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

Jenya Kahn-Lang

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Abstract

This paper 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.

Keywords: Price discrimination, social inequality, price dispersion, retail electricity markets, door-to-door marketing

JEL Codes: Q4, L1, L2, L5, L9

*Department of Agricultural and Resource Economics and Energy Institute at Haas, UC Berkeley. Email: jenya_kahn-langberkeley.edu. I am grateful for the generous financial support of the National Science Foundation under grants DGE 2146752 and 2217111, The Abdul Latif Jameel Poverty Action Lab, and Berkeley Xlab. I thank my advisors Meredith Fowlie, Jim Sallee, Severin Borenstein, and Kei Kawai for their guidance and support. This paper has also benefited from comments and suggestions from Matthew Backus, Nano Barahona, Pete Cappers, Lucas Davis, Matthew Grennan, Ben Handel, Hilary Hoynes, Koichiro Ito, Chris Knittel, Ashley Langer, Jing Li, Steve Puller, Andy Satchwell, Joe Shapiro, Lisa Schwartz, Reed Walker, and numerous seminar participants and industry experts. I am also thankful for the invaluable support of the Maryland Public Service Commission, Baltimore Gas and Electric Company, the Connecticut Public Utilities Regulatory Authority, GEDCO CARES, and Central Maine Power. All errors are my own.

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.

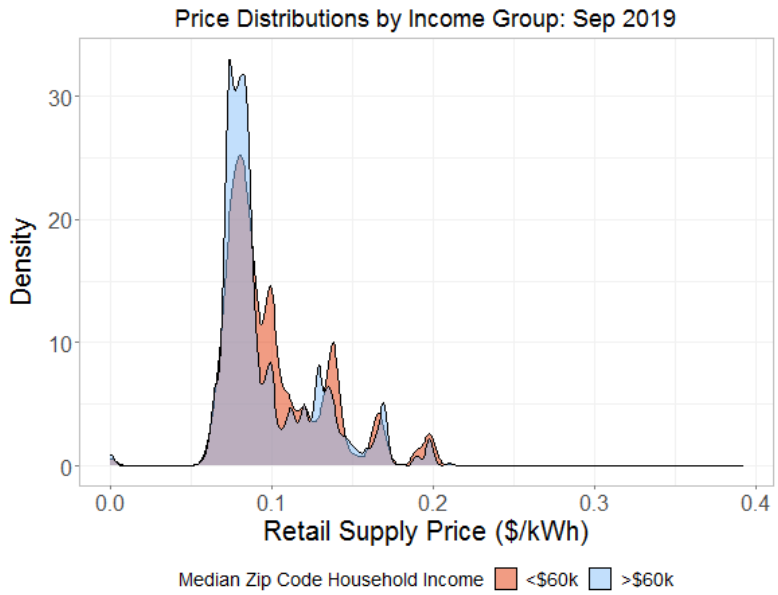
Inefficient and regressive pricing may be particularly concerning in the electricity context. Researchers have linked high energy prices to mortality (Chirakijja et al. 2019). Many low-income households keep their homes at unsafe temperatures and sacrifice food or medical care due to high energy costs (NEADA 2018). Inefficiently high electricity prices may also deter all households from investing in greenhouse-gas-reducing electrification (Borenstein and Bushnell 2022).

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 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 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

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

states, time, data sources, and metrics of marginalized communities.

Figure 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.

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 12% 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 experience fewer attention shocks.

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

I also consider alternative explanations for the incosme 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 Man-

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

chanda 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 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) 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.

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; Joskow 2008).

Although a key goal of restructuring was to reduce retail prices, 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.[7]

[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.

[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] 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.[8]

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.[9] Suppliers 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.[10] 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

[8] 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.

[9] Renewable energy certificates are tradeable permits that give the owner financial rights to the renewable content of electricity previously generated by a renewable generator.

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

aggressive marketing tactics.[11] 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.[12]

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.

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

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

[12] 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/

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.

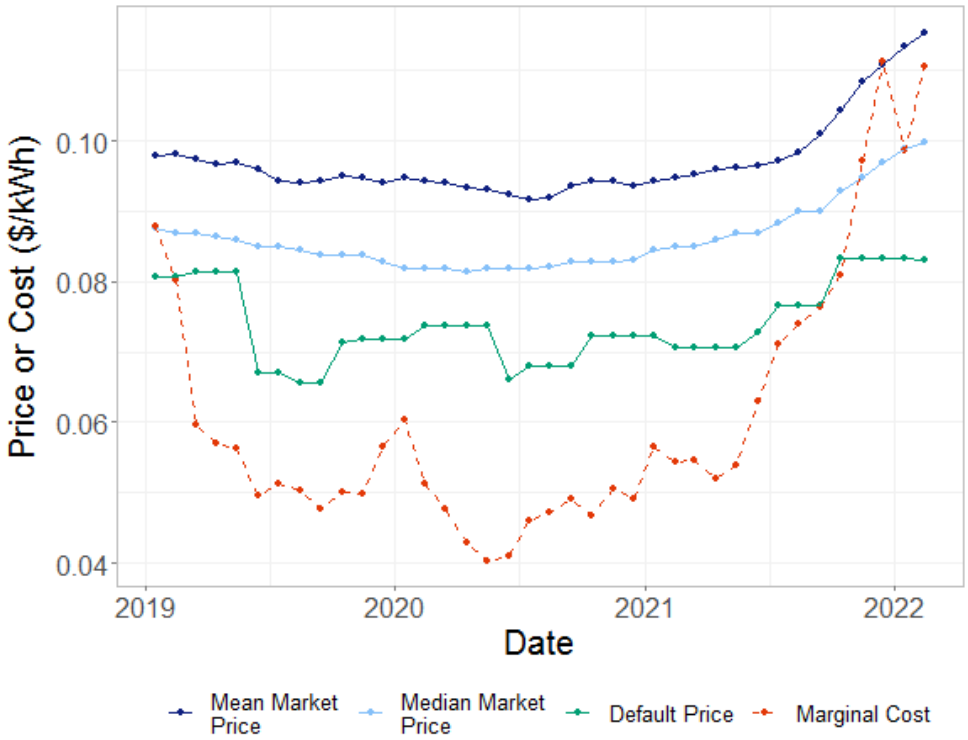
To analyze geographic variation in marketing presence, I use a cross-section of data on door-to-door marketing presence in the Baltimore metropolitan area. These data come from the PSC (PSC 2020). The PSC requires all suppliers to report when and for how long they plan to conduct marketing activity by 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 G for a detailed discussion of cost calculations.

Figure 2 displays one-month-ahead estimated marginal costs for each month of the analysis time-frame. 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 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

Figure 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.

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 H for a copy of the survey instruments and Appendix I for all survey response summary tables.

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

4 Descriptive Evidence

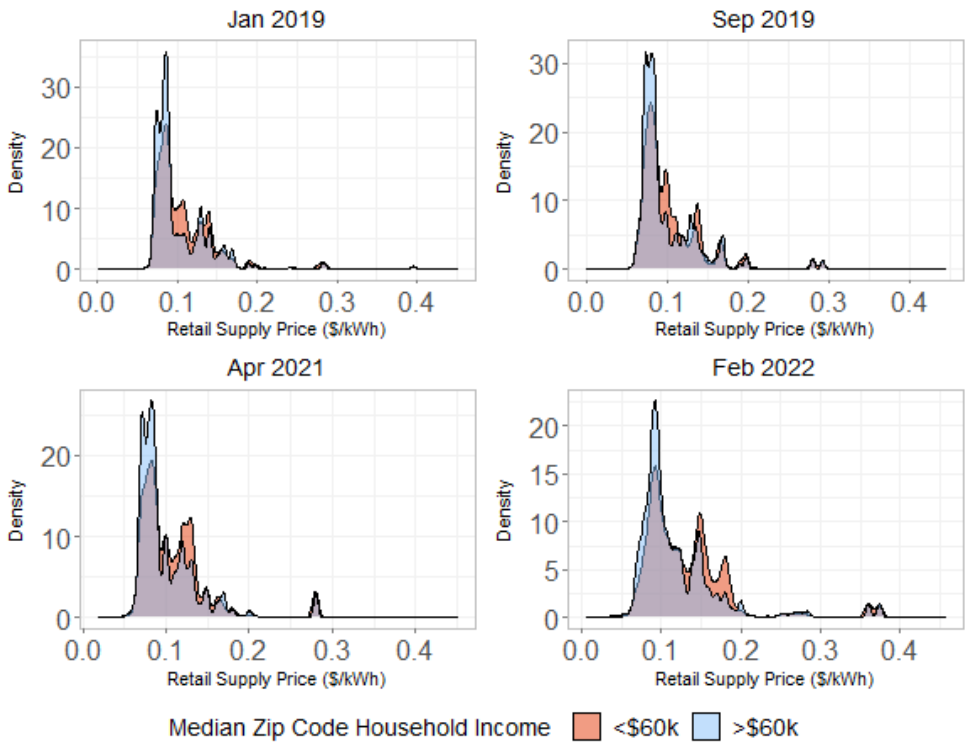
This section presents some descriptive and reduced-form evidence to support six key facts about the BGE residential electricity market. The first two facts document the extent of price heterogeneity and provide evidence of adverse implications on social equity. The remaining facts illuminate the

importance of price discrimination based on inattention-driven inertia and price discrimination through marketing for explaining this price heterogeneity.

4.1 Stylized Fact 1: Markets exhibit large price variation

Figure 3 presents cross-sectional distributions of all billed prices in the BGE retail choice market in four months.[13] 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.[14] 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.

Figure 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.

[13] These distributions do not include prices on the default regulated rate or BGE charges for electricity delivery.
[14] Source: Energy Information Administration Form EIA-861.

The months included in Figure 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.

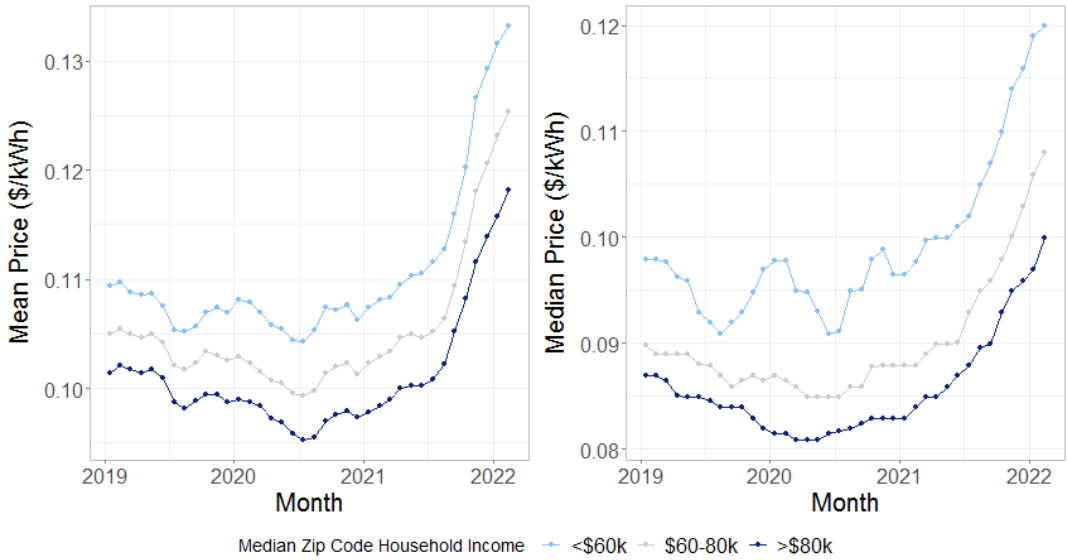
4.2 Stylized Fact 2: Low-income households and marginalized communities face particularly high prices

Figure 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 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, 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.

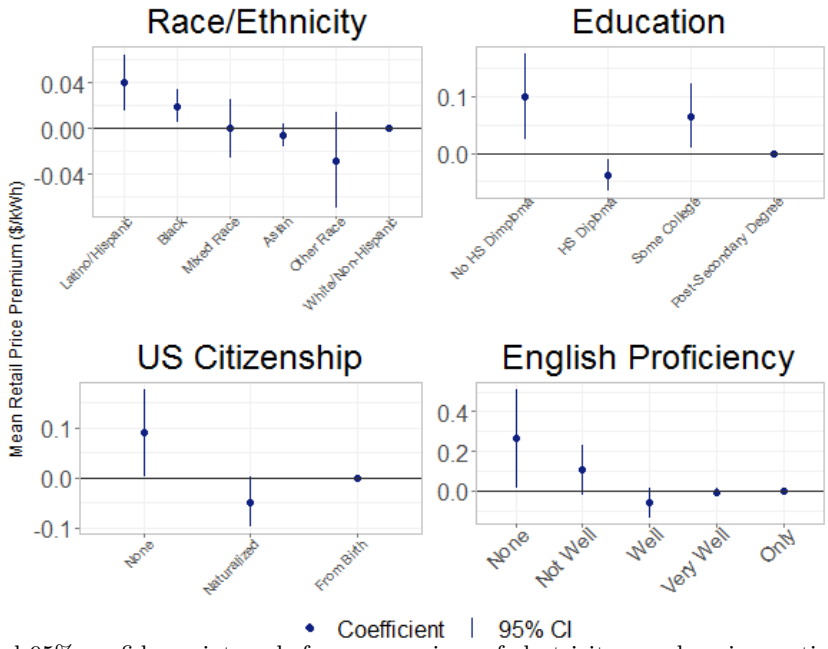
Many of these demographic variables are correlated. Median household income is highly correlated

Figure 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.

Figure 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.

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 3 combined contracts that started in different months as well as "new" and "renewal" contracts. When a consumer switches 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 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 ($t = 38$).[15]

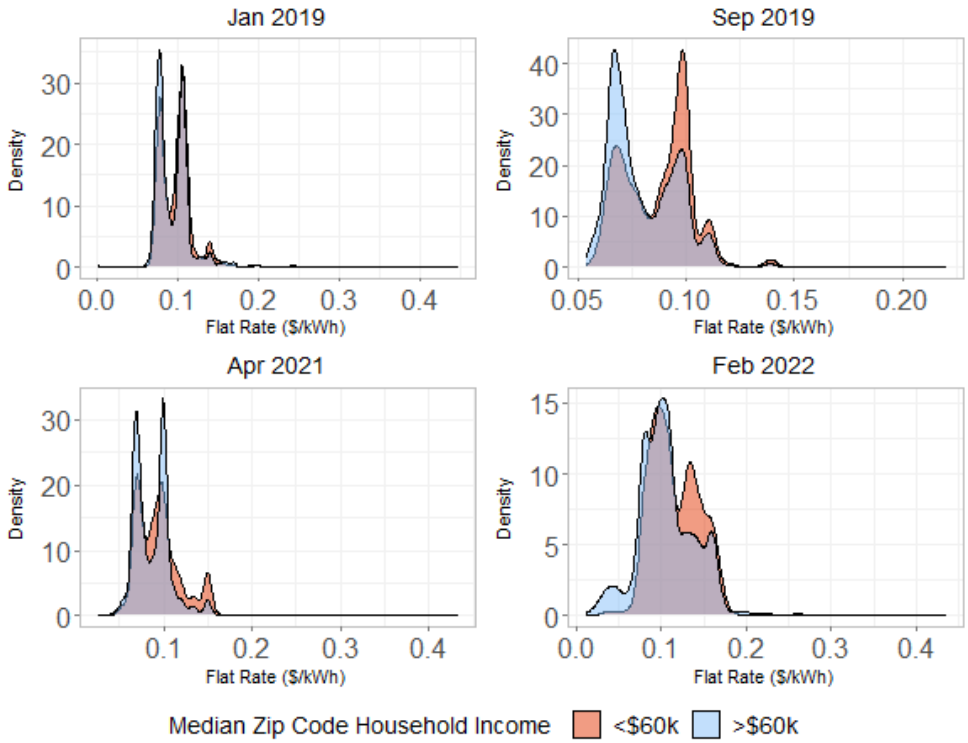
Contracts that were renewed display an even larger income-price gap. As an approximation, I identify contract renewals as any instance in which a consumer has the same supplier but a different price than they had the previous month. This definition includes households who actively renewed a contract 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.

4.3 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

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

Figure 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.

market in a given month, on average.[16] Comparable participation rates in moderate- and high-income communities were 22% and 20%, respectively.[17] 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 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

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

[17] 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.

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.[18] While point estimates may suggest low-income households look at their prices especially frequently, this does not translate to better price estimates.

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

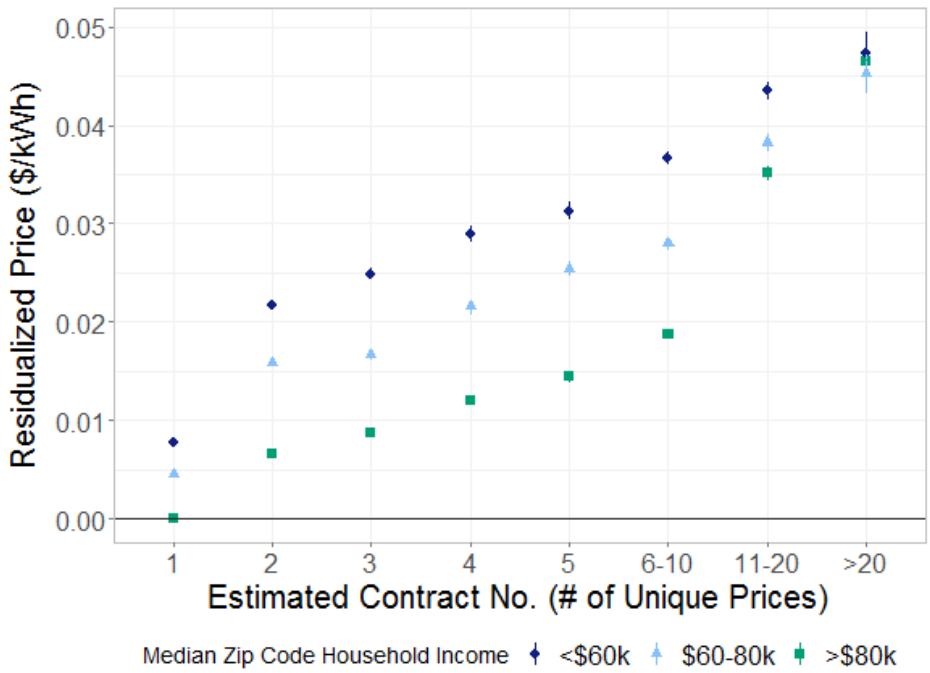
Suppliers appear to be aware that consumers are partially inattentive to price, and they seem to price discriminate on this inattention through gradual price increases over a customer's tenure. The renewal price distributions discussed in Stylized Fact 2 described renewal prices irrespective of customers' 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 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.[19]

As shown in Figure 7, prices tend to increase with the number of renewals for all income groups.

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

[19] 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.

Figure 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.

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.[20]

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.

Figure 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

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

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 7 shows that marketing can reconcile these findings.

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

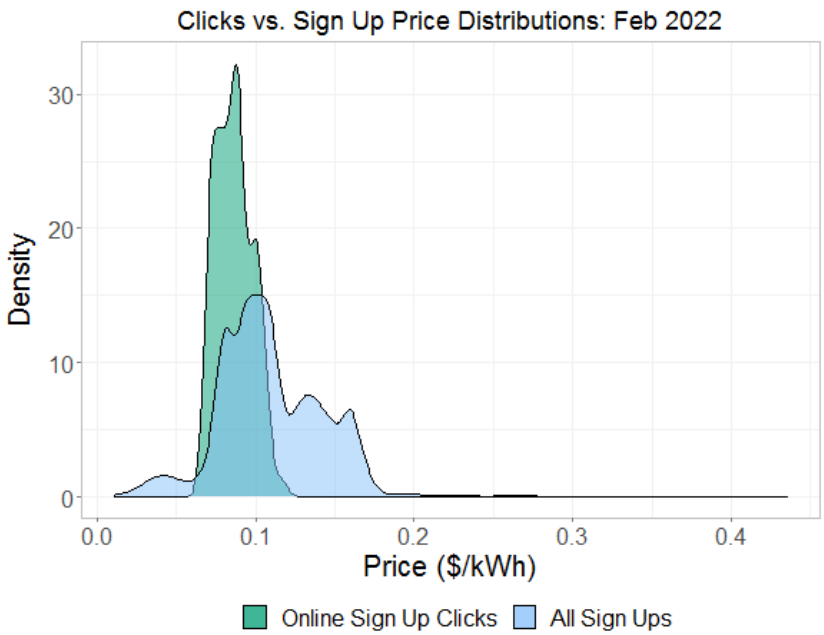
This subsection further explores the sign-up price gap by asking two questions about consumers' sign-up methods: 1) How do consumers sign up with electricity suppliers? 2) Do prices differ by sign-up method? I cannot explicitly observe sign-up prices by the associated sign-up method. Instead, I use survey 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 8 plots these two price distributions in February 2022, and Table 1 displays associated summary statistics.[21] 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.

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

Figure 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.

Table 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.

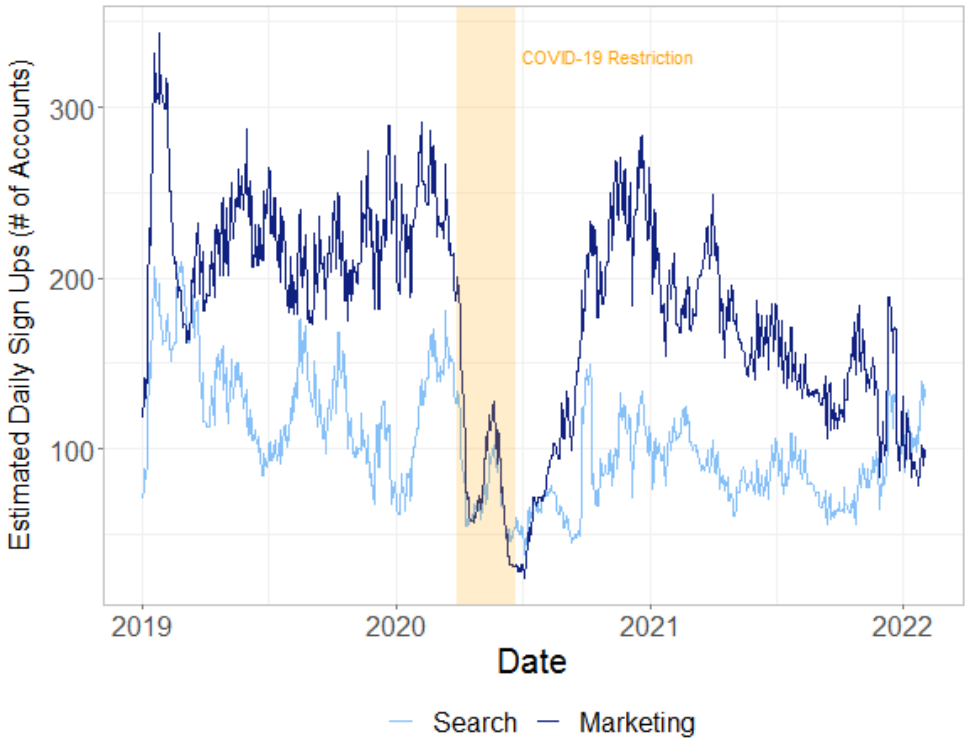
To estimate the distributions of low and high sign-up prices, I leverage the bimodal nature of sign-up price distributions demonstrated in Figure 6.[22] I assume the higher mode reflects the mode of marketing-related sign-up prices and the lower mode is the search-related sign-up price mode. Assum-

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

ing each of these distributions is symmetric, I estimate the two underlying sign-up price distributions. For more estimation details, see Appendix E.

Figure 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.[23] Each observation is a daily estimate based on a two-week rolling average. The orange-shaded region indicates when 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.[24]

Figure 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.

[23] Comparing cross-sectional variation across zip codes, I find an 89% correlation between these estimates of the number of suppliers marketing door-to-door by zip code and the reported numbers in the administrative marketing activity data.

[24] 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.

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 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:

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

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.

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

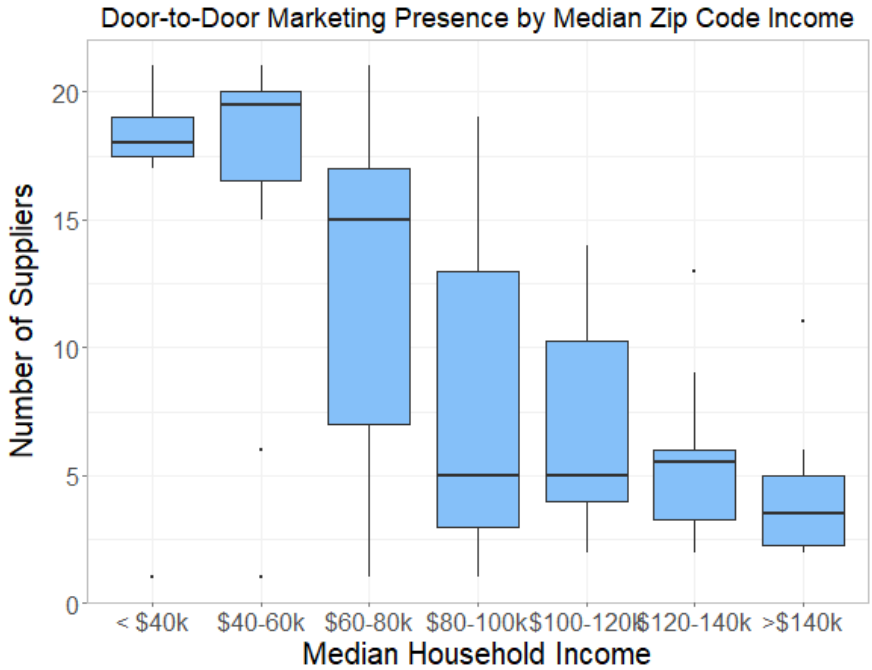
Sign-up prices in Figure 7 (i.e., contract #1) show that even when consumers actively choose to switch suppliers, low-income consumers tend to sign up at higher-priced plans than high-income consumers, on average. Is this because consumers in low-income zip codes are relatively more likely to sign up through marketing than through active search? Figure 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 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 ($\chi^2 = 6.2$).[25] 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 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 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.

The survey confirms that there is more direct marketing in low-income areas. As shown in Table

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

Figure 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.

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 8 explores the individual contributions of marketing costs and demand-side drivers in detail.

4.7 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 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 F 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 F for details.

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 D for additional details.

5.1 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 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.

5.2 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.[26]

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.[27] 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 4.

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

[27] 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.

5.3 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.

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,[28] 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 D for details.

5.4 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 D for details.

[28]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.

5.5 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.[29] 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 D for a detailed analysis of pricing differences between low-income program applicants and non-applicants.

5.6 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.

6 Theoretical Model

6.1 Overview

This section outlines the general model I will use in Section 7 to explain the stylized facts and then estimate in Section 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

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

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.

6.2 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.[30] 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.

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

[30] 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.

in electricity models.

6.3 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

6.4 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 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.

7 Analytical Model to Explain Stylized Facts

7.1 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 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 $\bar{p} >> c$.[31] 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.

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 B and C for a detailed discussion and proofs for the dynamic case.

7.2 Single-period Model

7.2.1 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, $D(p_m) \equiv (1 - \alpha)(1 - F(p_m))$.

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

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:[32]

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

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.

7.2.2 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,*

[32] 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.

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 C. □

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.

7.3 Additional Dynamic Results

Appendix B 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 B for formal propositions and Appendix C for proofs of these results.

7.4 Discussion

Combining these theoretical results with evidence about differences across low- and high-income areas can explain the stylized facts in Section 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.

8 Structural Model

By adding more structure to the model in Section 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.

8.1 Additional Model Assumptions

I now assume functional forms for the general model presented in Section 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 E 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.

8.2 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.[33] 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 4 and described in detail in Appendix E 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

[33] 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 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 E 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 consumer characteristics, including type, location, total bill, and duration with the supplier. See Appendix E 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:

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

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,[34] 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:

$$\pi_1 = 1 - \int_0^\infty \frac{exp(-p_t/\sigma_1)}{exp(-p_t/\sigma_1) + exp(-y/\sigma_1) + \sum_{j \in \mathcal{J}} exp(-p_j/\sigma_1)} g_{p_m}(y)dy$$
$$\pi_2(p_t) = \int_0^\infty \frac{exp((\gamma - y)/\sigma_2)}{exp(-p_t/\sigma_2) + exp((\gamma_1 - y)/\sigma_2)} g_{p_m}(y)dy$$

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.[35]

[34] I impose $M_{zt}/N_{zt} = 0$ during April and May 2020. I exclude March, June, July, and August 2020 from the analysis.
[35] This number reflects the median number of plans listed on MDElectricChoice.gov from February through July 2022.

Marketing sign-up decisions vary by zip code and whether the consumer switches from another supplier or from the default option.[36] The unconditional probability of switching when engaging with a marketer given a marketing offer p_t is

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

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 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

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

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.

8.3 Results

Tables 2 and 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.

Table 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.

To further facilitate choice probability comparisons across income groups, Figure 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

Table 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.

with a marketer when offered a relatively low marketing price. However, the relation reverses at high marketing prices. 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 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.

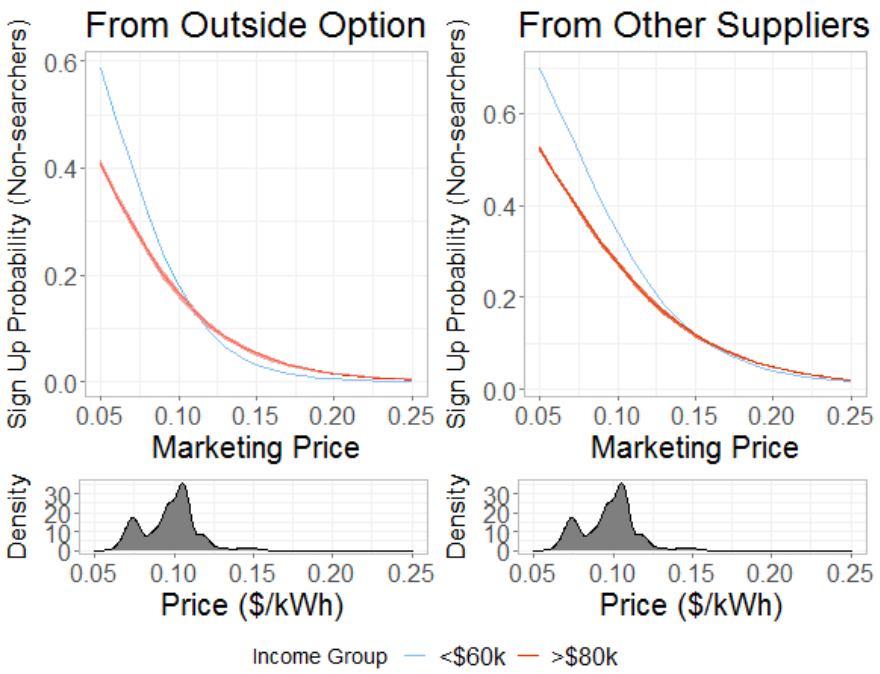
Marginal marketing costs are convex in marketing level and decreasing in population density. Figure 13 shows marginal marketing cost by population density for a marketing level of 100 marketing interactions. For comparison, the chart also includes the population density distributions for low- and high-income 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.

8.4 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-up and renewal prices remain unchanged

Figure 11: Estimated Non-searcher Marketing Sign-up Probability: April 2019

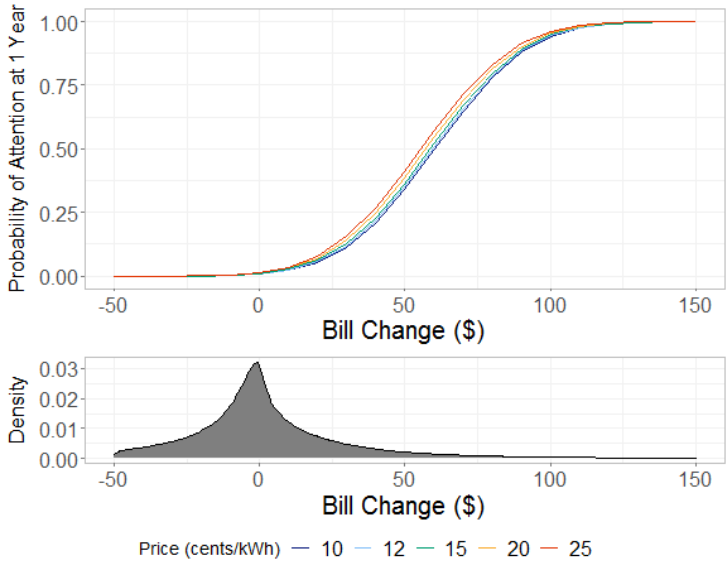


Width of curves reflect 95% confidence intervals estimated via parametric bootstrap. Top charts show estimated probabilities that a non-searcher will sign up with a marker by marketing offer price and whether the consumer is on the outside option (left) or active in the market (right). Bottom charts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

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.

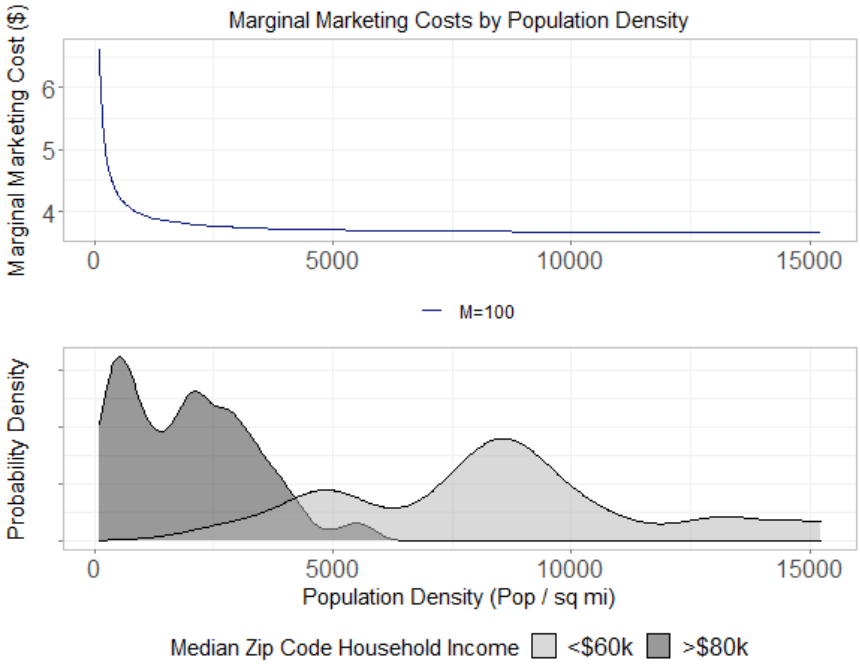
What happens when marketing ends? Market prices increase, market participation decreases, and switching decreases. Low-income households would still pay a premium in the absence of marketing due to attention differences. As Figure 14 shows, the income-price gap disappears initially and then gradually 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 counter-

Figure 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.

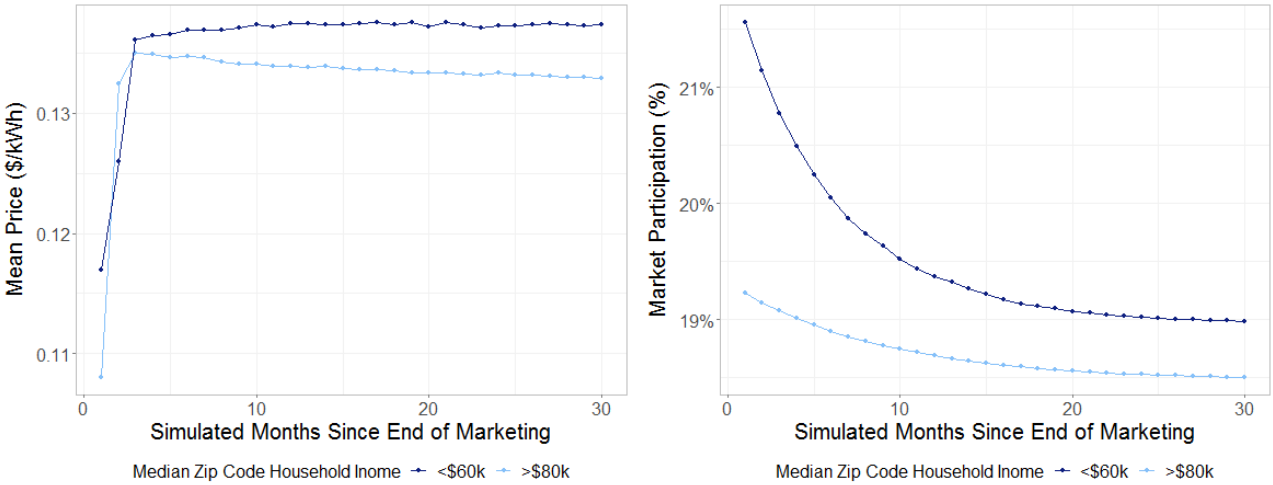
Figure 13: Marginal Marketing Costs by Population Density



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.

factual with marketing due to the lower prices of consumers who choose the regulated rate. Supplier profits decrease because they have fewer customers.

Figure 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.

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 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.[37] 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.

[37] 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.

8.5 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 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 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 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.

8.6 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

Table 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
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 on mean sign-up price
Marketing and 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

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.[38] 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,[39] or any direct welfare reduction from engaging in a marketing interaction.[40]

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

[39] 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.

[40] Model parameter estimates in Table 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.

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.[41] See Appendices H and I for details.

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 welfare loss to be 12% 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

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

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.[42] Regulators in New York used price caps as a policy instrument.[43]

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.

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

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

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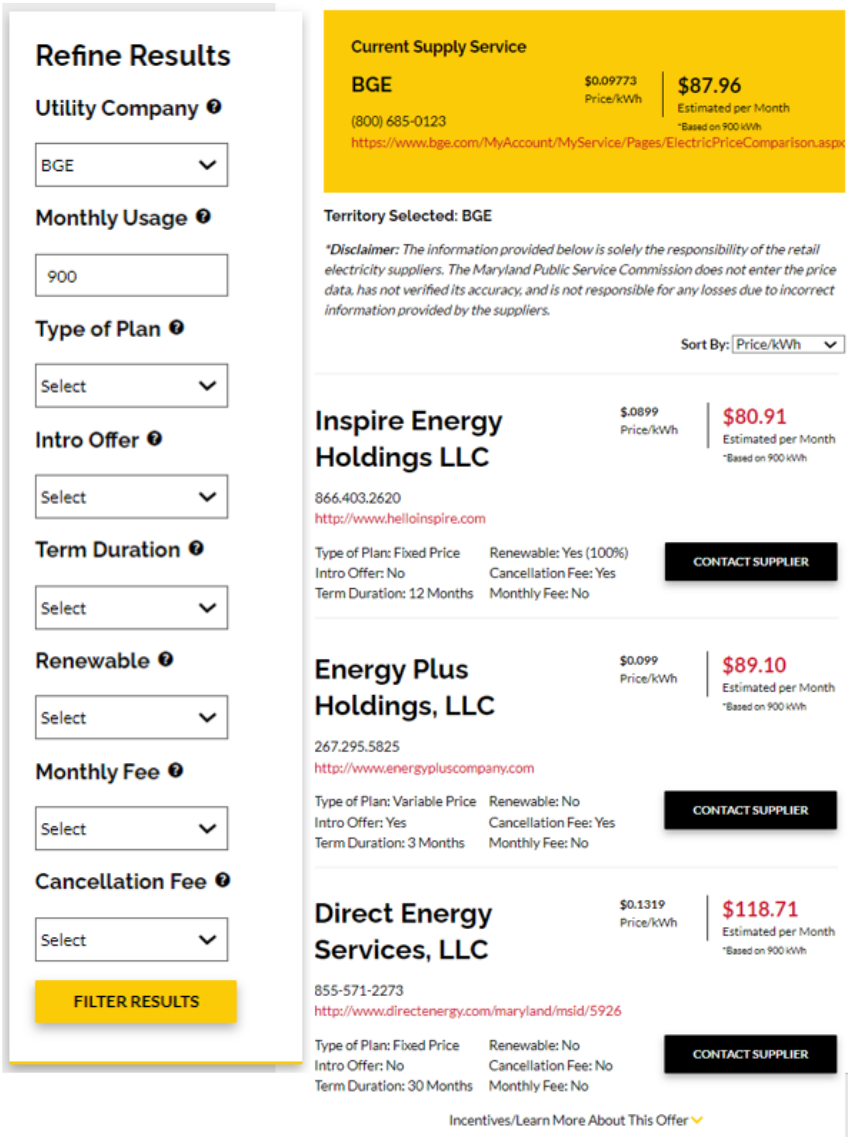
Appendices

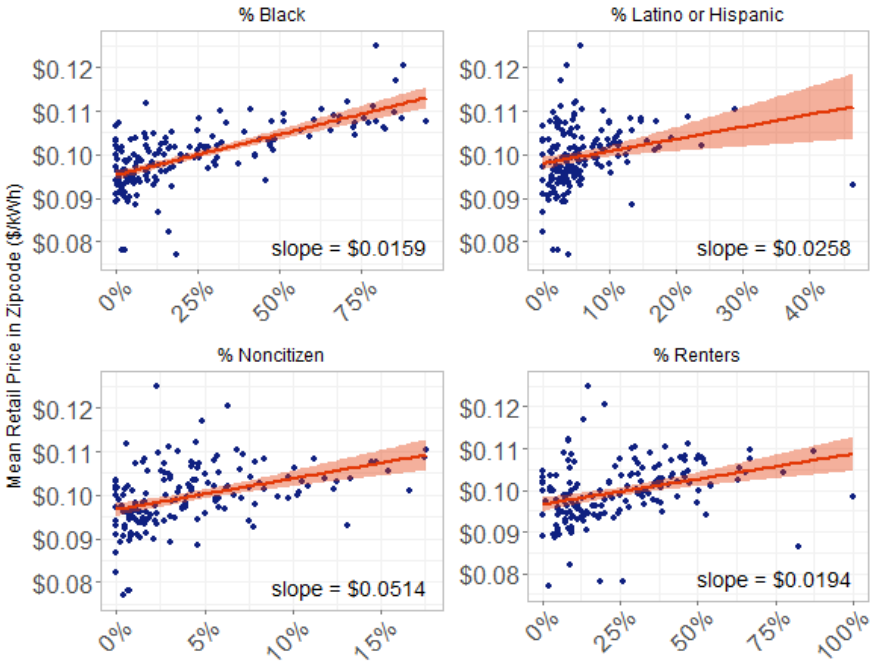
A Additional Tables and Charts

Figure A1: Screenshot from MDElectricChoice.gov



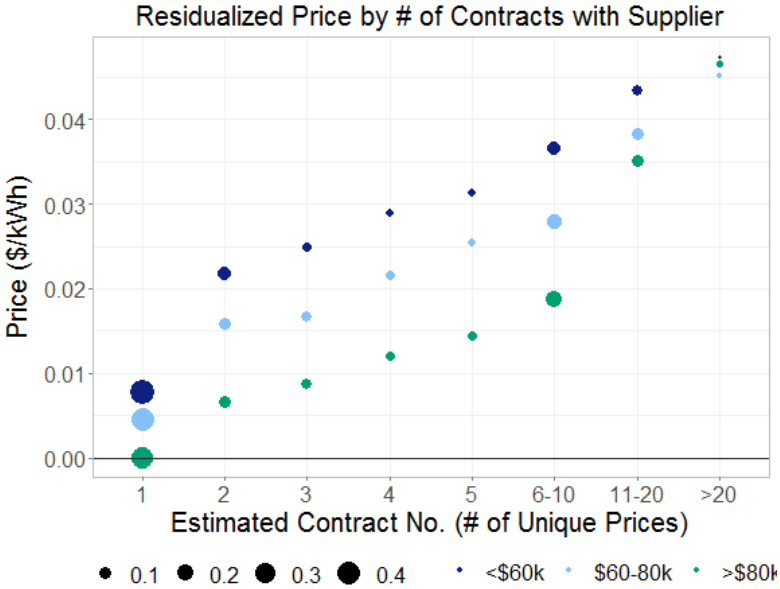
Accessed October 2022.

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



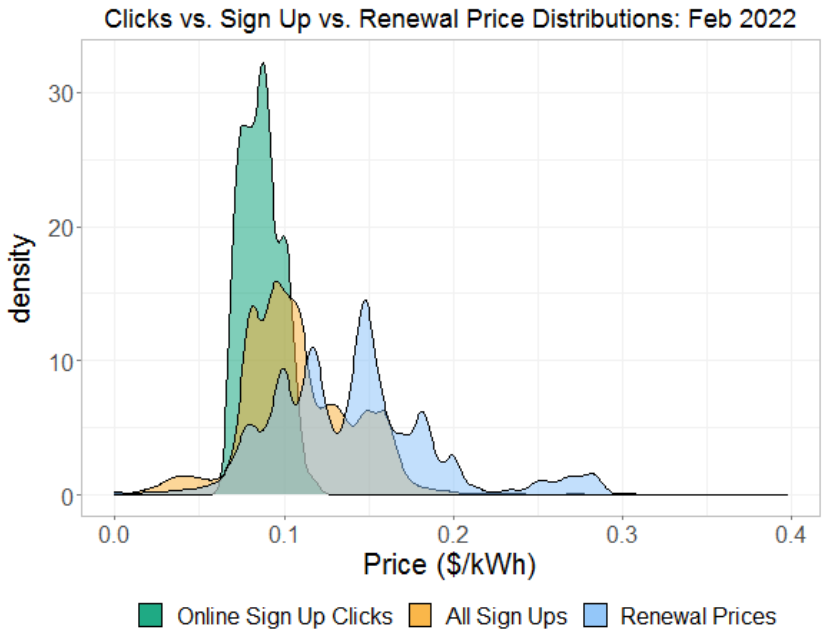
Generation supply prices for residential retail choice customers in Baltimore Gas and Electric Company service area in September 2019. Zip code tabulation area (ZCTA) demographics from the 2019 American Community Survey. A dot represents one ZCTA. Best linear fit line and 95% confidence intervals in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

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



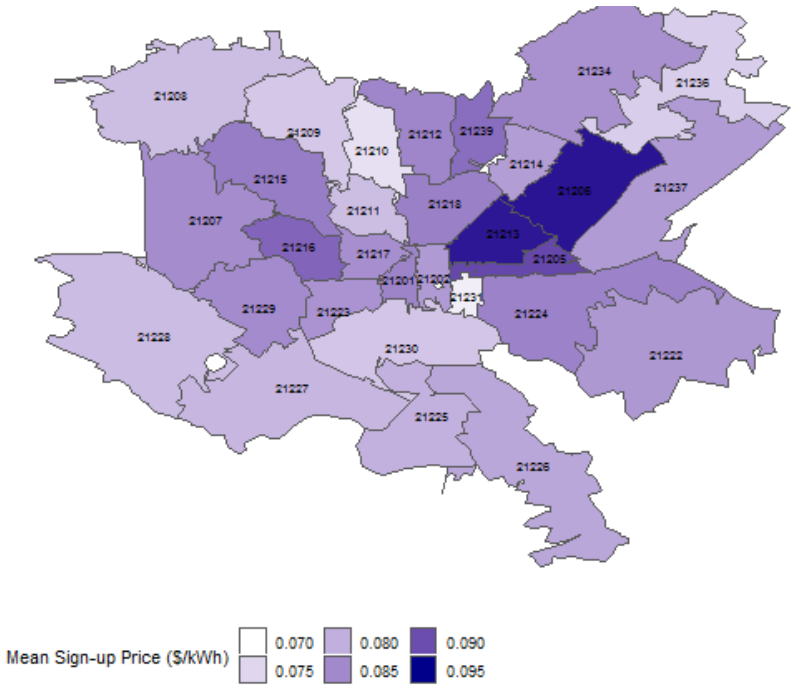
Estimates from a regression of electricity supply price on time fixed effects, number of unique prices a consumer has faced since last switching suppliers, and income group. Excludes standard offer service prices. Only includes linear tariffs that are not time-differentiated. Sizes reflect the share 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 Baltimore City zip code.

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.

B 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 C. □

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 C. □

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.

C 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 $\frac{\partial\pi_M}{\partial\lambda} < 0$. □

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

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

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. □

D Alternative Theories

D.1 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.

D.2 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.[44] During the analysis timeframe, an average of 95% of consumers faced linear

[44] 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.

per-kWh rates, 5.0% had plans with fixed charges, and 0.006% were on time-differentiated rates.[45]

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.[46] 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 4.

D.3 Cost to Serve

D.3.1 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 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

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

[46] 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.

outside of Baltimore City. The income-price gap persists within Baltimore City itself.

D.3.2 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,[47] 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

[47] 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.

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 3 and Appendix G 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 I), 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.

D.4 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 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.

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.

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 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.

D.5 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.[48] 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

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

receive a relatively large amount of marketing conditional on income bin. A shown in Figure 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.

D.6 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.

E Structural Model Pre-processing Steps

This section describes the pre-processing steps outlined in Section 8.2. 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.

E.1 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 8.[49]

E.2 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

[49] These are also the distributions used in the regression discontinuity and differences-in-differences analyses in Section 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.

specification for predicting February 2019 continuation value. I allow for 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

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

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

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.

F Results from Other States

This section presents descriptive evidence that some key stylized facts presented in Section 4 also hold in several other Northeast U.S. residential electricity markets. Pricing data 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).

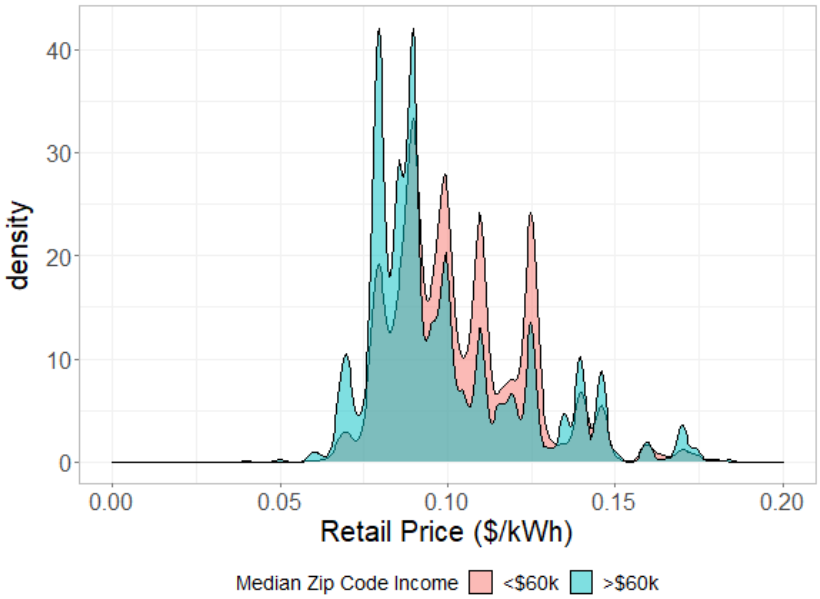
Data richness vary by location. I have household-level panel billing data for Central Maine Power in Maine from November 2018 through October 2021.[50] Eversource Connecticut data are repeated monthly cross-sections of electricity supply prices that suppliers billed to consumers on retail choice. For 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.

[50] Data came in three separate annual panels.

F.1 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.[51] These percentage price differences are 9% and 38%, respectively, in Maine. Figures A6 and A7 show cross-sections of these price distributions.

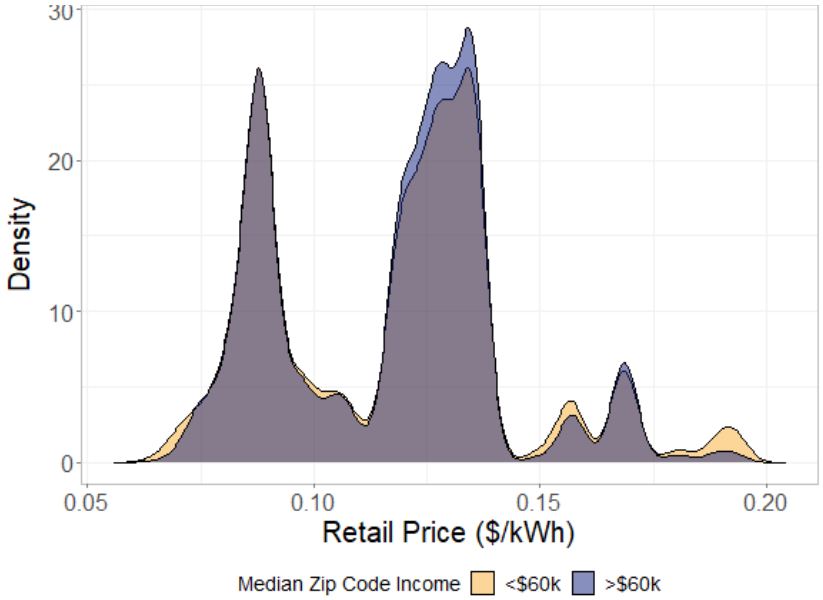
Figure A6: Prices by Zip Code Median Household Income (June & Sep 2018): Connecticut



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.

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

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

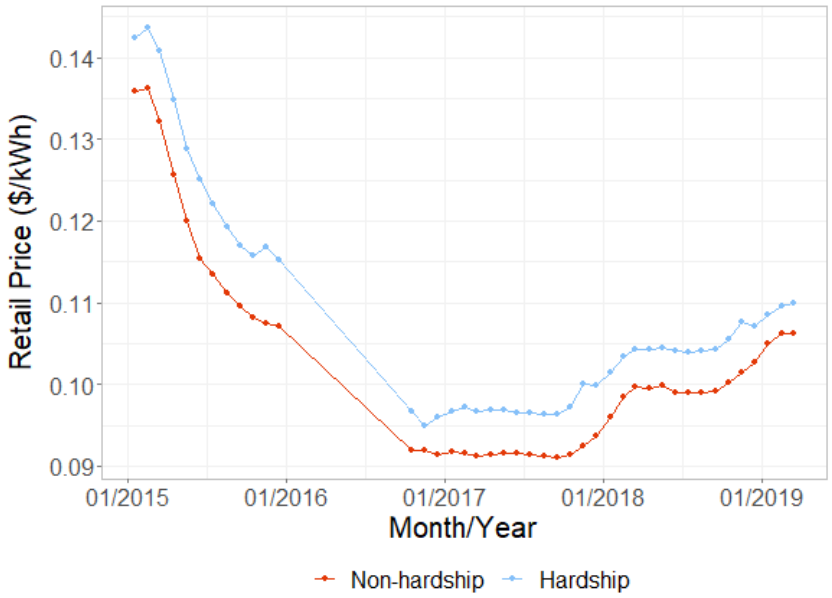


Probability density of generation supply prices for residential retail choice customers in Central Maine Power service territory by 2019 American Community Survey zip code tabulation area median annual household income.

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.[52] 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.

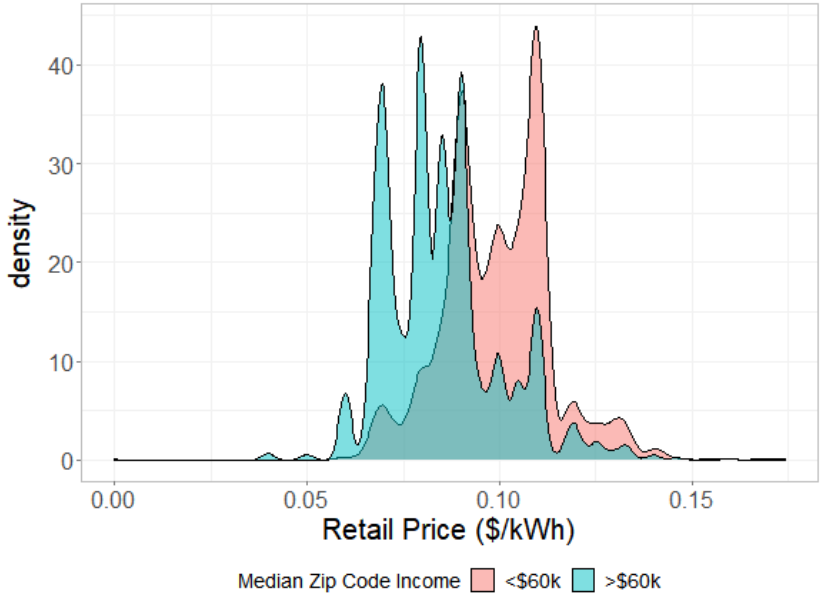
[52]Shortly after this period, hardship customers were banned from the Connecticut retail choice market.

Figure A8: Mean Retail Price by Hardship Status: Connecticut



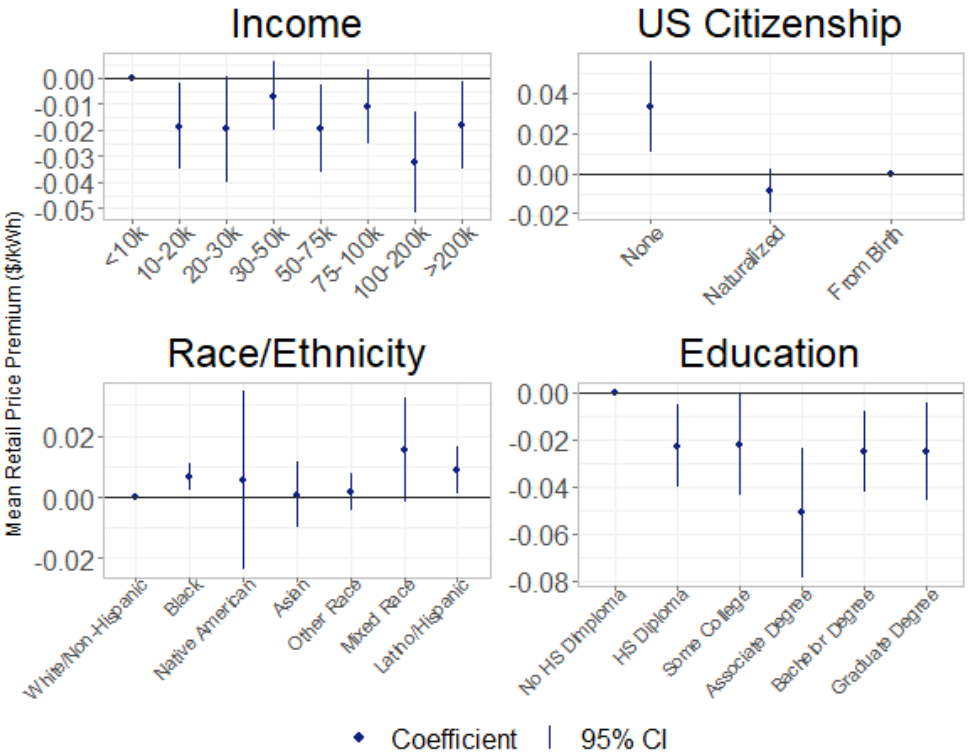
Mean electricity supply prices billed in Eversource's Connecticut service area by month and whether the consumer was awarded hardship status. Income definitions reflect 2019 American Community Survey zip code tabulation area median household income.

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 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.[53]. In New York in 2016, mean prices of retail choice participants in zip codes with median

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

annual household income less than \$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.

F.2 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.

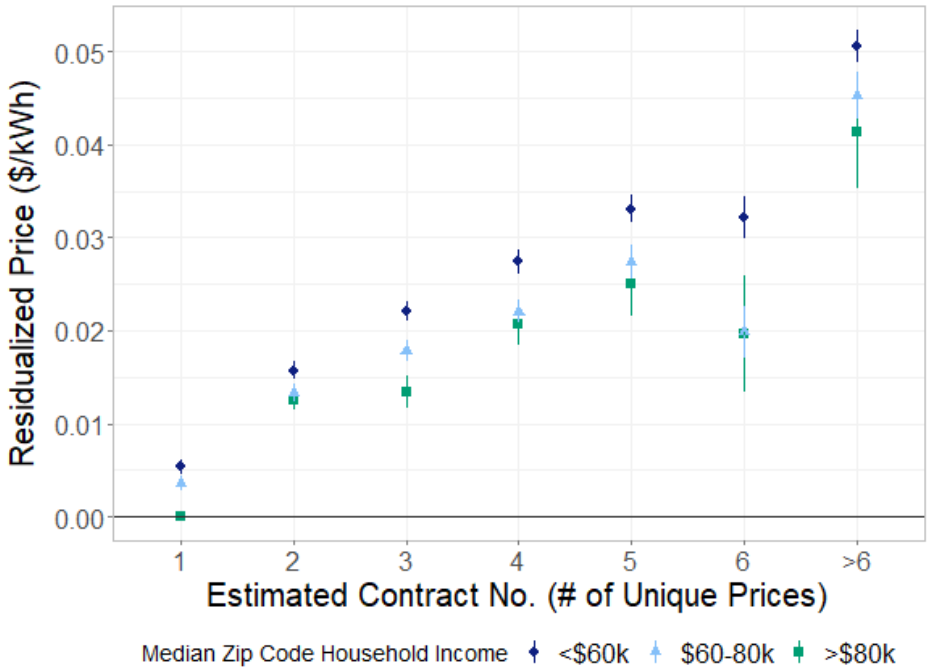
I also observe more frequent switching in low-income communities than high-income communities in Maine ($t = 13$). These estimates come from a regression of whether each consumer signed up with a supplier on income group, controlling for time fixed effects. I restrict the sample to consumers who were active in the retail choice market in each analysis month.[54] In Connecticut, low-income households with hardship status switch with a higher probability in a given month than other retail choice participants ($\chi^2 = 106$).

F.3 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.

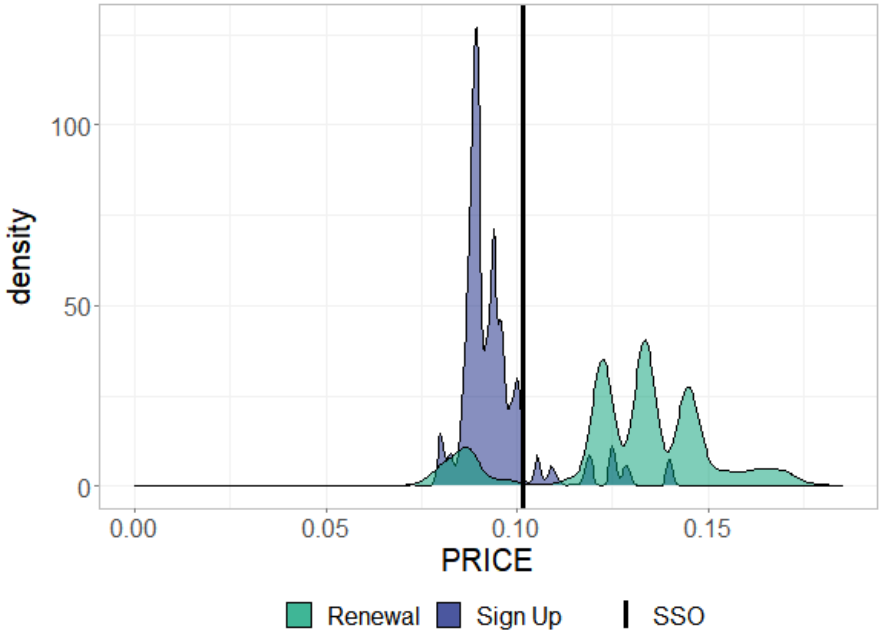
[54] This result is robust to a probit specification.

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.

F.4 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$).

G 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[55] 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

[55]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 ($r > 0.999$).

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.

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.

H 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

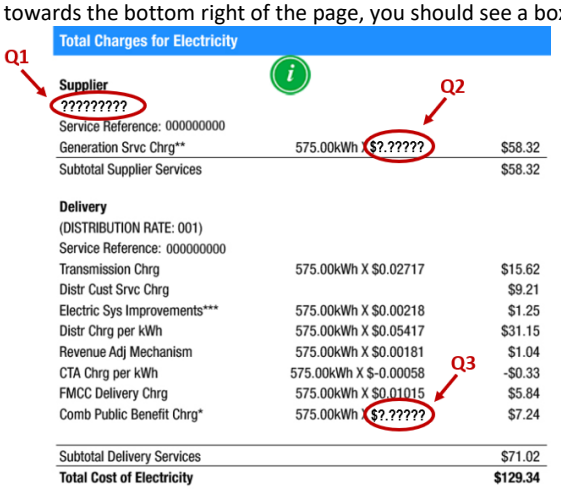
Description	Price ($/kWh)	Typical Total Bill ($/Month)	Price Fixed For:	Electric Supplier	Phone Number	Website Link
Government-regulated plan	[Data]	[Data]	1 month, followed by regulated changes	[Data]	[Data]	[Data]
Cheapest plan	[Data]	[Data]	[Data]	[Data]	[Data]	[Data]
Cheapest plan with a fixed price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



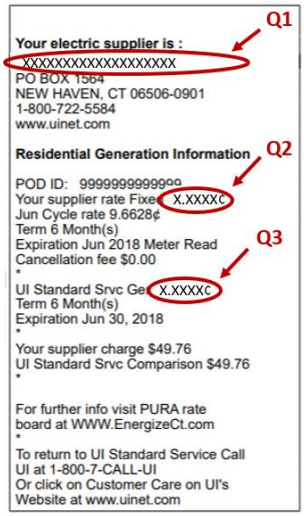
Total Charges for Electricity		
Supplier		
?????????		
Service Reference: 000000000		
Generation Srvc Chrg**	575.00kWh X $?.?????	$58.32
Subtotal Supplier Services		$58.32
Delivery		
(DISTRIBUTION RATE: 001)		
Service Reference: 000000000		
Transmission Chrg	575.00kWh X $0.02717	$15.62
Distr Cust Srvc Chrg		$9.21
Electric Sys Improvements***	575.00kWh X $0.00218	$1.25
Distr Chrg per kWh	575.00kWh X $0.05417	$31.15
Revenue Adj Mechanism	575.00kWh X $0.00181	$1.04
CTA Chrg per kWh	575.00kWh X $-0.00058	-$0.33
FMCC Delivery Chrg	575.00kWh X $0.01015	$5.84
Comb Public Benefit Chrg*	575.00kWh X $?.?????	$7.24
Subtotal Delivery Services		$71.02
Total Cost of Electricity		**$129.34**

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"

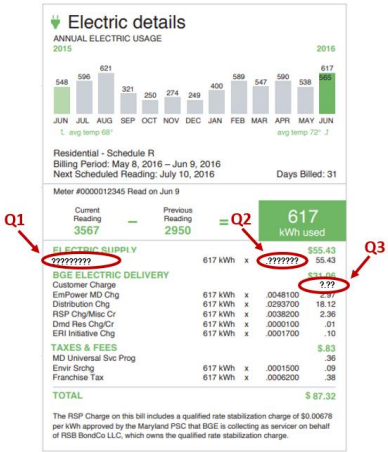
7. [If 1 = Yes and Utility = United Illuminating] Please find a recent United Illuminating electricity bill. On Page 1 towards the bottom right of the page, you should see a box that looks like the following:



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?

I Consumer Survey

I.1 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.[56] 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 H 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.

I.2 Results

I.2.1 Summary

The consumer survey supports some key aspects of the theory described in section 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.

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

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.

I.2.2 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 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.

I.2.3 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.

I.2.4 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.

I.2.5 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.

I.2.6 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.

I.3 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