the analysis. County-level population comes from the U.S. Census Bureau.

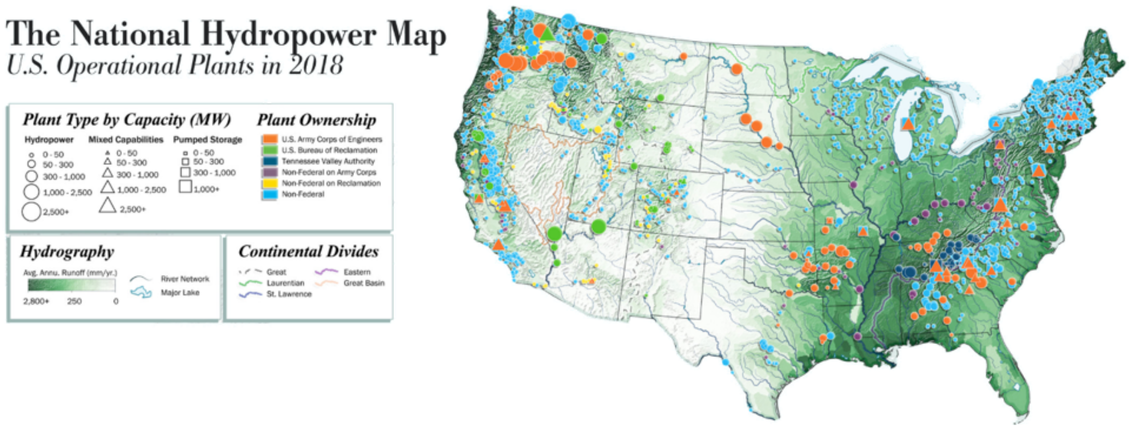
B.4 Location, Ownership, and Capacity of Hydroelectric Power Plants

Figure A2: Location and Capacity of Hydroelectric Power Plants



Source: Energy Information Administration (Accessed April 2019)

Figure A3: Ownership of Hydroelectric Power Plants



Source: Oak Ridge National Laboratory

Appendix C

Appendix for *Does Timing Matter? Impact of Time-based Rates on Energy Efficiency, Rooftop Solar, and Building Electrification*

C.1 Tables

Table A1: Over-investment Regression Results

	Dependent variable: Over-investment					
	EE			PV		
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Charge (\$/year)	0.001		0.003^{**}	0.004^{**}		0.002
	(0.002)		(0.001)	(0.002)		(0.002)
Flat Price (\$/kWh)	6.288^{***}		6.376^{***}	7.390^{***}		7.718^{***}
	(1.065)		(1.025)	(0.829)		(1.192)
\$/kWh Price Variance	28.270	98.260^{***}		-55.968^{**}	75.069^{**}	
	(31.675)	(25.630)		(22.497)	(30.507)	
cor(Price, kWh)	-0.265^{*}	-0.151		-1.522^{***}	0.033	
	(0.138)	(0.155)		(0.363)	(0.746)	
cor(Price, Avoided Costs)	-0.585	-2.363^{***}		0.903	-2.803^{***}	
	(0.454)	(0.715)		(0.543)	(0.970)	
Max \$/kW Charge	0.010	0.017		-0.047^{***}	-0.025^{*}	
	(0.012)	(0.013)		(0.007)	(0.014)	
Constant	x	x	x	x	x	x
Observations	241,168	241,168	241,168	42	42	42
Adjusted R^2	0.540	0.247	0.517	0.876	0.400	0.673

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by utility, rate, and energy efficiency investment package for columns 1-3.

Table A2: Incentive Deviation Regression Results

	Dependent variable: | Bill Savings - Avoided Costs |					
	EE			PV		
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Charge ($/year)	−0.0003*		−0.0001	−0.0003***		0.0001
	(0.0002)		(0.0002)	(0.0001)		(0.0001)
| Flat Price - Avoided Costs |	0.423***		0.442***	0.987***		0.892***
	(0.096)		(0.115)	(0.074)		(0.073)
$/kWh Price Variance	3.331	4.490**		5.108***	11.732***	
	(2.353)	(1.950)		(1.421)	(2.391)	
cor(Price, kWh)	0.018	0.002		0.041*	0.180***	
	(0.013)	(0.013)		(0.022)	(0.048)	
cor(Price, Avoided Costs)	−0.081	0.024		−0.194***	−0.242**	
	(0.062)	(0.099)		(0.040)	(0.093)	
Max $/kW Charge	0.0001	−0.001		0.002***	−0.0002	
	(0.001)	(0.001)		(0.0004)	(0.001)	
Constant	x	x	x	x	x	x
Observations	171,450	171,450	171,450	30	30	30
Adjusted R^2	0.217	0.143	0.192	0.960	0.658	0.879

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by utility, rate, and energy efficiency investment package for columns 1-3.

Table A3: Targeting Regression Results

	Dependent variable:	
	Savings − Avoided Costs	Δ(Savings − Avoided Costs)
	(1)	(2)
Flat Price ($/kWh)	0.834***	
	(0.215)	
System Mean Social Marginal Costs ($/kWh)	−1.093***	
	(0.415)	
Savings per kWh Increase (bool)		0.031***
		(0.004)
Constant	x	x
Observations	171,450	171,450
Adjusted R^2	0.597	0.520

Table A4: LMPs and System Lambda Value Summary Statistics ($/MWh)

Percentile	Ameren	APS	GMP	OG&E
5^{th}	15.4	8.8	13	-2.2
25^{th}	20.2	15.1	18.7	14.1
50^{th}	22.6	19	24.1	18.6
75^{th}	25.8	21.7	35.3	23.4
95^{th}	39.3	31.4	66.9	52.7

C.2 Social Marginal Avoided Costs

Calculation of Marginal Cost Components

The following subsections describe the marginal avoided cost estimation in detail. Each subsection covers one of the cost components outlined in Table 3.1.

Energy, Transmission Losses, and Transmission Congestion

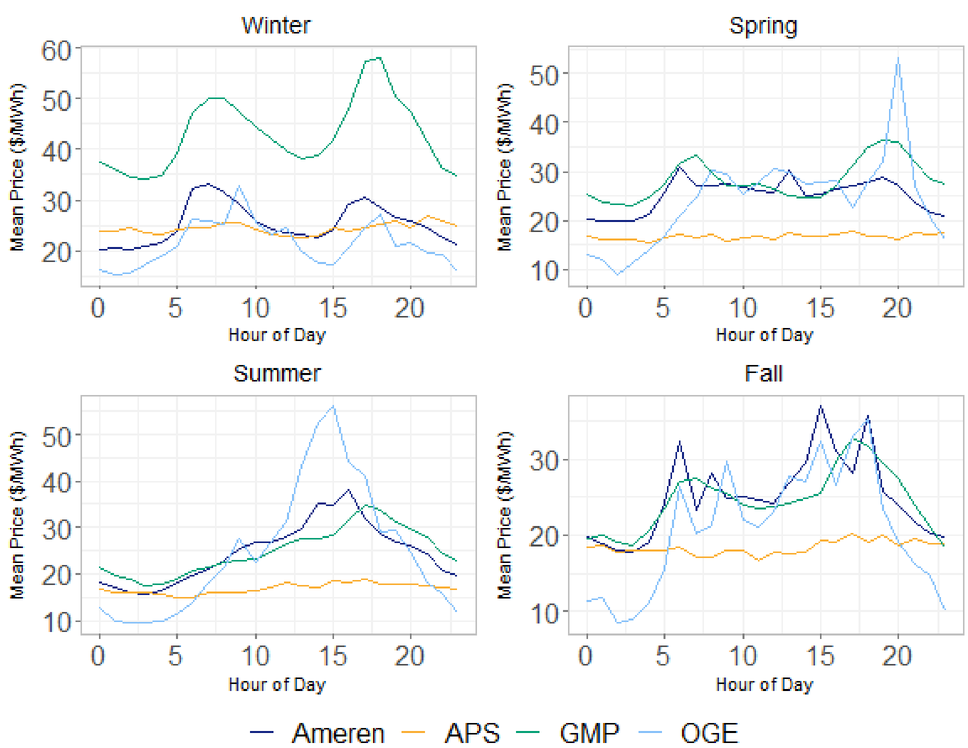
Three of the utilities in our analysis participate in wholesale electricity markets run by a Regional Transmission Operator (RTO) or an Independent System Operator (ISO). We use 2019 hourly real-time locational marginal prices (LMPs) from SNL Financial as an estimate of the combined marginal costs of electricity generation, scaled up for transmission losses, and congestion on the transmission lines. We choose the ISO New England aggregated node.Z.VERMONT for GMP, the Midcontinent ISO node AMIL.ACL9 for Ameren, and the Southwest Power Pool aggregated node OKGE_OKGE for OGE. Assuming there is no market power or other market distortions and the total amount of generating capacity in the system is fixed, these LMPs should reflect the combined marginal costs of electricity generation, transmission losses, and transmission congestion.

For APS, we use Federal Energy Regulatory Commission (FERC) Form-714 hourly system lambda values, which we accessed through Ventyx.[1] These are APS estimates of the private cost of increasing electricity production by one MWh in a given hour. In other words, these are the APS estimates of energy marginal costs. Following Borenstein and Bushnell (2022a), we scale the lambda values up by 2% for transmission losses. We do not estimate APS congestion costs.

Table A4 displays summary statistics of these LMPs and system lambda values, and Figure A1 displays averages by season and hour of day. The prices in GMP tend to be highest in the winter and in the early evening. Ameren and OGE prices tend to be highest in the summer late afternoons. The APS system lambda values vary less seasonally and across hours of the day than the LMPs in the other three locations.

[1] We impute one missing system lambda value by linearly interpolating the adjacent values.

Figure A1: Mean LMP and System Lambda Values by Utility, Season, and Hour of Day



Ancillary Services

Ancillary services are non-energy services typically provided by generators to improve grid reliability. Most ancillary services help ensure that generation sufficiently matches real-time electricity usage at all times. Marginal ancillary service costs reflect the impact of 1 additional kWh of electricity usage on the costs of providing ancillary services. We use the E3 2019 ACC assumption that marginal ancillary service costs are 0.9% of marginal energy costs. This value comes from a historical comparison of energy and ancillary service costs in the California ISO market. This approach implicitly assumes that ancillary service requirements are linear in system-wide electricity usage, at least near typical electricity usage levels.

Distribution Losses

In addition to transmission system electrical losses, there are also distribution system electrical losses and theft within the distribution system. Borenstein and Bushnell estimate hourly marginal distribution losses for each U.S. investor-owned utility for the years 2014 through 2016. We use their estimates of average annual losses for the four utilities in our analysis to compute 2019 values. We follow their assumption that 25% of losses are fixed

Table A5: Mean Marginal and Average Losses by Utility

	Ameren	APS	GMP	OG&E
Mean Marginal Losses	9.95%	9.42%	9.38%	9.04%
Average Losses	6.83%	6.85%	6.47%	6.28%

and do not vary with electricity usage. The remaining 75% of these losses vary with the square of electricity usage. As shown in Equations 5 and 6 of the Borenstein and Bushnell Appendix, this assumption allows us to estimate marginal hourly distribution losses as

$$Marginal\ Losses = 2 \times .75(Average\ Annual\ Losses)_i \frac{\sum_{t=1}^{8760} Q_{it}}{\sum_{t=1}^{8760} Q_{it}^2} Q_{it}$$

where Q_{it} denotes total electricity usage for utility i in hour t. The summations sum over all hours of the 2019 year, which we index from 1 to 8760. For hourly electricity usage estimates, we use 2019 FERC 714 Planning Area Load filings.

Table A5 shows the resulting mean marginal loss estimates by utility. Table A5 also includes the average annual losses for comparison. To translate loss factors to \$/kWh marginal costs, we multiply marginal losses by the sum of energy and external marginal costs in each hour.

Generation Capacity

Generation capacity marginal costs reflect the net incremental cost of building a new generator due to an increase in electricity demand during peak system hours. Generation capacity is innately a lumpy investment. Under most circumstances, meeting a small increase in peak load will not require building any new generation. Occasionally, a small increase in peak load will lead to investment in a large new generator with capacity orders of magnitude greater than the increase in load. We smooth out this investment decision and treat generation capacity decisions as continuous, allowing arbitrarily small increases in generation capacity to meet small increases in peak load. We also assume that systemwide electricity generation is increasing over time, so a marginal reduction in electricity usage can delay an investment in new generation capacity.

The Independent System Operator of New England (ISONE) runs a market for generation capacity. For Green Mountain Power, we estimate the annual marginal generation capacity cost as the annual \$/kW ISONE forward capacity auction price. This is the price per kW paid to generators for being available to generate during peak hours. ISONE conducts capacity auctions three years ahead of the commitment period. They determine future capacity need based on historical electricity demand. Since we are considering the impact of an unexpected marginal change in 2019 electricity usage, we use the auction-clearing price from the annual Forward Capacity Auction #13, which was conducted in 2019 for capacity commitment period 2022/2023.

The other three utilities do not participate in capacity markets. For these utilities, we follow the E3 2019 Avoided Cost Calculator approach and calculate net capacity cost as gross costs less the profit that a new single-cycle combustion turbine generator could make in the wholesale energy and ancillary services markets.[2] The intuition for this approach comes from the fact that the past costs of building existing generators are sunk. When the new generator enters the wholesale energy and ancillary services markets, it earns profit whenever its costs are below market-clearing prices. This displaces profit that other generators would have otherwise earned in the market. In aggregate, these profit changes offset each other and do not produce any net societal costs. However, the fact that the new generator anticipates earning revenue in the wholesale markets enables ratepayers and utility shareholders to pay less than the full gross costs of building the generator. Our calculation of marginal cost aims to estimate these required payments.

We assume that the change in generation capacity is small enough to not change wholesale market prices. To the extent that the generator's entry would cause a reduction in wholesale electricity prices, this benefit would be offset by a commensurate decrease in the generator's profit, which would reduce the net cost of new capacity. On net, we assume the impact of any market price suppression on societal costs would be negligible.

We use the E3 2019 ACC estimate of the gross annualized fixed cost of building a new simple cycle combustion turbine, \$163.92/kW-yr. To calculate generator revenue in non-capacity markets, we first calculate whether the generator would operate in each hour, ignoring any dynamic considerations, such as start up costs. We assume the generator will operate in a given hour if the wholesale energy price is above the variable operating costs, i.e.,

$$(Natural\ Gas\ Fuel\ Costs)_h + (Variable\ O\&M\ Costs) < \frac{LMP_h}{1 + Transmission\ Loss\ Cost}$$

where the righthand side of the inequality reflects our estimate of energy prices.[3] We use the E3 2019 ACC variable operation and maintenance (O&M) estimate, which is \$5.52/MWh in 2019 dollars and the Borenstein and Bushnell transmission loss factor of 2%. We estimate hourly natural gas costs using monthly state citygate natural gas prices from the U.S. Energy Information Administration (EIA) and E3 2019 ACC assumptions about the assumed heat rate of the marginal generator. We allow the generator's heat rate to vary with hourly temperature. To estimate this relationship, we use the E3 2019 ACC temperature derate curves and actual 2019 temperature from the U.S. National Oceanic and Atmospheric Administra-

[2]An alternative approach would be to assume the marginal resource is a renewable generator. In fact, later updates of the E3 Avoided Cost Calculator make this assumption for California. We estimate that renewables have a lower required cost of entry in some of the geographic areas analyzed. However, we chose the CT assumption because APS, OG&E, and a developer in Illinois proposed new CTs in 2019.

[3]We abstract from the fact that locational marginal prices may also include transmission congestion costs, which do not accrue to the generator.

tion (NOAA) Integrated Surface Database.[4] We estimate average daytime temperature by month for each utility using the E3 2019 ACC definition of daytime hours. We extend the E3 2019 ACC temperature derate curves linearly a few extra degrees to capture particularly high temperatures in the APS service area.

After determining whether the marginal generator would operate in each hour, we calculate the profit the generator would earn in the wholesale energy market in each hour by using the same variable operating costs and estimated energy prices used to determine the operation decision. We use the E3 2019 ACC assumption that ancillary service revenues are 2.7% of the generator's wholesale energy revenues. We subtract the variable costs from the combined revenues, adjusting for the impact of temperature on the generator's output. We use the E3 2019 ACC outage factor of 7.3% to derate this profit value for generator outages. This leads to the following profit equation:

$$Profit = \Bigg[\sum_{h \in (Operating\ Hours)} \bigg(1.027 \Big(\frac{LMP}{1 - (Transmission\ Loss\ Factor)} \Big) - (Operating\ Costs)_h \bigg) (TemperatureOutputDerate)_h \Bigg] \times (1 - Outage\ Factor)$$

To calculate annual generation capacity costs, we subtract this profit value from the annualized fixed capital costs. We scale this net value up for losses during the peak system hour. This provides the cost if the generator operated at its nameplate capacity during the peak hour. We also make a temperature derate adjustment to convert this value to cost per delivered peak capacity. This produces the following formula:

$$Marginal\ Generation\ Capacity\ Cost = (Annualized\ Fixed\ Cost - Profit) \left(\frac{Peak\ Loss\ Factor}{Average\ Output\ Derate} \right)$$

Conceptually, we should only apply this marginal capacity cost in the peak demand hour. In practice, the precise hour of the year in which peak demand occurs differs year-to-year depending on weather among other factors. To avoid overfitting our estimates to the 2019 calendar year, we spread out the capacity cost over 40 hours of the year. We allocate costs equally to the 40 hours of the year with the highest aggregate electricity usage. More sophisticated methods exist to estimate the probability that peak demand will occur in any given hour. This simple method of allocating costs across the top hours is appropriate in our setting because we apply these marginal costs to simulated energy usage based on a typical meteorological weather year.

[4]We use temperature at the Phoenix Airport, Springfield Abraham Lincoln Capital Airport, Oklahoma City Will Rogers World Airport, and Burlington International Airport weather stations for APS, Ameren, OGE, and GMP, respectively.

Distribution Capacity

Distribution capacity costs capture the expected costs of a distribution system upgrade to accommodate higher electricity consumption levels. Since distribution capacity expansion is lumpy, the true marginal impact of a 1 kWh load increase is likely to be very large in a few hours and locations and zero otherwise. We do not attempt to estimate this geographic heterogeneity in distribution capacity marginal costs. Instead, we aim to estimate an average marginal cost value across all residential customers in each hour. To achieve this, we use the average avoided distribution cost of $48.37/kW-yr from the Mendota Group LLC (2014) literature review of 35 utility estimates. We allocate this value to the 200 hours of the year with the highest estimated load on residential feeders.[5] We use aggregate ResStock electricity usage for each utility to determine these 200 hours.

There are a few assumptions worth highlighting. First, our analysis applies marginal costs to reductions in load. In doing so, we implicitly assume a symmetry in all marginal cost components that makes increases and reductions in electricity usage have equal and opposite effects on societal costs. This is a reasonable assumption if other electricity usage on the relevant feeders is increasing over time, which is stronger than the generation capacity assumption that systemwide electricity usage increases over time. Under this assumption, the load reductions we analyze are effectively slowing down this aggregate increase in electricity usage and, thereby, delaying a distribution upgrade for some marginal amount of time. Second, distributed PV may also conceivably cause distribution upgrades at large enough penetrations. We assume these costs are zero and apply the same marginal distribution capacity costs to distributed PV and energy efficiency.

Renewable Portfolio Standard Compliance

Three of the utilities in the analysis have to meet a minimum percentage of their retail sales with renewable generation due to a state Renewable Portfolio Standard (RPS) or Renewable Energy Standard. Since these two types of standards have the same structure, we will refer to both of them by the acronym RPS. If it costs more to generate electricity with renewable resources that comply with an RPS standard than to generate the same amount of electricity with the least-cost portfolio of resources, then an additional kWh of electricity usage increases the cost of complying with the RPS. The RPS marginal cost captures this incremental private cost. We assume that the RPS is binding, and meeting the incremental RPS obligation requires building new renewable generating capacity.

[5] For precedence, see San Diego Gas and Electric's rate scheduel VGI. Available at: `https://www.sdge.com/sites/default/files/elec_elec-scheds_vgi.pdf`. Accessed May 2023.

Table A6: Renewable Portfolio Standard Compliance Obligations

	Ameren	APS	GMP	OG&E
Total Obligation (% of Retail Sales)	14.5%	9.0%	57.67%	N/A
Wind Carve Out (% of Retail Sales)	10.875%	N/A	N/A	N/A
Solar Carve Out (% of Retail Sales)	0.87%	N/A	N/A	N/A

We calculate RPS costs using the following formula:

$$
\begin{aligned}
RPS\ Cost = \Big(&PPA\ Price + Integration\ Cost + Transmission\ Cost \\
&- Energy\ Market\ Revenue - Capacity\ Revenue\Big) \\
&\times (RPS\ Compliance\ Obligation)
\end{aligned}
$$

where PPA price is the price of a utility power purchase agreement (PPA) for renewable generation, integration cost captures the cost of additional reserves needed to meet grid reliability goals due to the intermittency of renewable generation, and transmission cost is the cost of building new transmission to connect the renewable generators to the rest of the grid as well as any other transmission upgrades needed to deliver the electricity to end users. We subtract out revenues that the RPS generator could make in wholesale energy and capacity markets and from payments for providing resource adequacy in areas without capacity markets. We multiply the net costs by the compliance obligation specified in the state RPS. For example, the Arizona RPS required APS to meet 9% of its retail sales with renewable generation, so the RPS compliance obligation is 9%. This calculation follows pre-2019 versions of the E3 ACC approach closely.[6] The one departure is that we do not deduct an emissions value from the PPA price. We separately capture carbon and local air pollution benefits from an RPS in our estimates of marginal carbon and environmental damages.

Table A6 displays the 2019 RPS compliance obligations for the four utilities in our analysis. RPS-qualifying resources differ somewhat by state, but we assume the marginal resource is either wind or solar for all utilities. One state, Illinois, has different minimum percentages ("carve outs') for each of wind and solar. Some states also have distributed generation carve outs. We neither increase compliance costs for any distributed generation carve outs nor allow distributed PV in our analysis to receive credit for their contribution to the RPS.[7]

We assume the cost of RPS grid integration is \$5/MWh in 2014 dollars based on a literature review by Luckow et al. (2015). We use a levelized transmission cost of \$5/MWh in 2018 dollars, which is the mean and median of the estimates from Gorman et al. (2019). For PPA prices, we use the cheaper of the solar and wind PPA price estimates from Wiser

[6]The E3 2019 ACC assumes the RPS value is zero in 2019, which is consistent with our APS and Ameren estimates.

[7]We estimate an avoided RPS cost of zero for all utilities with carve outs.

Table A7: Power Purchase Agreement Resource and Price Assumptions

	Ameren	APS	GMP	OG&E
PPA Resource	Wind	Solar	Wind	Wind
PPA Price ($/MWh)	27.6	23.5	42.6	14.7

et al. (2022) and Bolinger et al. (2022) in each region. For Ameren, we assume the wind and solar carve outs are met and select the cheaper resource for the remaining compliance obligation. Table A7 shows the cheaper marginal resource and the resulting PPA price by utility, converted to 2019 dollars. These values come from executed PPAs and embed tax incentives, including the Investment Tax Credit and the Production Tax Credit.

We estimate energy and capacity revenues by multiplying our hourly energy and capacity marginal costs by estimated hourly renewable generation, which we normalize to generate 1 kWh over the entire year. We use Lawrence Berkeley National Laboratory's Renewables and Wholesale Electricity Prices (ReWEP) Tool for wind generation profiles. For solar PV generation profiles, we use NREL's Solar Power Data for Integration Studies. We selected the utility scale PV profiles located closest to Springfield IL, Phoenix AZ, Burlington VT, and Oklahoma City OK for Ameren, APS, GMP, and OGE, respectively. The database does not include any utility scale PV shapes in Vermont, so we use a distributed PV shape, which is assumed to be a fixed tilt system instead of having single axis tracking. For simplicity, we assume the amount of renewable generation is known with certainty. In practice, a renewable generator's contribution to capacity is highly uncertain and capacity payments may reflect this uncertainty.

Carbon and Local Air Pollution

Electric generation also emits pollutants that may cause humans harm through climate- and health-related impacts, among other factors. We consider the marginal effect of electric generation on external damages caused by carbon dioxide (CO_2), sulphur dioxide (SO_2), nitrogen oxides (NO_X), and particulate matter smaller than 2.5 micrometers. Our approach does not capture the impact of electricity usage on emissions from any source except electric generator smokestacks. We use estimates of the impact of a 1 kWh kWh increase in electricity usage on carbon- and criteria pollutant-related damages by region and load tercile from Borenstein and Bushnell. Borenstein and Bushnell segment the U.S. into nine regions they call North American Electric Reliability Corporation (NERC) subregions.[8] These regions are similar to NERC electric reliability organization regions. The Borenstein and Bushnell estimates are the product of two values: the effect of an increase in electricity usage on pollutant emissions and estimated damages per ton of pollutant emitted. Borenstein and Bushnell estimate the impact of an increase in electricity usage in one region on electricity generator smokestack emissions in that and other regions empirically using historical NERC

[8]See Figure A2 in Borenstein and Bushnell (2021) for a diagram of these regions.

subregion electricity usage and power plant emissions data. The damages per ton underlying the Borenstein and Bushnell estimates come from the AP3 integrated assessment air pollution model (Clay et al., 2019; Holland et al., 2016). These damage estimates aim to capture the effect of emissions on ambient pollutant concentrations and the monetary impact of ambient air pollution on human well-being measured by human health, crop and timber yields, degradation of buildings and material, visibility, and recreation.

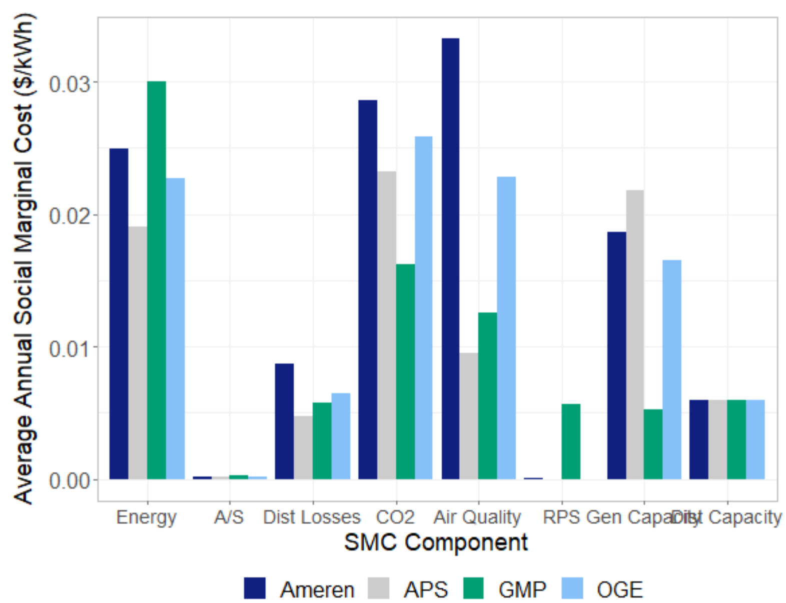
To calculate 2019 hourly external costs, we first calculate NERC subregion load in each hour of 2019 by adding FERC Form 714 electricity usage for all planning regions in the NERC subregion. For cases where a planning region crosses NERC subregion borders, we allocate the entire planning region load to the NERC subregion that contains the majority of the planning region. We also split MISO electricity usage equally between the SPP, SERC, and MRO subregions. For each subregion and hour of year, we then identify whether electricity usage was in the bottom, middle, or top tercile of the distribution of 2019 hourly electricity usage. Combining this information with the Borenstein and Bushnell estimates, adjusted for inflation, gives us hourly external CO_2 and criteria pollutant marginal costs for each utility. We adjust the GMP CO_2 damage estimates since the private energy marginal cost estimates include the cost of compliance with the Regional Greenhouse Gas Initiative (RGGI). To avoid double counting, we subtract the average 2019 RGGI permit price from the GMP carbon damage estimates.

Results

Figure A2 displays the resulting mean annual social marginal costs by cost component and utility. The largest private marginal cost components are energy and generation capacity costs. These costs are negatively correlated since higher energy prices reduce the capacity payments needed to incentivize construction of a generator or retirement of an existing generator. Capacity payments also tend to be higher in hotter areas since the temperatures reduce generator efficiency. We estimate that external marginal costs range from 58% to 118% of private marginal costs across the four locations. The variation in CO_2 costs across utilities reflects differences in which resources tend to have the marginal bid in wholesale electricity markets and differences in thermal generator heat rates across utilities. The air quality marginal costs largely depend on these factors and population density near the pollution-emitting generators. This explains why utilities in areas with relatively low population density, such as APS, may have relatively high CO_2 marginal costs and relatively low air quality-related marginal costs. GMP is the only utility with positive RPS marginal costs. We estimate that renewable resources have reached parity with thermal resources in APS and Ameren service areas. This may change with the removal of tax credits and higher RPS obligations in these areas.

Figures A3-A6 break these annual estimates down temporally for each utility. The figures show average social marginal costs by season and hour of day. Generation capacity is especially seasonal with values concentrated in summer and winter months for GMP and in the summer and early fall months for the other three utilities. RPS costs are constant

Figure A2: Average Annual Social Marginal Costs by Utility and Cost Component



throughout the year. External marginal costs tend to be largest during high load hours for GMP and Ameren and during low load hours for APS and OGE. The other marginal cost components tend to move with electricity usage. Costs tend to be highest in the morning and evening in winter months and in the late afternoon in summer months. This is not the case for APS, which may be due to data quality issues in the APS system lambda estimates.

Figure A3: Social Marginal Costs by Season, Hour of Day, and Component: APS

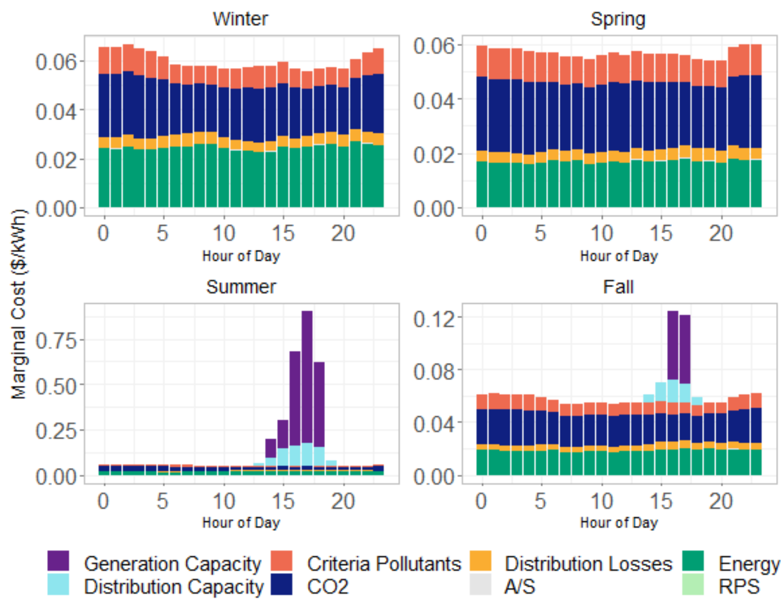


Figure A4: Social Marginal Costs by Season, Hour of Day, and Component: Ameren

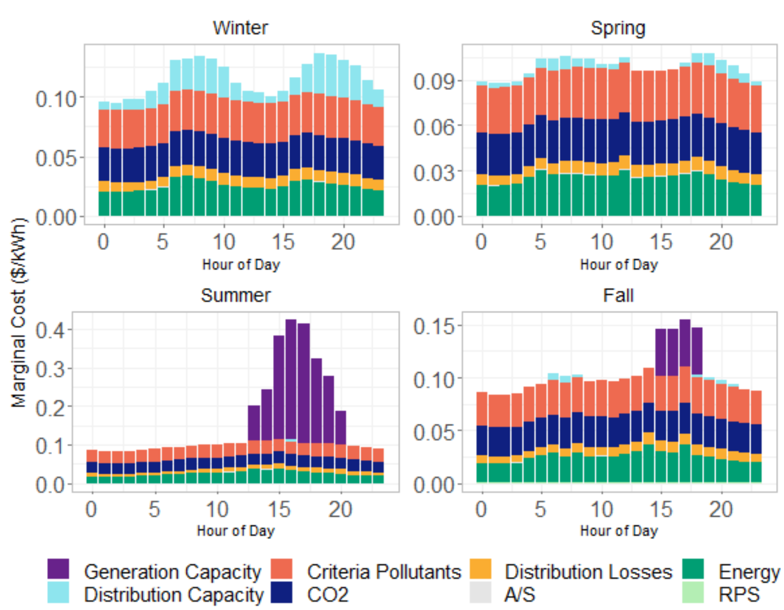


Figure A5: Social Marginal Costs by Season, Hour of Day, and Component: GMP

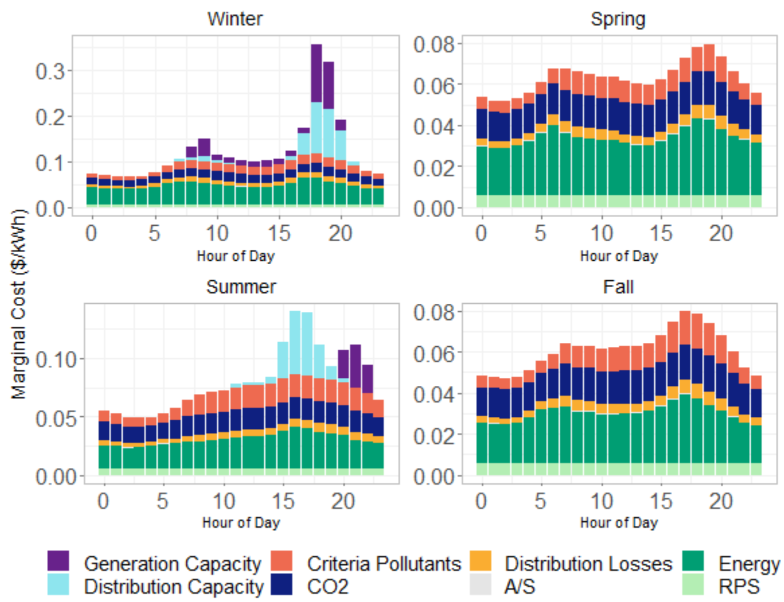
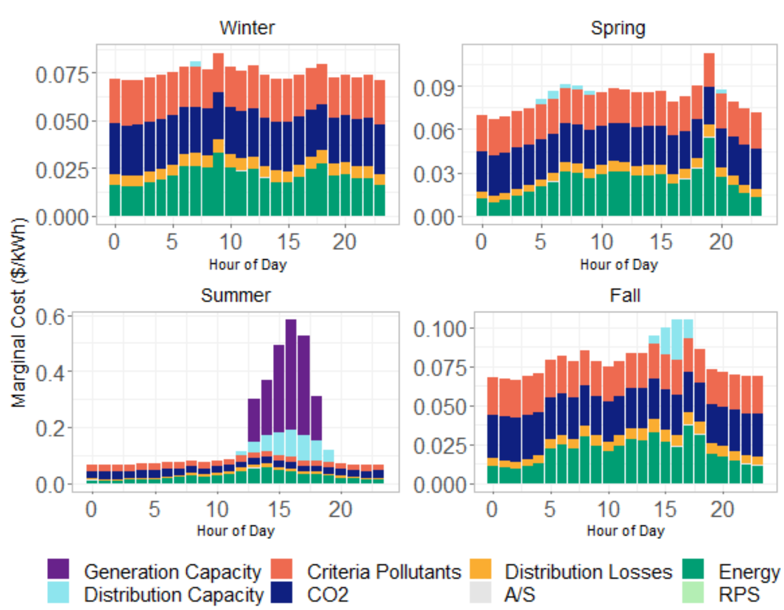


Figure A6: Social Marginal Costs by Season, Hour of Day, and Component: OG&E



C.3 Energy Efficiency Upgrade Package Details

Package with fuel switching

Components:

- ASHP
    - SEER 22, 10 HSPF
    - Applied to all homes with ducts
- MSHP
    - SEER 25, 12.7 HSPF
    - Applied to all homes without ducts
- Ducts improved to 10% Leakage, R-8
    - Applied to all leakier and/or less insulated ducts
- Heat pump water heaters
    - 50 gal, 3.45 UEF for 1-3 bedroom homes
    - 66 gal, 3.35 UEF for 4 bedroom homes
    - 80 gal, 3.45 UEF for 5+ bedroom homes
- Clothes washer efficiency
    - Rated at 123 annual kWh
    - Applied to all homes with less efficient clothes washers
- Dishwasher efficiency
    - 199 rated kWh dishwasher
    - Applied to all homes with less efficient dishwashers
- Refrigerator efficiency
    - EF 21.9
    - Applied to all homes with less efficient refrigerators
- Clothes dryer efficiency
    - Electric premium, efficiency = 3.42
    - Applied to all homes with a less-efficient electric clothes dryer, or a non-electric clothes dryer
- Cooking range efficiency
    - Induction range
    - Applied to all homes with a less-efficient electric range, or a non-electric range

Equipment package (no fuel switching)

- AC efficiency
    - AC, SEER 18
    - Applied to homes with non-electric heat and a lower-efficiency AC
- Window AC efficiency
    - Room AC, EER 12.0
    - Applied to homes with non-electric heat and a lower-efficiency room AC
- ASHP
    - SEER 22, 10 HSPF
    - Applied to homes with electric heating and ducts
- MSHP
    - SEER 25, 12.7 HSPF

  - Applied to homes with electric heating and no ducts
- Heat pump water heaters
  - 50 gal, 3.45 UEF for homes with 1-3 bedrooms and electric water heating
  - 66 gal, 3.35 UEF for homes with 4 bedrooms and electric water heating
  - 80 gal, 3.45 UEF for homes with 5+ bedrooms and electric water heating
- Refrigerator: same as package 1
- Clothes washer: same as package 1
- Clothes dryer
  - Electric premium, efficiency = 3.42
  - Applied to all homes with less efficient electric clothes dryers
- Cooking range
  - Induction range
  - Applied to all homes with a less efficient electric range

Envelope package

- Attic insulation
  - Note: Overriding logic is to give less well insulated homes with vented attics R-values from 2021 IECC
  - R-30 ceiling insulation for homes with vented attics and insulation ≤ R-19 in IECC 1A
  - R-49 ceiling insulation for homes with vented attics and insulation ≤ R-38 in IECC 2A, 2B, 3A, 3B, or 3C
  - R-60 ceiling insulation for homes with vented attics and insulation ≤ R-38 in IECC 4A, 4B, 4C, 5A, 5B, 6A, 6B, 7A, 7B
  - This also came with a 13% whole-home infiltration reduction
- Exterior wall insulation
  - R-6 (1” polyiso) exterior insulation added
  - Applied to homes older than 1990 with <R-19 nominal wall insulation
  - This also comes with a 19% whole-home infiltration reduction
- Exterior storm windows
  - Exterior low-E storm windows added
  - Applied to homes with double pane metal framed windows or single pane windows
  - This also comes with a 30% whole-home infiltration reduction for single-pane windowed homes and 10% for homes starting with double pane or single pane with clear storm

Lighting package

- 100% LED lighting for all homes