

Power to Choose?

An Analysis of Consumer Inertia in the Residential Electricity Market

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Abstract

Many jurisdictions around the world have deregulated utilities and opened retail markets to competition. However, inertial decisionmaking can diminish consumer benefits of retail competition. Using household-level data from the Texas residential electricity market, we document evidence of consumer inertia. We estimate an econometric model of retail choice to measure two sources of inertia: (1) search frictions/inattention, and (2) a brand advantage that consumers afford the incumbent. We find that households rarely search for alternative retailers, and when they do search, households attach a brand advantage to the incumbent. Counterfactual experiments show that low-cost information interventions can notably increase consumer surplus.

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1 Introduction

The deregulation of formerly regulated utilities has brought about more choice for energy consumers. Across the world, electricity and natural gas consumers increasingly have the ability to choose their retail provider. For example, households in over a dozen U.S. states and over one-half of households in Europe have retail choice in electricity and/or natural gas. Consumers who previously purchased services from a utility are allowed to buy from other retailers at prices that are not regulated. This creates new markets where entrant retailers procure wholesale energy and market that energy to customers. This expansion of retail choice has been touted to have several benefits. Creating competition for the provision of utility services can lead to more competitive pricing in the short-run. In addition, introducing competition can create incentives to provide customers with new value-added services.

However, choice frictions can diminish the benefits of retail choice. Households who never have had the “power to choose” may not exercise the option to select an alternative lower-priced energy retailer. For example, households may not actively acquire information about other energy retailers, even if that information would indicate that “better” options exist. Alternatively, households may value the brand name of the incumbent – the old utility – and this may reduce the amount of switching to new entrant retailers. Both of these sources of choice frictions can reduce consumer gains of retail choice.

In this paper, we study a particular retail choice program to measure the size of choice frictions and to understand the underlying mechanisms. The Texas residential electricity market provides an excellent setting to investigate retail choice. Beginning in 2002, residential electricity customers in Texas were allowed to choose their retail provider. Initially, all households were by default assigned to the incumbent. In every subsequent month, households had the option to switch to one of several new entrant electricity retailers. In order to inform consumers and provide transparency to the search process, the Public Utility Commission of Texas created a website – *www.powertochoose.com*. This website was intended to create “one stop shopping” where households can search all retail options and switch to an alternative provider.

Aggregate data from this market suggest strong evidence of consumer inertia. Figure 1 plots the prices being charged by both the incumbent and new entrant retailers. Although prices varied over time, the incumbent’s price was consistently higher than several of the new entrants.¹ This suggests that households could reduce their electricity bills by switching

¹The rise in prices in fall 2005 was caused by a run-up in wholesale electricity prices, which was largely driven by a spike in natural gas prices that resulted from supply-side disruptions from Hurricane Katrina.

from the incumbent to a new entrant retailer. However, Figure 2 shows that the incumbent held on to its market share leadership throughout the first four years of the market. The incumbent share only gradually eroded over time, and even after more than four years of retail choice, the incumbent's market share was over 60%. As we show in section 3.1, the majority of households did not switch away from the incumbent, even though they would have significantly reduced their electricity bills. Switching to a new entrant retailer – a one-time action that would take approximately 15 minutes to complete – would reduce the average electricity bill by around \$100 in the first year, which represents about 8 percent of electricity expenditures.

This evidence of consumer inertia presents a puzzle for policymakers who are considering the deregulation of retail energy. Why do consumers of a relatively homogeneous product not switch to a lower-priced energy provider? And can retail policy be designed to reduce consumer inertia? The goal of this paper is to understand the causes of the inertial behavior of residential electricity consumers. We develop a model to distinguish between two different mechanisms that could account for this inertia:

1. *Search frictions/inattention*: Households may not choose to search for, or, equivalently, pay attention to offerings by other retailers. Even though *www.powertochoose.com* is a click away, the household may not be aware of it, or, although informed of the existence of alternatives, the household chooses not to expend the effort to pay attention.
2. *Incumbent Brand Advantage/Product differentiation*: Even if a household is aware of other retailers, consumers may view the retailers, especially the incumbent, as vertically differentiated. For example, households may believe that service during power outage events or other dimensions of power quality could differ across retailers. Such beliefs, even if technically incorrect, may be a source of vertical product differentiation. Alternatively, consumers may believe that characteristics of customer support such as ease of paying bills vary across retailers.

Understanding the mechanism driving the inertial behavior will inform the design of policy to enhance the consumer benefits of retail choice. For example, if search frictions are the cause of observed inertia, then regulatory attempts to lower the cost obtaining information about retail options could encourage switching and benefit consumers. On the other hand, suppose that the primary reason households continue to purchase from the incumbent is that they believe the incumbent provides more reliable power. (Technically, the delivery of power and all metering operations are not a function of the retailer, but consumers may be

unaware of this.) In this case, information campaigns to inform consumers that “it’s all the same power” may induce households to choose lower price retailers. Finally, if the incumbent brand effect diminishes with time, then the resulting inertia may be viewed by policymakers as merely part of the consumer learning process during the transition from regulation to retail competition: while consumers may start with the belief that the incumbent delivers the superior product, over time they learn that “it’s all the same power.”

In order to estimate the magnitude of each source of inertia, we develop an econometric model of household choice that nests both sources of inertia within a two-stage discrete choice framework. In each month, the household enters a two-stage process. In the first stage, the household decides whether to consider an alternative retailer. If it does not consider alternatives, then the household stays with its current retailer for the following month. However, if it does consider alternatives, the household enters the second stage. In this stage, the household observes the retailers in the choice set (which are available on *www.powertochoose.com*) and chooses the retailer that maximizes utility. In this second stage, we allow for vertical product differentiation to enter the household’s decision, thus capturing potential brand advantage by the incumbent. In section 4.3, we provide transparent conditions for the identification of model parameters from sample moments. We show that the first stage “decision” probabilities that capture inattention are separately identified from the second stage “choice” probabilities that capture incumbent brand advantage.

We estimate the model using household-level choice data from the first four years of retail choice in Texas. We find that both search frictions and the perception of brand differentiation explain the market dynamics shown in Figures 1 and 2. First, search frictions/inattention plays a role in the inertial behavior. We estimate that the average customer of the incumbent only searches for retail options in about 2% of months, or approximately once every 4-5 years. However, the seasonality of search generates interesting insights about the determinants of consumer search in this market. Our model does not impose a structure on whether households are forward-looking when deciding to consider alternatives or, equivalently, the decision to not pay attention. Rather, households can either search in anticipation of seasonal patterns in consumption or as a reaction to a large bill caused by high consumption. We do not find evidence of forward-looking search activity: consumers are most likely to search in the month after receiving a large bill, which is likely to occur in the summer in Texas.

But inattention is not the only driver of inertia – the incumbent enjoys a very significant brand effect. In the earliest years of retail choice, consumers value the incumbent’s brand at about \$60/month. However, this effect quickly diminishes over time and is estimated to

be less than \$15/month by the fifth year of retail choice. These findings suggest a model of consumer learning where households who gather more experience with retail choice update their prior beliefs about the quality of the incumbent relative to new entrant retailers.

In order to evaluate the implications for policy, we simulate the effect of a low-cost information intervention that targets each source of inertia. The information intervention serves to reduce inattention and mitigate misperceptions about the quality differences across retailers. This intervention would be akin to sending a flyer in the monthly bill telling consumers two important pieces of information: (1) they can go to *www.powertochoose.com* to view options and (2) that their power quality will be the same under any retailer. We view this as a fairly low-cost policy intervention that combines a nudge with an information treatment. This counterfactual is modeled as increasing the probability that a household searches in a given month and reducing the relative size of the perceived incumbent brand effect. We use model parameters to simulate this counterfactual experiment under various interpretations of the incumbent brand effect, and we find that consumer surplus could increase a hundred dollars per year or more for each household.

A variety of countries have offered retail choice in utilities such as natural gas and electricity, and this has led to a mixed record on the number of consumers who switch away from the incumbent.² This paper contributes to the literature on studying retail choice in utilities. In the most closely related paper, [Giulietti et al. \[forthcoming\]](#) estimate an equilibrium model of search costs to explain price dispersion in the British electricity market. Retail choice has been investigated in natural gas ([Giulietti et al. \[2005\]](#)) and telecommunications ([Miravete \[2003\]](#) and [Miravete and Palacios-Huerta \[2014\]](#)). Our study of deregulated retail markets expands upon a rich literature on deregulated electricity markets that has focused on wholesale markets (e.g. [Wolfram \[1999\]](#), [Borenstein et al. \[2002\]](#), [Bushnell et al. \[2008\]](#), [Sweeting \[2007\]](#), and [Hortacsu and Puller \[2008\]](#)).

More generally, the phenomenon we study – frictions associated with allowing choice in settings where consumers previously did not have options – is not confined to formerly regulated utilities. In the healthcare sector, the prescription drug benefit program under Medicare Part D provides the elderly with multiple private plan options rather than a single plan specified by the government; likewise, health exchanges are an alternative to employer-provided insurance.³ In primary education, parents in some jurisdictions are offered a menu

²For an analysis of the merits of retail choice in electricity, see [Joskow \[2000\]](#). For a review of experiences in residential electricity choice and a representation of consumer search in such markets, see [Brennan \[2007\]](#).

³For example, see [Abaluck and Gruber \[2011\]](#), [Kling et al. \[2012\]](#), [Ketcham et al. \[2012\]](#), and [Dafny et al. \[2013\]](#).

of public schools that their children can attend rather than a single school that children are zoned to attend.⁴ And in the arena of retirement savings, the traditional role of government in pay-as-you-go systems has been replaced by privatized retirement planning where individuals choose from among a set of privately managed funds.⁵

Our paper is also related to a recent literature developing methods to estimate preferences in settings where decisionmaking is influenced by search frictions/inattention. [Hong and Shum \[2006\]](#), [Hortacsu and Syverson \[2004\]](#) and [Moraga-Gonzalez and Wildenbeest \[2008\]](#) are early attempts that utilize aggregate market level data, and more recent efforts by e.g. [Kim et al. \[2011\]](#), [De Los Santos et al. \[2012\]](#), [De Los Santos et al. \[2013\]](#), [Honka \[2014\]](#), [Koulayev \[2014\]](#) and [Honka et al. \[2014\]](#) utilize detailed consumer level data on both choices and the search process/consideration sets (as obtained, e.g., from website clicks) to test and estimate models of consumer search. Our empirical setting is one where we observe the choices of consumers, but do not observe their search process/consideration sets. However, we show that the search friction/inattention component of consumer behavior and the “frictionless” preference component can be separately identified under reasonable assumptions. Indeed, as we show in our results section, applying standard discrete choice models to our data without taking into account the presence of search frictions/inattention can yield distinctly different and implausible estimates of preferences. Several papers in the recent empirical literature on consumer inertia exploit the institutional feature that some customers are new to the market while others are existing market participants (e.g. [Handel \[2013\]](#) and [Luco \[2014\]](#)). In some settings, new customers face different sources of inertia than existing customers, and comparing the decisions of these different groups allows for the identification of inertia. In other institutional settings (including our setting), there may be relatively few new customers to exploit for identification. As we describe below, our empirical strategy does not require new customers, although it can incorporate new customers if they are present.

2 Retail Electricity Choice in Texas

Residential electricity customers in Texas, as in many states, historically were served by vertically integrated utilities at regulated prices. The state was divided into separate service territories, each with a vertically integrated firm. Beginning in 2002, residential electricity customers in Texas were allowed to choose their retail provider. In January 2002, all cus-

⁴See, for example, [Hastings et al. \[2010\]](#), [Neilson \[2013\]](#) and [Hastings and Weinstein \[2008\]](#) on school choice and the effects of information provision.

⁵See [Hastings et al. \[2013\]](#), [Duarte and Hastings \[2012\]](#) and [Luco \[2014\]](#).

tomers by default were assigned to a retail firm that was affiliated with the old incumbent utility. In any subsequent month, a customer can switch to any other retailer at no cost. Texas is not alone in this regulatory change – over a dozen U.S. states have opened the retail electricity sector to competition.

Any customer choosing to procure power from another retailer is entering into a *financial* agreement with the retailer. Importantly, retail choice does not impact the *technical* operations of power provision. The former utility was split into a “lines” company and a retailer.⁶ The operations of all electricity transmission, local powerlines, and meters is now operated by a regulated firm (with a different name) that is a separate business entity from the incumbent retail firm. As a result, the quality of power service (e.g. outages) is independent of the retailer chosen by a household. (It is possible that consumers were not aware of the independence of operations, as we discuss below when interpreting our results).

The incumbent’s price was regulated by the public utility commission and called the “price-to-beat”.⁷ The incumbent could request an adjustment to this regulated rate up to two times a year, however the size of the adjustment was indexed to natural gas input costs.

The new entrant retailers are firms that procure power in the wholesale market and sell retail power to residential customers. These retailers need not own any physical infrastructure to be market participants. Unlike the price of the incumbent, the prices of the entrant retailers were not regulated. In 2002, most parts of Texas had between three to five entrant retailers, and by the end of our sample in 2006 the choice set expanded beyond ten.

Because of relatively low wholesale electricity prices during the first few years of retail competition, the price-to-beat was considered to be higher than competitive prices for retail power. This so-called “headroom” was an intentional market design feature by the regulatory commission to ensure new retailers of sufficient price-cost margins to encourage entry. As a result, entrant retailers were able to price more than one cent per kWh below the price-to-beat. As we discuss below, this created the potential for average savings of about \$12 per month for switching away from the incumbent.

Households had multiple sources of information on potential electric retailers. The most salient source of information was a well-publicized website established by the state’s public utility commission – *www.powertochoose.com*. A screenshot of the website is shown in

⁶The generation (i.e. powerplant) sector had already been separated from the utility prior to 2002.

⁷This rate was the only tariff allowed to be offered by the incumbent. Starting in 2005, the incumbent could offer alternative rates to incumbent customers but were still required to offer the price-to-beat tariff. By January 2007 after our sample period ends, the price-to-beat was lifted and the incumbent could charge existing customers any rate.

Figure 5 in the Appendix. Consumers enter their zip code and view a list of all retailers. Households could follow links on this website to switch to a new retailer in a process that was online and relatively quick.

The public utility commission sought to reduce the costs of switching in several ways. First, the incumbent was not permitted to charge the customer to switch to another retailer. In addition, a household switching away from the incumbent could switch back to the incumbent’s price-to-beat later if it chose to do so. Regardless of the retailer chosen, a household would still receive a single monthly bill that included charges for all electricity services (energy, transmission, distribution, metering, and billing). Finally, any customer moving to a different residence after the beginning of retail choice is required to choose a retailer; the default is “no power”. Less than 1% of observations in our sample are “movers.”

3 Data

We study the retail choice behavior of all residential electricity customers in the service territories covered by one of the formerly vertical integrated regulated utilities – TNMP. This utility has the appealing feature that it was formed by several mergers and therefore has customers spread throughout the state, including both urban and rural areas.

We use monthly data on each of the approximately 192,000 residential meters in TNMP territory from January 2002 until April 2006. For each meter, we have information on the electric retailer used by the household and the electricity consumption for every month.⁸ We use the meter address to match to Census block group data on demographics.

We focus on customers of the six retailers that had at least 1% of the market at some point in time from January 2002-April 2006.⁹ These six retailers are the incumbent, two retailers that were new in the TNMP service territory but were affiliated with incumbents from other parts of the state, and three retailers that were new to the Texas marketplace.

We can calculate each household’s bill with high precision. For each household-month, we have data on the household’s retailer and its electricity consumption. We match these data to information on the tariffs that were charged by each retailer in a given month.¹⁰

⁸Meter reads do not occur exactly on the last day of the month, so we perform an interpolation to estimate the consumption occurring during each calendar month.

⁹We exclude one entrant retailer with 1.1% market share for which no price data are available.

¹⁰The Public Utility Commission of Texas collected monthly information on the rate plans offered by each retailer in the different service territories. In many cases, the retailer offered only a single rate plan, so we can precisely measure the monthly bill. In fact, only one rate plan was offered by four of the six retailers that we model, including the incumbent. However, a complication is presented by the fact that two retailers

All of the tariffs for the new entrant retailers were 12-month fixed rates; early termination fees were waived by law if the customer moved. The incumbent’s tariff was the regulated price-to-beat which would only change if the incumbent requested an adjustment based on natural gas prices. The tariff data allow us to calculate the total electric bill that a household paid to its chosen retailer as well as counterfactually how much the household would have paid to purchase the same amount of power from any of the other retailers.¹¹

Most of the retailers use multi-part, or non-linear, tariffs.¹² Because the rate plan is an important determinant of consumer choices, we need to choose an appropriate measure of price that is likely to drive a household’s decision process. Two options are available – the marginal price and the average price. The marginal price is likely to be the same for all households with any given retailer because even those retailers with increasing block tariffs have the highest block begin at a low usage level (400kWh/month). However, the average price differs by (expected) consumption because all but one retailer employ non-linear tariffs.

Although some theoretical work on non-linear tariffs assumes that consumers respond to the marginal price, the assumption is problematic in this setting. Responding to the marginal price requires households to have full information on the multi-part tariff function. This assumption is not likely to hold in this market. First, *powertochoose.com* saliently displays only the *average* price for customers consuming 1000kWh/month. Figure 5 in the Appendix shows a sample screenshot. Consumers who want to gain more detailed information about the tariff may click to download the “Facts Label” that is required to contain specific parameters of a retailer’s service. The rate information on the Facts Label is the *average* price for customers consuming either 500, 1000, or 2000 kWh. It is, in fact, impossible to recover the shape of some of the nonlinear tariffs using this information.

Recent empirical work suggests a second reason that marginal price may not be a suitable metric of the price that affects consumer choice. Ito [2014] studies residential electric customers in California who face different non-linear tariffs and finds evidence that customers

offer a menu of rate plans, and we have no information on which plan is chosen by a given household. In these two cases, we chose the plan that was thought to be most popular by the analyst at the public utility commission with responsibilities of overseeing the retail market.

¹¹We should note that about 6% of customers received discounts as part of a low-income program. However, eligibility for this program was independent of retailer. We do not have data on which customers qualified for this program, so we are forced to assume that these customers pay the standard tariff.

¹²For the incumbent, the tariff is a fixed fee of \$5.17 and then an increasing block tariff with the second block beginning at 400 kWh per month. Three of the other retailers had similar tariff structures – fixed fees around \$5 and increasing block tariffs beginning in the middle of the sample period. One retailer had a relatively higher fixed fee of \$8.70 followed by a single block tariff. And the last retailer had a linear tariff – no fixed fee and a single block tariff.

respond more to the average than to the marginal price. More generally, utility bills in the U.S. typically display information that make the average price (total bill due divided by usage) much more salient than the underlying non-linear tariff schedules.

For this reason, when we develop a discrete choice model in section 4, we use the retailer’s *average price at 1000 kWh/month* as the metric of price. Our rationale is two-fold. First, the *powertochoose.com* website saliently displayed the average price at 1000 kWh as the price used to sort retailers. Second, this usage level is close to the typical usage level of customers in our sample – the average consumption is 1140 and the median consumption is 968 kWh/month.

Figure 1 shows the evolution of the average price at 1000kWh by retailer in the TNMP service territory. Rates ranged from about 8.5 to 14 cents per kWh from 2002-2006. Rates were generally rising over the sample period with much of this driven by increases in the price of natural gas, a primary determinant of wholesale electricity prices in Texas. In particular, rates jumped several cents in late 2005 following the natural gas price spikes caused by Hurricanes Katrina and Rita.

The average price of the incumbent (i.e. the price-to-beat rate) was systematically higher than one or more other retailers throughout most of the sample period. In fact, by the Fall of 2002, the first year of retail choice, at least one entrant offered an average rate at least one-half cent cheaper than the incumbent in every month except one month in late 2005. Moreover, in many months in the middle of the sample, an entrant’s average rate was over one cent cheaper than the incumbent’s price-to-beat.

Some households move between residences during our sample. In order to identify movers, we use information on disconnect/reconnect status for each meter.¹³ The number of household-months involving a move comprises less than 1% of all observations in our sample. We discuss how we include movers into the analysis in section 5.3.1.

3.1 Summary Statistics

First, we provide a basic description of observed switching behavior and the dollar magnitude of expenditure reductions of purchasing from alternative retailers. These summary statistics yield patterns that are consistent with results that arise from our model’s estimates in

¹³Specifically, our data on monthly choice of retailer is reported for the meter/address. We do not know the names of the customers on the bills, so we only directly measure when the residence is served by a different retailer. To identify movers, we assume that the resident at the meter does not change unless there is a disconnect of service. If electric service is disconnected for more than 30 days, we assume that new residents occupy the residence. Otherwise, we assume the same residents are making decisions for the residence.

Section 5, thus providing support for our modeling assumptions.

3.1.1 Switching: Timing and Frequency

The incumbent maintained a large market share despite charging higher rates than entrant retailers. Figure 2 shows the market shares of the six largest retailers over the first four years of retail choice. The incumbent exhibited a slow erosion of market share throughout the sample, but still maintained over a 60% share by April 2006. Two other retailers had over a 10% share while the remaining retailers had less than a 5% share.

The total number of switches per month was relatively low in the first year of retail choice but then rose in the following three years. Figure 3 displays the total number of switches from one retailer to another for each month. There appears to be a seasonality in switching behavior with a peak in the summer months. The peak month for switching was July in 2002, June in 2003, and August in 2004 and 2005. Summer is the season with the highest monthly bills due to the electric cooling; summer electric bills can be twice as high as winter bills. This seasonality in expenditures may create greater saliency of electricity bills in a household’s decisionmaking and could increase switching in the summer. Our model below allows for seasonality in the decision to consider alternative retailers, so that we can explore this channel of decisionmaking.

Finally, we measure the frequency with which a household switches retailers. Approximately two-thirds of households never switch away from the incumbent. Among those households that do switch, most switch only once (21% of meters) or twice (9% of meters). A histogram of the number of times that a given household switches retailers during the first four years of retail choice is shown in the Appendix in Figure 6.¹⁴

3.1.2 Potential Savings from Switching

Either of the two potential sources of inertia – search frictions/inattention or an incumbent brand effect – could cause consumers to purchase from the incumbent while lower-priced retail options are available. A descriptive metric of inertia is the dollar savings to consumers of purchasing from an entrant retailer rather than the incumbent. This section measures the potential dollar savings from switching. These savings should be viewed as *descriptive* evidence of inertia; we develop a model to decompose the sources of inertia in section 4.

¹⁴In this figure, we only include households that are classified as ‘non-movers’. Any changes in residence for a household or changes in tenancy of a residence are excluded. ‘Non-movers’ are defined according to the procedure described in section 3.

We measure the savings to households of buying the same amount of power from an alternative retailer. To do so, we calculate the bills for each household in months it purchased from the incumbent and the counterfactual bill if the household had purchased the same amount of power from other retailers. As noted above, these reductions in expenditures should be not seen as consumer surplus calculations.

Consider two extremes of the frequency with which a household switches. First, consider a scenario in which a consumer switches *only once* during the four year sample and does so in the first month of retail choice (January 2002). We calculate the monthly savings if each household had switched to one of the two large entrant retailers. The mean savings of purchasing from one of the larger retailers is \$7.69/month and the mean savings purchasing from the other is \$9.97/month.

At the other extreme, consider a scenario in which a consumer switches to the lowest price retailer *each* month. For households buying from the incumbent, the mean savings per month of switching to the lowest price retailer is \$12.47 and the median savings is \$7.63. The savings is over \$17 per month for about one quarter of the household-months and over \$30 dollars for about one-tenth of the household-months.¹⁵

These savings suggest that there is sizeable inertia to switching in the early years of this market. Households could purchase the same amount of the same power for less – averaging between roughly \$7-\$12 dollars per month, or \$84-\$144 dollars if scaled up to one year. This savings represents about 8 percent of *total* electricity expenditures. Our model below estimates the extent to which consumers continue to purchase from the higher-priced incumbent because consumers do not consider alternative retailers or because the consumers view the incumbent as a higher-valued product.

These metrics could mask considerable heterogeneity across different demographic sub-populations. In our structural model below, we estimate the size of specific sources of inertia – inattention and incumbent brand advantage – and how those sources of inertia differ across income, education levels, and age. We will show that both sources of inertia are larger in neighborhoods with lower income, lower education levels, and more senior citizens. In the Appendix, we break down savings from switching by demographic group. We find that more of the potential savings of switching is realized by households in neighborhoods that are wealthier, have higher education levels, and fewer senior citizens.

¹⁵We also assess the savings realized by those households that switched rather than purchase from the incumbent, using similar assumptions as above. For those months in which households purchased from any retailer other than the incumbent, the average bill would have been \$8.86 higher per month if the same consumption were purchased from the incumbent.

3.1.3 Factors Associated with Switching Away from Incumbent

Finally, we document the relationship between switching behavior and key variables in the model we present below. Specifically, we show that a household is more likely to switch away from the incumbent when recent monthly electricity bills are large and when there are more entrant retailers with lower prices than the incumbent. To show these correlations, we estimate a linear probability model using data for each household-month for the sample period used in our structural model below. We focus on household-months when the household was served in the previous month by the incumbent, and we estimate the probability of switching away from the incumbent. The baseline probability that a household served by the incumbent switches to another retailer in a given month is 1.0%.

Table 1 reports correlations based on regressions that include fixed effects for each household. Thus, we exploit within-household variation in the probability of leaving the incumbent for an entrant retailer. Column 1 shows that a household is more likely to switch away from the incumbent when there are more entrant retailers with lower prices than the incumbent. The presence of one additional entrant with lower prices increases the probability of switching by 15% relative to the baseline switch rate. In column 2 we show that households are more likely to switch after receiving a large monthly bill. Large differences in a customer’s bill are primarily driven by the large seasonality in electricity consumption. Electricity usage in Texas peaks in the summer, and monthly electricity bills are about twice as large in the summer months as compared to the spring, which creates the potential for “bill shock”. A doubling of the last bill increases the switch rate by 0.27% or about one-quarter of the baseline rate. Column 3 shows that there is seasonality in switching, even after controlling for the number of lower-priced retailers and the size of the most recent bill. Column (3) includes calendar quarter fixed effects, and we find that switching is more likely *during* and *after* the summer demand peak as compared to the lead-up to the peak in the spring.

These relationships show that switching is associated with both past information received by the household – the size of the last bill – and by characteristics of the plans offered by entrants. Next, we use these relationships to develop a model of switching.

4 Model

In this section, we build an econometric model that allows us to separately identify the two sources of inertia – search frictions/inattention and an incumbent brand effect. We model the household-level choice of electricity retailer as a two stage process that occurs each month.

Each month, in stage 1, the household has a current retailer and decides whether to consider alternative retailers with some probability. We refer to this stage as the “Decision to Choose” Stage. In stage 2, the households who choose not to consider alternative retailers in stage 1 will maintain their current retailer for the following month.¹⁶ However, households who choose to consider alternative retailers in stage 1 will then choose the retailer that maximizes utility among those in the market. These households may choose a different retailer or may continue with their current one. We refer to this second stage as the “Choice Stage”. We allow for heterogeneity across households and across time at both the Decision to Choose Stage and the Choice Stage, as we describe below.

One empirical complication is that we do not observe the outcome of the Decision to Choose Stage. We only observe households who change retailers, i.e. those who decide to consider alternative retailers *and* then choose a different one. From the analyst’s viewpoint, households who do not switch are both those who do not consider alternatives and those who do consider alternatives but choose their current retailer. We describe a model below that allows us to separately identify parameters of the Decision Stage and the Choice Stage.

4.1 Stage 1: Decision to Choose

Each month a household decides whether to consider alternative retailers. We model the probability of considering a (possibly new) retailer to vary by characteristics of the household. First, the probability varies by the household’s current retailer. For example, a household’s experience with its existing retailer may induce it to consider alternatives. Anecdotal evidence from industry analysts suggests that households are driven to consider alternative retailers in response to events such as a large summer bill or by a bad experience with the current retailer. This envisions the decision to choose as a “push” rather than a “pull” effect.

Second, we allow for seasonality in the months of the year that customers actively decide upon their retailer. This allows the model to attribute some of rise in switching during summer months observed in Figure 3 to result from more searching during the summer. In some specifications, we allow the decision probability to vary in household characteristics.

We denote the *current* retailer by k and the *new* retailers by j (again, recall that k and j can be the same if the households searches and chooses its current retailer). The month of the sample is indexed by t .

¹⁶Again, we do not take a stance as to whether the choice to consider alternatives is “rational” or “forward-looking.”

We model the decision probability for any household that is currently a customer of retailer k at time t , denoted λ_t^k , with a standard binary logit:

$$\lambda_t^k(\gamma) = \frac{e^{W_t^k}}{1 + e^{W_t^k}} \tag{1}$$

where $W_t^k = \sum_r \gamma_r Z_{rt}^k$ and $\{Z_{rt}^k\}$ is a set of observable characteristics including dummy variables for each existing retailer k and month-of-year dummy variables to allow for seasonality in deciding to search. In some additional specifications discussed below, we also include the dollar change in the size of customer i 's most recent bill as compared to the previous bill in order to capture an increase in salience due to “bill shock”. (In those additional specifications, the λ_t^k and W_t^k have additional i subscripts but we do not include them here).¹⁷

We view this specification of the Decision to Choose as a reduced-form representation of the drivers of inattention. This is a critical feature of modeling choice in settings with inertia due to inattention. As we show in section 5.3.2, if one were to exclude this stage of the model and only use a standard discrete choice model in which households chose from the choice set *every* month, then one would make incorrect inferences about preference parameters.

Our descriptive evidence in section 1 suggests that modeling the impediment to search with a model of *inattention* is appropriate in this setting. In other settings, researchers have used *switching costs* to explain choice frictions. Switching costs can be viewed as generating choice frictions - via state dependence - even if buyers are fully informed about other options. In contrast, search cost/inattention represents not having information, or being willing to gather information, about alternatives. There are several reasons that switching costs are unlikely to be primary drivers of inertia in this market. First, as discussed above, there are no monetary costs to switching and powertochoose.com makes time costs small. But more importantly, the data are not consistent with full information about options – one of the key features of a switching cost model. To see this, recall that the data strongly suggest seasonal patterns in both search and switching. (As we document in section 3.1, switching peaks in the summer, and as we discuss later in section 5.2, the number of visitors to www.powertochoose.com also peaks in summer). It is difficult to explain why a large bill would induce search if households had perfect information about alternatives.

4.2 Stage 2: Choice of Retailer

¹⁷This formulation can be seen as a reduced form representation for an underlying search protocol or rational inattention model.

In this stage, each household who enters the choice stage in month t chooses the retailer from the choice set that yields highest utility, as in a standard discrete choice model. For households who enter the choice stage, the indirect utility for each household i of choosing retailer j in period t is:

$$U_{ijt} = V_{ijt}(\theta) + \varepsilon_{ijt} \quad (2)$$

where $V_{ijt}(\theta)$ is a parameterized utility term, and ε_{ijt} is a random utility shock that is *i.i.d.* across consumers, retailers, and time. We assume ε_{ijt} to be a Type I Extreme Value random variable. $V_{ijt}(\theta)$ is further specified as $V_{ijt}(\theta) = \sum_s \theta_s X_{jt,s}$ where $X_{jt,s}$ is the s 'th characteristic of retailer j at time t . The product characteristics include the price, an indicator for whether the retailer is the incumbent, and the incumbent indicator interacted with a linear time trend. This specification allows for vertical product differentiation – a brand effect – by the incumbent. Specifically, the variables comprising X_{jt} are:

1. p_{jt} is the price of retailer j in month t for 1000 kWh usage per month (as reported on the website *powertochoose.com*). As we discuss in section 3, average price is arguably the most salient metric of price that affects choice. Note that by using the current price, we assume that consumers expect future retail prices to reflect current prices. This assumption is consistent with Anderson et al. [2013] who find that consumers' beliefs about another energy commodity – gasoline – are consistent with a no-change forecast. This allows us to view the household-level choice to a static model.
2. *INCUMBENT* is an indicator variable for the incumbent retailer, allowing for an incumbent brand effect
3. *INCUMBENT · MONTHCOUNTER* is the incumbent indicator interacted with the number of months since the market began, allowing for a linear time trend in the incumbent brand effect

Because ε_{ijt} is a Type I Extreme Value random variable, the probability that household i chooses retailer j in month t is given by the familiar logit probability:

$$P_{ijt}(\theta) = \frac{\exp(V_{ijt}(\theta))}{\sum_{k \geq 1} \exp(V_{ikt}(\theta))} \quad (3)$$

This probability is used in GMM estimation that is described below.

4.3 Simultaneously Estimating Decision and Choice Stages

We simultaneously estimate both the decision to consider alternative retailers (Stage 1) and choice (Stage 2). In order to do so, we exploit our data on observed switching behavior to derive a set of moment conditions. As noted above, one empirical challenge is that we do not directly observe the outcome of Stage 1. Rather, we observe switches to other retailers for those who decide to consider alternative retailers. Thus, households who do not switch can be either households who did not consider alternatives or households who searched and choose to stay with their existing retailer.

To address this complication, we exploit the observed month to month aggregate switching from the old retailer k to the new retailer j to estimate the probability of search. This model of the “flow” of customers from one retailer to another provides moments for our GMM estimation. First we provide a simple example to illustrate the empirical strategy and then we present the formal model.

Illustration of Empirical Strategy. We illustrate the empirical strategy with a simple example that also allows us to show how we can separately identify the search and decision stages. Assume that we only observe two months of data – the customer’s retailer “last month” and “this month”. In addition, assume that there are only 3 retailers. Let each household served the previous month by retailers 1, 2 and 3 decide to consider alternative retailers with probability given by λ_1 , λ_2 , and λ_3 respectively. And let the probability of choosing retailer 1, 2, and 3 conditional upon entering the Choice Stage, be given by P_1 , P_2 , and $1 - P_1 - P_2$, respectively. We want to estimate these five probabilities, $\{\lambda_1, \lambda_2, \lambda_3, P_1, P_2\}$.

Conceptually, we can create a matrix of counts of the number of customers switching from retailer k to retailer j during the month. See Figure 4 for an illustration. The cells of this matrix provide us with statistical moments that we use to estimate the 5 parameters/probabilities.

Consider all households who were served by retailer 1 the previous month, and denote this number $N^{(1)}$. Some of these households will be observed to use retailer 1 in the current month; such households are ones who did not consider alternative retailers (occurring with probability $1 - \lambda_1$) *and* those who considered alternatives but chose to remain with retailer 1 (occurring with probability $= \lambda_1 * P_1$). Likewise consider households observed to use retailer 1 in the previous month and retailer 2 in the current month. These households are ones previously with retailer 1 who considered alternatives and chose retailer 2 (occurring with probability $= \lambda_1 * P_2$). Likewise, we can characterize households previously with retailer 1 who

considered alternatives and chose retailer 3 (occurring with probability = $\lambda_1 * (1 - P_1 - P_2)$).

The *expected* number of customers who were initially with retailer 1 and continue to use retailer 1 is: $N^{(1)} \cdot [(1 - \lambda_1) + \lambda_1 P_1]$. The *expected* number of customers who were initially with retailer 1 and switched to one of the other retailers is: $N^{(1)} \cdot \lambda_1 P_j$ for $j = 2, 3$. This provides 3 moments to match to sample moments on the number of customers flowing between retailer 1 the previous month and the 3 retailers in the current month.

One can derive similar sets of 3 moments for customers who were initially served by retailer 2 and retailer 3. This provides us with 9 moment conditions. However, one moment in each set is redundant because any customer who does not stay with, say retailer 1, must switch to retailer 2 or 3. Thus, we exclude the redundant moments for customers who stayed with the same retailer and use the “off diagonal” terms of the flow matrix as the moments for estimation. This yields six moments to estimate the five probabilities of interest.

This simple example provides the basic intuition for estimating the model. In our setting, we have more than two months of data so we have $T - 1$ flow matrices and could estimate decision and choice probabilities for each period. In practice, we parameterize the decision and choice probabilities to specific variables of interest, as described in sections 4.1 and 4.2.

Formal Specification of Empirical Strategy. We formalize the estimation strategy described above and allow for households to be heterogeneous in their search and choice probabilities. Let $B_t^{(k)}$ be the set of households whose retailer was k at time $t - 1$. $N_t^{(k)}$ is the total number of households in $B_t^{(k)}$. $\lambda_{it}^{(k)}$ is the probability that a household in $B_t^{(k)}$ chooses to search in period t . For those households who choose to search, P_{jt} is the probability that the household chooses j in period t . Finally at the end of the two stage process each month, $N_{jt}^{(k)}$ is the total number of households in $B_t^{(k)}$ who use retailer j at time t .

Suppose household i is in the set $B_t^{(k)}$. Let $d_{ijt}^{(k)}$ be an indicator function of whether household i (who had been served by retailer k in time $t - 1$) is served by retailer j at time t . The expected value of this indicator variable prior to period t is:

- For $j \neq k$ (households changing retailers):

$$E_{t-1} [d_{ijt}^{(k)}] = \underbrace{\lambda_{it}^{(k)} P_{jt}}_{\text{Pr(deciding \& choosing } j)}$$

- For $j = k$ (households keeping the same retailer):

$$E_{t-1} [d_{ikt}^{(k)}] = \underbrace{\lambda_{it}^{(k)} P_{kt}}_{\text{Pr(deciding \& staying with } k)} + \underbrace{1 - \lambda_{it}^{(k)}}_{\text{Pr(not deciding)}} \quad (4)$$

Because $N_{jt}^{(k)}$ is the total number of households in $B_t^{(k)}$ with retailer j at time t , we have:

$$N_{jt}^{(k)} = \sum_{i \in B_t^{(k)}} d_{ijt}^{(k)} \quad (5)$$

Thus, our moment equations tell us that the expected number of customers previously served by k who are now served by j is given by:

- For $j \neq k$:

$$E_{t-1} [N_{jt}^{(k)}] = \sum_{i \in B_t^{(k)}} \lambda_{it}^{(k)} P_{jt} \quad (6)$$

- For $j = k$:

$$E_{t-1} [N_{kt}^{(k)}] = \sum_{i \in B_t^{(k)}} (\lambda_{it}^{(k)} P_{kt} + 1 - \lambda_{it}^{(k)}) \quad (7)$$

The last flow equation (7) showing the flow from k to k is redundant because the probabilities of moving away from k and staying with k add up to 1. Thus, we use the “off-diagonal” ($j \neq k$) moments for estimation. This yields $J(J - 1)$ moments for each time t .

We use GMM to estimate (γ, θ) , the parameters determining decision $(\lambda_{it}^{(k)})$ and choice $(P_{jt}^{(k)})$ using the objective function:

$$\min_{\gamma, \theta} \eta' W \eta$$

where $\eta \equiv \langle \eta_{jt}^{(k)} \rangle$ and $\eta_{jt}^{(k)} = \frac{N_{jt}^{(k)} - \left(\sum_{i \in B_t^{(k)}} \lambda_{it}^{(k)} P_{jt} \right)}{N_t^{(k)}}$ and W is a weighting matrix.

The intuition behind the objective function is straightforward. Consider the numerator of each moment. $N_{jt}^{(k)}$ is the number of households in our data that switch from retailer k to retailer j in month t . Our model says that the expected number of households switching from k to j is $\sum_{i \in B_t^{(k)}} \lambda_{it}^{(k)} P_{jt}$. We plug in the specified functional forms for the decision and choice probabilities, given in equations (1) and (3). GMM finds parameters that make the model most closely fit the data on the number of switchers. The denominator simply downweights moments with larger variance; it adjusts for the fact that the number of customers for which the model is “off” is likely larger for retailers that have a large number of customers.

Identification. The identification argument is a generalization of the simple example considered above and illustrated using Figure 4. The matrix capturing the flow of customers from retailer k to retailer j allows for separate identification of the probabilities of search λ^k and the probabilities of choice P_j . Mathematically, this matrix provides moments of the order J^2 while we are only estimating probabilities on the order J . Embedded in this model are two key assumptions. First, the decision probability is a function of the last retailer k but not the next retailer j . As we note above, this envisions a “push” rather than a “pull” model of search, and is consistent with views of industry analysts. Second, the choice probability is a function of the next retailer j and not the last retailer k . This assumption implies that upon deciding to consider alternative retailers (e.g. on *www.powertochoose.com*), consumers consider all retailers “on equal terms” and do not have private information on any retailers based on their past experience. One might be concerned that prior experience with a retailer influences choice (for reasons beyond observed product characteristics). However, keep in mind that very few customers switch multiple times during our sample period, so the vast majority of customers have experience with only one or at most two retailers.

Importantly, this identification strategy of consumer inertia does not require us to have choice data for both consumers with pre-existing market experience and consumers new to the market. Several papers in the existing literature on inertia exploit the fact that some customers are new while others have pre-existing market experience (e.g. see [Handel \[2013\]](#) and [Luco \[2014\]](#)). The presence of new market participants – ‘movers’ in our case – fits into our modeling approach, but we do not require the movers in order to separately identify inattention bias from vertical product differentiation. To see this, a mover in our setting must choose a retailer (otherwise they have no power), so the probability of considering retailers in Stage 1 must equal one ($\lambda_{it} = 1$). Non-movers may or may not consider alternative retailers in any given month ($\lambda_{it} \leq 1$). Any customer who considers alternative retailers – whether a mover or non-mover – then enters into the Stage 2 Choice of Retailer.

Therefore, our model can be estimated where movers decisions are given by $\lambda_{it} = 1$ and the choice probability given by equation (3), and where non-movers decisions are given by λ_{it} as specified in equation (1) and the choice probability from equation (3). But it is also clear that the parameters of the model are identified even if no movers are present (i.e. we could use only non-movers – those existing customers who can switch from retailer k to retailer j – to estimate the model parameters using equations (1) and (3)). In our setting, we have only a small number of movers – less than 1% of our observations – so an empirical strategy that does not depend on new market participants is valuable.

5 Results

We organize our results into several sections. First, we show estimates of our benchmark model that estimates how often incumbent customers search and how much those customers differentially value the incumbent brand when they do search. Then, we allow the probability of searching in any given month to vary so that we are able to identify important patterns in inattention bias. Following those preliminary estimates, we illustrate the importance of using our modeling framework rather than a standard discrete choice model in section 5.3.2. Specifically, we show that failing to account for inattention bias and using only the second stage of our model yields estimates that are not sensible. Next, in section 5.4 we estimate the model separately for neighborhoods with different demographic characteristics in order to identify heterogeneities in how consumers respond to retail choice. Finally, these results are used to motivate our counterfactual policy experiments that we present in section 6.

For all of the results presented below, we estimate the model on a 20% random sample of meters in our data in order to ease the computational burden. In addition, we restrict attention to the period of January 2004-April 2006 when all six firms that we analyze are present in the market. In most of our results, we include all customers who currently have a retailer and study their decisionmaking to chose another retailer, however we show results that include new customers (‘movers’) in section 5.3.1.

5.1 Benchmark Estimates of Inertia

In our benchmark specification, we model the Stage 1 decision of household i in period t to consider alternative retailers to be a function of whether the household’s existing retailer is the incumbent or not. Then conditional upon deciding to search, the Stage 2 choice model is a logit model where each product is characterized by the price of consuming 1000 kWh. We include an incumbent brand effect and allow the brand effect to have a linear time trend.

Our benchmark model results are reported in column 1 of Table 2. The table reports the parameters of both the Stage 1 “Decision” step and the Stage 2 “Choice” Step. In addition, we use the parameter estimates to calculate other metrics that aid in the economic interpretation of these parameters. Specifically, for the Decision step, we calculate the probability that a customer with a given firm chooses to consider alternative retailers in a given month. Also, we use the choice parameters to calculate price elasticities of each firm (evaluated at the average price) and the dollar value of the incumbent brand effect.

The parameters of the “decision to choose” model indicate that households do not fre-

quently search. Specifically, when the parameters of $\lambda_{it}^{(k)}$ are converted to probabilities, our model estimates that customers of the incumbent only search in 1.8% of months. This identifies a large source of inertia in the market. For many households, who by the design of retail choice in Texas were defaulted to the incumbent, a search will not occur until many months into the new market. This probability can be used to calculate that only 19% of households have searched at least once within one year of market opening, 35% within two years, and 61% by the end of our sample over four years after retail choice begins.¹⁸ Thus, our model implies that inattention bias is an important driver of inertia. In our counterfactual experiments in section 6, we estimate the impact of policies that increase search.

Our model also estimates the probability that a customer of an entrant retailer considers alternative retailers. We find that the search rate for customers of entrants – searching in 3.3% of months – is larger but still relatively small. One possible reason that these customers may search more is a selection effect; these customers necessarily have searched at least once before if they are customers of an entrant retailer.

The parameters of the choice model show that the incumbent brand effect is another source of inertia. The positive coefficient on the incumbent brand dummy variable indicates that, conditional upon deciding to choose, customers attach higher utility to the incumbent’s product than to the entrant retailers. Notably this brand effect declines with time, as indicated by the negative coefficient on the brand effect interacted with a month-of-sample counter. We monetize the size of this brand effect using the coefficient on the price. As shown in the last rows of the table, the brand effect is \$61.86 per month in January 2004.¹⁹ This means that after accounting for price differences between the incumbent and entrant retailers, consumers value purchasing from the incumbent nearly \$62 *per month* more than purchasing the same amount of power from any of the entrant retailers. This product differentiation yields differences in the own-price elasticities of demand. As shown in the table, the incumbent’s price elasticity is -2.52 while the entrant retailers have elasticities averaging -4.51.

Importantly, the size of this brand effect declines as more months pass since the beginning of retail choice. By the end of our sample period in April 2006, the incumbent brand effect is significantly smaller; it has declined to \$14.87 per month. This suggests that the large

¹⁸This calculation assumes a simple i.i.d. structure to the decision to choose process; in later specifications we allow for a richer process.

¹⁹This uses the standard logit model approach to calculating consumer surplus. The price is measured in cents/kWh. We use the incumbent brand coefficient, the time trend in that coefficient, and the price coefficient to estimate in dollars the brand effect for 1000kWh of usage = $((2.764 + (-0.076) * t)/0.435) * (1000/100)$ for $t = 1$ (January 2004) to 28 (April 2006).

incumbent brand effect does not persist after the market matures and customers have more experience with retail choice.

Several plausible explanations exist for this sizable brand effect. One possibility suggested to us by market analysts is that customers believe that the quality of their power depends on the firm providing electric service. As we discuss above, this is not the case – retail choice is a financial relationship between customer and retailer that has no impact on the physical distribution of power. Because the physical transmission and distribution system is operated by a firm that is independent from retailers, a customer will not see any difference in factors such as power outages, restoration of power in the event of an outage, or meter reading services. However, customers may not have been aware of this fact because of an incomplete understanding of the market.²⁰

“Consumer learning” is a related interpretation of the very large incumbent brand effect at the beginning of deregulation followed by its gradual erosion. Consumers may have started out with the belief that the incumbent is the more reliable provider. However, over time, either through observational learning or by social interactions, they may have revised their priors via Bayesian learning towards believing that service quality is not differentiated. It is beyond the scope of this paper to model the evolution of the brand effect; rather we focus on implications of a brand effect for policy that allows retail choice.²¹

Another possible source of the incumbent brand effect may have been a fear that entrant retailers would go bankrupt and leave them without service. Technically, if a retailer exits the market, customers are automatically shifted back to the incumbent at a price set at 130% of the wholesale price, however this may have been unknown to customers. Finally, customers may have feared bait-and-switch tactics by new entrant retailers. Although such tactics are possible, we do not see such an expectation borne in the data.²²

Unfortunately, our data does not allow us to isolate the exact mechanism driving the estimated brand effect and its evolution over time. However in our counterfactual experiments in section 6, we estimate the effect on consumer surplus if the relative size of the brand effect (whatever the cause) were made smaller.

²⁰Some of these customers may have experienced the deregulation of long-distance telecom where service quality was a function of retailer.

²¹A rich literature in marketing has explored identification in models of Bayesian learning including [Erdem and Keane \[1996\]](#) and [Shin et al. \[2012\]](#).

²²As discussed above, the rise in prices late in our sample period was driven by wholesale cost shocks.

5.2 When Do Households Search?

The descriptive analysis in section 3.1.1 shows that there are strong seasonal patterns in both bill size and switching behavior, with peaks occurring during the summer. In our next specifications, we allow for temporal and consumer level heterogeneity in the probability to decide to search so that we can better understand potential determinants of search. Specifically, we quantify the seasonality of search and the extent to which a customer receiving a large bill induces search. Results are shown in columns 2-4 of Table 2.

The first new specification allows for seasonality in the decision to search by adding separate dummy variables for each month of the year to the decision probability $\lambda_{it}^{(k)}$. As seen in column 2, the coefficient of the monthly dummy variables are substantially higher during and immediately after the summer months, implying that search behavior is most intense at the end of the summer.

We can validate this result of the model with outside data on search. Data on the number of visitors to www.powertochoose.com were provided to us by the Public Utility Commission for the period 2005-2009. (Unfortunately, data covering our sample period were not recorded). In these later years, the pattern of website visitors exhibited similar seasonal patterns, with the highest number of visits occurring in August. Thus, our model findings, corroborated with outside evidence, suggests that large electric bills may make electric choice more salient and induce households to assess their retail options.

In order to explore the effect of bill size, we estimate another specification that incorporates whether the household recently received a large bill. We modify our benchmark model so that the decision probability $\lambda_{it}^{(k)}$ includes a household-specific measure of the dollar difference between the most recently received monthly bill and the previous bill. This variable – “Bill Shock” – primarily reflects increases in consumption rather than changes in prices. As shown in column 3, “Bill Shock” has a positive and statistically significant affect on the decision probability, suggesting that receiving an unusually large electric bill induces customers to search for alternative retailers. In column 4, we include both “Bill Shock” and monthly dummies simultaneously. It appears that much but not all of the “Bill Shock” effect is driven by seasonality of electricity consumption.

This relationship between recent bill size and the probability of searching offers insights into the determinants of household search behavior. A priori one might expect that households would search for lower-priced retailers in the spring *in anticipation* of the summer peak in electric consumption and expenditures. The potential savings from switching to a lower-priced is highest if the switch occurs before the summer. However, we do not find evi-

dence of anticipatory search. Rather, consumers appear to react to large increases in summer consumption and respond by searching. Overall, we do not find evidence that consumers are forward-looking when choosing the time to search.

The results in columns 2-4 also suggest that our estimates of inertia are robust to different specifications of the decision to search probability. The estimates of the two major sources of inertia – the average decision probability and the incumbent brand effect – are quantitatively very similar to the estimates from the benchmark model.

5.3 Illustrating the Implications of our Modeling Framework for Estimating Inertia

In this section, we compare our two-stage model of choice to other empirical methodologies that study choice in the presence of inertia. First, we show that our model can incorporate (but does not require) customers that are new to the market, which is an empirical strategy used in the existing literature on inertia. Second, we show that if one were to use a standard discrete choice model – the second stage of our two-stage model – then one would obtain results that are not plausible, illustrating the value of our two-stage model.

5.3.1 Incorporating Movers Into the Model

As we discuss in the Introduction, some papers in the existing literature on inertia have exploited new market participants that face different levels of inertia. Our model does not require new customers for identification, but it can incorporate them into the model. Specifically, new customers – or “movers” in our setting – do not face inattention because they must choose a retailer to get power to their house but they still may face an incumbent brand effect. In our setting less than 1% of the observations are movers. Nevertheless, we can include additional moments into our model to include the decisionmaking of movers. To do this, we include observations in which a household transitioned from no retailer to some retailer, generating new moments for GMM given by equation (6). The probability of entering the choice stage is set equal to one ($\lambda_{it}^{mover} = 1$). The probability of choosing retailer j is given by equation (3).

We allow the preference parameters to differ between movers and non-movers because the incumbent brand effect could be quite different for the two groups. On one hand, some customers moving from outside the service territory of the incumbent may not know the incumbent and thus have a smaller incumbent brand effect. On the other hand, some movers

may come from locations that do not have retail choice, which could make those customers more attached to the incumbent per se, regardless of the identity of that incumbent.

Results are shown in Table 3. Column 1 re-displays the results of our benchmark model (the same as in column 1 of Table 2). Column 2 shows estimates from the model that includes both non-movers and movers. For the non-movers, our estimates of the two sources of inertia are unchanged. For the movers, we estimate an initial incumbent brand effect that is about 20% higher than for non-movers. However, this brand effect declines substantially slower for movers – the brand effect is \$75/month in January 2004 and only falls to \$52/month by April 2006. Thus, while movers do not face inertia from inattention, they continue to favor the higher-priced incumbent due to placing additional value on purchasing power from the firm known as the incumbent retailer in their area.

5.3.2 Illustrating the Need for a Decision Stage

Next, we explore the implications of modeling retail switching with our two stage process and why a standard one stage discrete choice framework would yield results that are implausible. Our decision to model switching as a two stage process is motivated by the belief that consumers in this market do not actively choose retailers every month. Thus if we were to estimate a standard one stage discrete choice model, we believe that we would make incorrect inferences about consumer choice.

To illustrate this point, we apply a standard discrete choice model to our data. We operationalize this by imposing that the decision probability $\lambda_{it}^k=1$; this is effectively “turning off” the Stage 1 Decision step and assuming that all households enter the Stage 2 choice step. Under this assumption, in every month where we observe a customer to stay with her current retailer, that customer is finding that the current retailer’s product maximizes utility. Column 3 of Table 3 shows estimates where we “turn off” the Stage 1 decision step.

Comparing these two sets of results, we see two major differences. First, the implied incumbent brand effect under no decision step is substantially larger (e.g. \$164 as compared to \$62 in January 2004). This is not surprising because imposing that consumers search every period means that the model must rationalize staying with the higher-priced incumbent entirely with a brand effect.

Second and more importantly, the own price elasticities of residual demand for the entrant retailers are implausibly small (around -0.08). Such a low own price elasticity contradicts standard oligopoly theory in which profit-maximizing firms price in the elastic portion of their residual demand. (Recall that the incumbent could not choose its price, but the new

entrants were free to set any price.) These estimated price elasticities strongly suggest model mis-specification. Both of these results illustrate the need to choose an empirical model that allows for consumers to infrequently search for alternative retailers.

5.4 Does Inertia Vary Across Demographic Groups?

The size of consumer inertia in markets with retail choice can vary in important ways across different parts of the population. As shown in the Appendix, the amount of realized dollar savings from switching varies notably across neighborhoods with different demographic characteristics. The descriptive analysis shows that the fraction of savings realized is nearly twice as large in neighborhoods that were more wealthy, more educated, and have few senior citizens. In this section, we test if the two sources of inertia vary across neighborhoods.

We estimate our benchmark model separately for different subpopulations based upon income, education, and age. We classify a household based upon whether its Census block group is above or below the median Census block group when ordered by household income, fraction of the population with at least a bachelor's degree, and the fraction of the population that is over age 65. Results are reported in Table 4.

We find that both sources of inertia are larger for neighborhoods with lower income, lower education, and more senior citizens. Specifically, customers of the incumbent consider alternatives at different rates, as estimated by the parameter $\lambda_{Incumbent}$ in Table 4. Customers of the incumbent search for alternative retailers with higher frequency in neighborhoods with higher income by 2.3% versus 1.3% (columns 1-2), in neighborhoods with a more college educated population by 2.6% versus 1.0% (columns 3-4), and in neighborhoods with fewer senior citizens by 2.4% versus 1.3% (columns 5-6).

We also find that the *initial* incumbent brand effect is larger in certain neighborhoods, however the effect declines to very similar levels by the end of our sample. In neighborhoods above the median in income, the brand effect is \$52/month in January 2004 while it is \$113/month in below median income neighborhoods. However, this vertical differentiation declines at rates such that both types of neighborhoods have similar brand effects by 2006 (\$13 and \$23). When splitting neighborhoods by education, the below median education neighborhoods have a very large brand effect at the beginning of the sample (\$267/month) but this brand advantage declines to \$17/month by 2006. In contrast, the higher educated neighborhoods have an initial brand effect of only \$47/month which declines to \$20. Finally, neighborhoods with more senior citizens have an initial brand effect that is larger than the brand effect in “younger” neighborhoods, but the difference disappears by 2006.

This convergence in the size of the incumbent brand effect across different types of customers provides suggestive evidence of “consumer learning”. Even though households with different demographics begin with different priors on the brand value of the incumbent, households converge on a very similar value after several years. This is consistent with a simple model of Bayesian learning in which consumers have different initial beliefs about the relative quality of the incumbent. However, the differences in the priors are eventually washed away as data accumulates from observational learning or social interactions.

6 Policy Counterfactuals: The Effects of an Information Intervention to Reduce Inertia

Our model estimates the size of two sources of inertia. The mechanisms that inhibit switching away from the higher-priced incumbent are that the incumbent’s customers only search in 2% of months, and when they do search, customers place a sizable brand effect on the incumbent’s service. Next, we estimate how much consumer surplus would increase under an information intervention that reduced the size of each source of inertia.

Our hypothetical policy intervention is targeted to households who are ‘inertial’ – those who continue to purchase from the incumbent after two years of retail choice in January 2004. Our intervention has two dimensions. The first dimension is to inform inertial customers that they have the ability to choose their retailer and tell them where they can go to find a list of retailers and each retailer’s offering. The second dimension is to inform customers that their power quality is entirely independent of their retailer. Specifically, purchasing from another retailer is buying power that is equally reliable from a technical point of view. As we discuss above, the brand effect captured by our model could include other dimensions of quality such as customer service, but there is strong anecdotal evidence that much of this brand effect captures the perception that the incumbent provides more reliable power.

Practically this intervention could be an informational flyer. Suppose that the regulator required the incumbent to attach a one-page flyer with the January 2004 monthly bill that prominently displayed two pieces of information:

- 1. “Go to *www.powertochoose.com* to quickly and easily search for another electricity retailer AND to switch your retailer”
- 2. “*It’s all the same power* – the quality of electrical service will not change because <<Firm X>> controls your powerlines rather than <<The Incumbent>> or any other retailer.”

We view this information intervention having two effects on customer decisionmaking. First, it will increase the probability of a customer searching for alternative retailers. Second, it will reduce the relative brand advantage of the incumbent. Of course, this information intervention is only a nudge – households still choose the retailer that maximizes utility.

The magnitude of the effect of this information intervention is an empirical question that we cannot assess without actually conducting a randomized controlled trial. Therefore, we conduct counterfactual calculations under different assumptions to provide a range of estimates of the consumer surplus effects of this low-cost information intervention.

We calculate the expected change in consumer surplus of moving from the status quo to the counterfactual information intervention. The change in expected consumer surplus per household is given by $\Delta E(CS)_i = \frac{1}{-\alpha} \left[\ln \left(\sum_{j=1}^{J^{CTF}} e^{V_{ij}^{CTF}} \right) - \ln \left(\sum_{j=1}^{J^{SQ}} e^{V_{ij}^{SQ}} \right) \right]$ (Small and Rosen [1981]), where *CTF* denotes counterfactual and *SQ* denotes status quo. This is the difference in *log-sum terms* divided by the price parameter which “converts” utils to dollars. Under this interpretation of the logit discrete choice model, the logit shock is interpreted as product characteristics observable to the consumer but not to the researcher.

We simulate this information intervention using the following procedure to calculate the log-sum terms under the status quo and policy counterfactuals. Under the status quo, 2% of the incumbent’s customers consider among *all* retailers and choose the retailer that maximizes utility; 98% of customers “choose” from a set that only includes the incumbent. (2% is the fraction of incumbent customers considering alternative retailers each month in our benchmark specification in column (1) of Table 2.) For the customers who do not consider alternatives the choice set is $J = 1$ (the incumbent), while for those considering alternatives the choice set is all $J = 6$ retailers. Under the counterfactual with less inattention, we increase the fraction of incumbent customers who consider all $J = 6$ alternatives and reduce the fraction who only “choose” the incumbent from the $J = 1$ choice set.

The second dimension of our policy experiment is to reduce the relative brand advantage of the incumbent. We conceptualize the information treatment that “*It’s all the same power*” to increase the brand effect of the entrant retailers to some fraction of the brand effect of the incumbent. To calculate this effect, we augment the product characteristics of each entrant retailer to have its own brand effect that is some fraction of the incumbent’s brand effect. This effect is plugged into the indirect utility function of the incumbent’s product under the counterfactual policy (V_{ij}^{CTF}), and consumer surplus is calculated as we describe above.

It is beyond the scope of this paper to model the change in pricing as a response to consumers who search more frequently or attribute less of a relative brand advantage to the

incumbent. However, it is worthwhile to keep in mind that the incumbent's price-to-beat is regulated and cannot be changed in response to any change in demand-side behavior. We leave an equilibrium model of the entrant retailers' supply side response to future work.

The estimated annual changes in consumer surplus are reported in Table 5. We find that for a relatively modest impact of the information treatment – inducing 25% of the customers to search and changing the perception of the new retailer brand to be 25% of the brand effect of the incumbent – the per household consumer surplus would rise by \$50/year. The gains in consumer surplus rise in both the fraction searching and the new entrant brand effect, especially the brand effect. If 50% are induced to search and the new entrant brand effect is half of the incumbent brand effect, the per household gains are \$149/year. And if 75% are induced to search and the new entrant brand effect is three-quarters of the incumbent brand effect, the per household gains are \$309/year. While we do not take a position on what fraction of households would read and respond to a bill insert, we view all of these percentages as a priori possible. Other research suggests that benchmark estimates of responding to information mailed by utilities to customers are over 50%.²³

These consumer surplus calculations assume that product characteristics other than price impact consumer utility. One could argue that such factors should not be factored into welfare calculations. Our calculations above assume that the brand effect of the incumbent represents utility to consumers that should be factored into welfare calculations. However, if a large part of this brand effect is the incorrect perception that the incumbent provides more reliable power, then one might argue that this is an information problem that should not impact welfare calculations. Likewise, the above calculations assume that the logit shocks represent product characteristics unobserved (to researchers) that impact consumer utility. However, an alternative interpretation is that the shocks represent consumer choice error or confusion. Under this interpretation, the Small and Rosen consumer surplus calculations would overstate the true gains to consumers.

In order to consider these alternative interpretations of observed and unobserved product characteristics, we calculate consumer surplus gains to our policy counterfactual if *none* of the product characteristics are modeled as affecting utility. Under the assumption that there are no product characteristics that impact utility, then retail electricity is a homogeneous product and the consumer benefit to switching retailers is merely the cost savings. Under the counterfactual where 75% of incumbent customers are induced to search and choose the

²³Navigant [2013] finds that over half of households read and respond to OPOWER Home Energy Reports; Seattle City Light [2014] find similar figures for reading newsletters.

lowest priced retailer, the expected consumer surplus gain per customer is \$96 per year.

This counterfactual experiment suggests that a relatively low-cost policy intervention – adding a flyer to an existing bill – could meaningfully increase consumer surplus. We should emphasize that we are modeling only changes in consumer surplus – each household is continuing to purchase the same amount of power each month, so our information treatment leads to a reallocation of rents from the incumbent to the consumers and new retail firms. Nevertheless, these results suggest that low-cost interventions to reduce choice frictions can meaningfully increase the consumer benefits of retail choice policy.

7 Conclusions

This paper investigates an important policy change that brings choice to consumers in a previously regulated setting. We find that even in a relatively homogeneous good market, factors other than price competition play a very important role in shaping market outcomes: after four years of deregulation, the incumbent still maintains over 60% market share, despite the fact that some competitors consistently offer lower prices. Our model shows that two sources of inertia are prevalent – households do not frequently consider offerings of alternative retailers and they attach a significant brand advantage to the incumbent, especially in the early years of retail choice. Moreover, different consumer groups face different magnitudes of the frictions.

This paper suggests that there may be low-cost information interventions that reduce both sources of inertia. These types of interventions are likely to be particularly valuable as policy instruments in the early years of retail choice in the many jurisdictions that are expanding choice. Future work in this area could model firm behavior to better understand supply-side responses to changes in the demand parameters.

Residential electricity is just one setting where policymakers are shifting to a regime where customers are first provided with choice. Other types of electricity customers – commercial and industrial – also are being offered retail choice, as are all types of customers of natural gas. Even more broadly, households are increasingly provided with choice in health care, retirement, and education. The types of inertia that we study in the residential electricity market are likely to present, perhaps to differing degrees, in many of these settings. Our paper provides a model to quantitatively assess the magnitude of different mechanisms that drive inertia. In addition, our framework allows one to measure consumer surplus gains from policies that reduce the sources of inertia.

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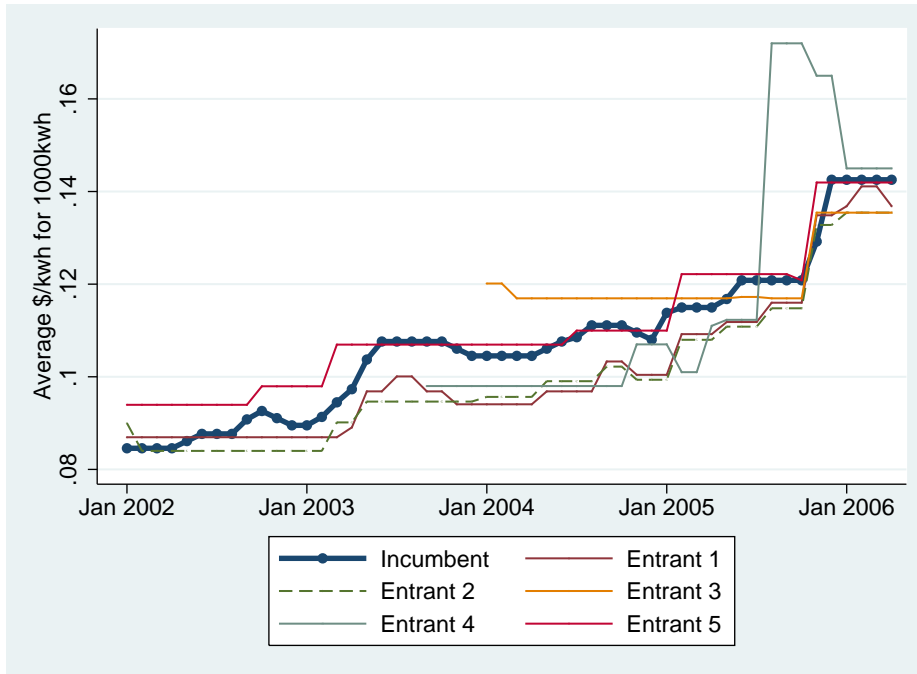


Figure 1: Prices Charged by Incumbent and New Entrant Retailers in First Four Years of Market

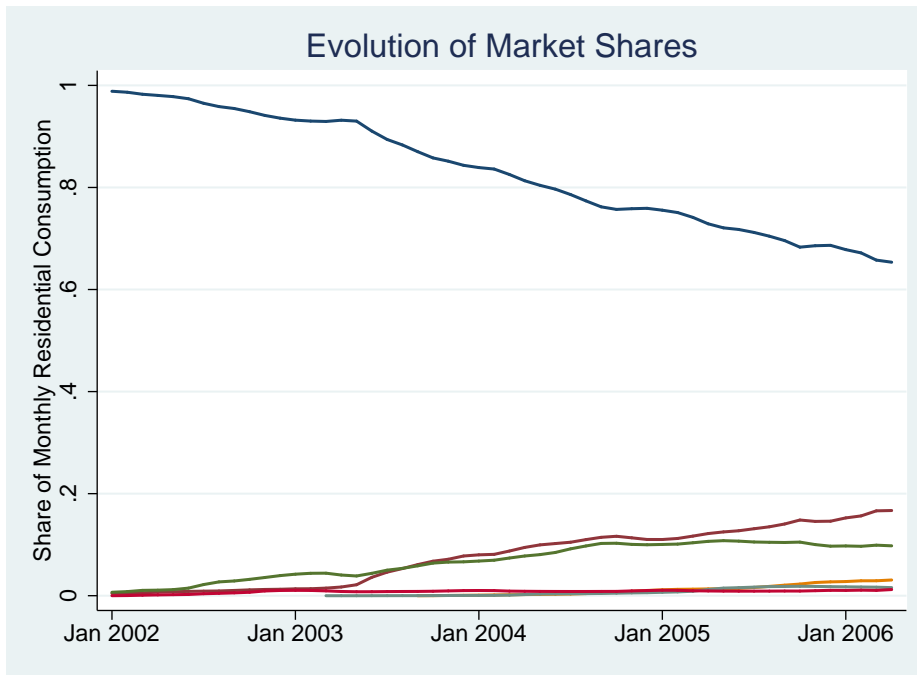


Figure 2: Market Shares of Incumbent and New Entrant Retailers in First Four Years of Market

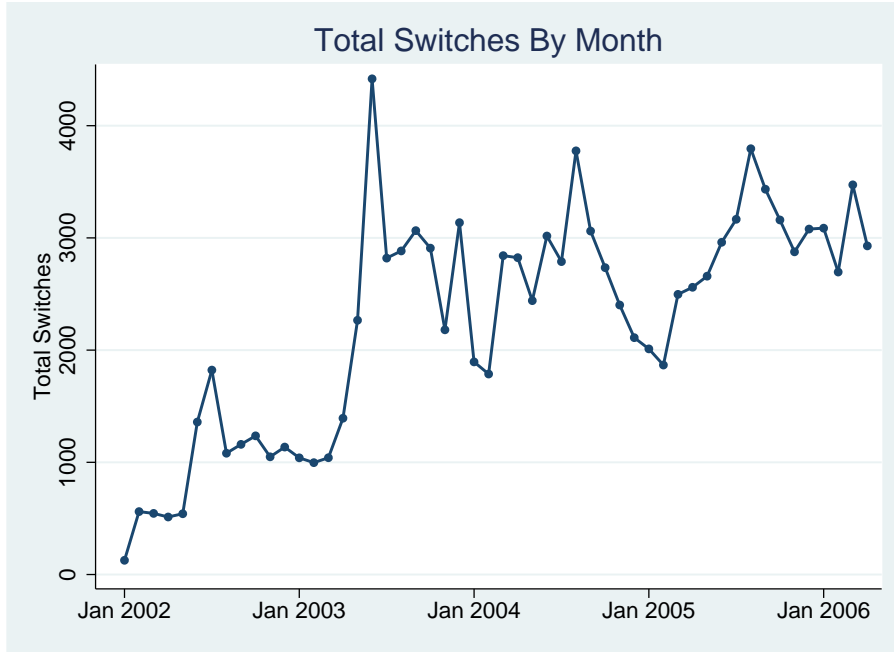


Figure 3: Total Number of Switches of Retailer By Month

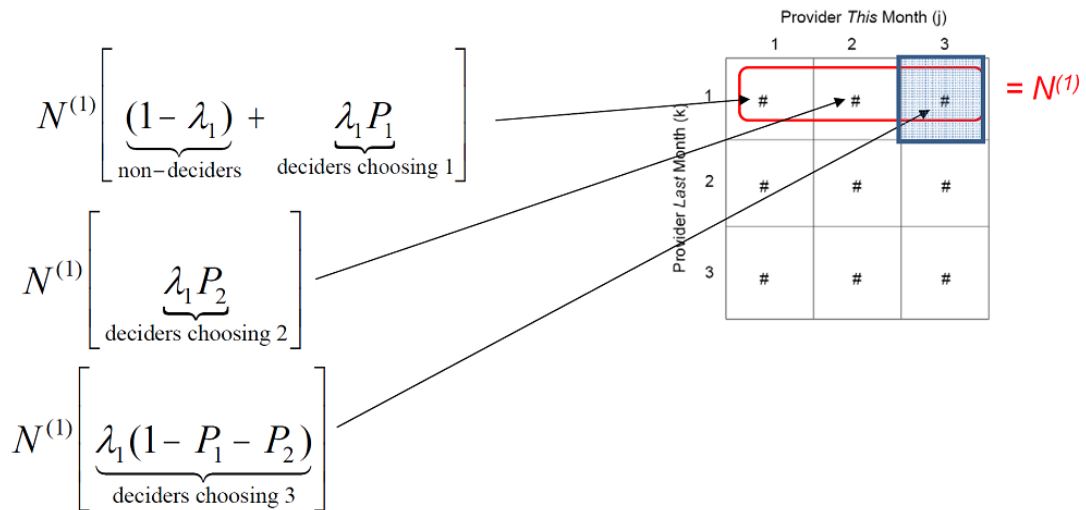


Figure 4: Illustration of Identification Strategy

Table 1: Descriptive Analysis of Switching Away from Incumbent

Dependent Variable: Indicator of Switching from Incumbent			
	(1)	(2)	(3)
Number of Cheaper Entrant Retailers	0.0015*	0.0016*	0.0020*
	(0.0001)	(0.0001)	(0.0001)
Log of Last Monthly Bill Received		0.0027*	0.0010*
		(0.0001)	(0.0001)
Calendar Quarter 2			0.0038*
			(0.0001)
Calendar Quarter 3			0.0069*
			(0.0001)
Calendar Quarter 4			0.0070*
			(0.0001)
Constant	0.0047*	-0.0081*	-0.0056*
	(0.0002)	(0.0005)	(0.0005)
Household Fixed Effects	Yes	Yes	Yes
Observations	3,729,919	3,729,919	3,729,919

Notes: This table reports factors that are associated with switching away from the incumbent. An observation is a household-month when the household was served by the incumbent in the previous month. The dependent variable is an indicator of whether the household switched away from the incumbent to an entrant retailer in that month; the mean switch rate is 1%. We estimate the correlations with a linear probability model using household fixed effects.

* indicates statistical significance at 1% level.

Table 2: Primary Model Results

	Benchmark	Seasonality in Search	Bill Shock Affects Search	All
	(1)	(2)	(3)	(4)
Stage 1: Decision to Choose				
<i>Parameters (γ)</i>				
Constant	-3.363*** (0.04493)	-3.72*** (0.1233)	-3.468*** (0.04824)	-3.643*** (0.1485)
Incumbent	-0.6432*** (0.06408)	-0.6471*** (0.06168)	-0.5893*** (0.06848)	-0.6255*** (0.06386)
January		0.2217		0.03844
February		0.3753		0.3148
March		0.2661		0.04284
April		0.04052		-0.1245
May		0.2098		0.1757
June		0.2279		0.1703
July		0.6384***		0.3638
August		0.6347***		0.4737
September		0.5412**		0.4238*
October		0.5466***		0.4288*
November		0.3833*		0.3652*
Bill Shock (\$ Change in Two Most Recent Bills)			0.007027*** (0.001629)	0.002581 (0.003098)
<i>Estimated Effects</i>				
Prob(Search in month) if Incumbent Customer (λ)	0.018	0.018	0.018	0.017
Prob(Search in month) if New Retailer Customer (λ)	0.033	0.033	0.032	0.032
Stage 2: Choice of Retailer				
<i>Parameters (θ)</i>				
Price (cents/kwh)	-0.4346*** (0.09054)	-0.4642*** (0.08343)	-0.4621*** (0.09619)	-0.4453*** (0.08476)
Incumbent Brand Dummy	2.764*** (0.2559)	2.946*** (0.2685)	2.789*** (0.2943)	2.834*** (0.293)
Incumbent*Month-of-Sample Counter	-0.07564*** (0.01427)	-0.08586*** (0.01449)	-0.07542*** (0.01578)	-0.07974*** (0.01569)
<i>Estimated Effects</i>				
Incumbent Price Elasticity	-2.52	-2.61	-2.67	-2.55
Avg Entrant Price Elasticity	-4.51	-4.82	-4.80	-4.62
Incumbent Brand Effect (\$/mo) in Jan 2004	\$61.86	\$61.61	\$58.72	\$61.85
Incumbent Brand Effect (\$/mo) in April 2006	\$14.87	\$11.67	\$14.66	\$13.50

Notes: This table reports results from the benchmark structural model of section 4 estimated via GMM. Parameter estimates are reported with standard errors in parentheses for the parameters of the two stages of the model. Then the table reports point estimates of model effects that are calculated using the parameter estimates, in order to facilitate model interpretation. We do not report standard errors for the month fixed effects in the interest of space.

Table 3: Illustrating Implications of Our Modeling Framework

	Benchmark	Include Movers	Turn Off Decision Stage
	(1)	(2)	(3)
Stage 1: Decision to Choose			
<i>Parameters (γ)</i>			$\lambda_{it}^k == 1$
Constant	-3.363*** (0.04493)	-3.363*** (0.04493)	
Incumbent	-0.6432*** (0.06408)	-0.6432*** (0.06408)	
<i>Estimated Effects</i>			
Prob(Search in month) if Incumbent Customer (λ)	0.018	0.018	== 1
Prob(Search in month) if New Retailer Customer (λ)	0.033	0.033	== 1
Stage 2: Choice of Retailer			
<i>Parameters (θ)</i>			
Price (cents/kwh)	-0.4346*** (0.09054)	-0.4346*** (0.09054)	-0.007849*** (0.002285)
Incumbent Brand Dummy	2.764*** (0.2559)	2.764*** (0.2559)	0.1322*** (0.02381)
Incumbent*Month-of-Sample Counter	-0.07564*** (0.01427)	-0.07564*** (0.01427)	-0.003858*** (0.001211)
Mover*Price		-0.0902 (0.1182)	
Mover*Incumbent		1.231*** (0.2759)	
Mover*Incumbent*Month-of-Sample Counter		0.02964** (0.01506)	
<i>Estimated Effects</i>			
Incumbent Price Elasticity	-2.52	-2.51	-0.08
Avg Entrant Price Elasticity	-4.51	-4.46	-0.08
Incumbent Brand Effect (\$/mo) in January 2004	\$61.86	\$61.86	\$163.51
Incumbent Brand Effect (\$/mo) in April 2006	\$14.87	\$14.87	\$30.80
Movers Incumbent Brand Effect (\$/mo) in Jan 2004		\$75.25	
Movers Incumbent Brand Effect (\$/mo) in April 2006		\$51.58	

Notes: This table reports results to illustrate the implications of our modeling framework, as described in section 5.3. Column (1) reports our benchmark model results, which is also Column (1) from Table 2. Column (2) includes new market participants (movers) by restricting movers to choose in stage 1 ($\lambda_{it}^k = 1$) and allowing movers to have difference preference parameters, as described in section 5.3. Column (3) illustrates the need for a Decision Stage of the model by removing the decision stage and imposing that $\lambda_{it}^k = 1$.

Table 4: Benchmark Model by Neighborhood Demographics

	Income		Education		% Senior Citizens	
	Below	Above	Below	Above	Below	Above
	Median	Median	Median	Median	Median	Median
Stage 1: Decision to Choose						
<i>Parameters (γ)</i>						
Constant	-3.298*** (0.09961)	-3.385*** (0.0481)	-3.3*** (0.1039)	-3.437*** (0.03929)	-3.426*** (0.04682)	-3.292*** (0.09318)
Incumbent	-1.019*** (0.1508)	-0.3501*** (0.06585)	-1.284*** (0.1546)	-0.1967*** (0.05506)	-0.291*** (0.07084)	-1.021*** (0.1481)
<i>Estimated Effects</i>						
Prob(Search) if Incumbent Customer (λ)	0.013	0.023	0.010	0.026	0.024	0.013
Prob(Search) if New Retailer Customer (λ)	0.036	0.033	0.036	0.031	0.031	0.036
Stage 2: Choice of Retailer						
<i>Parameters (θ)</i>						
Price (cents/kwh)	-0.2747* (0.1458)	-0.4989*** (0.1039)	-0.1343 (0.1106)	-0.4561*** (0.09459)	-0.4972*** (0.09309)	-0.4064* (0.2351)
Incumbent	3.204*** (0.5377)	2.641*** (0.2752)	3.707*** (0.6016)	2.194*** (0.1731)	2.327*** (0.225)	3.616*** (0.5068)
Incumbent*Month-of-Sample Counter	-0.0914*** (0.02991)	-0.07093*** (0.01531)	-0.1242*** (0.03207)	-0.04595*** (0.008963)	-0.05463*** (0.01179)	-0.1044*** (0.02776)
<i>Estimated Effects</i>						
Incumbent Price Elasticity	-1.35	-3.04	-0.59	-2.98	-3.23	-1.81
Avg Entrant Price Elasticity	-2.93	-5.13	-1.46	-4.67	-5.08	-4.36
Incumbent Brand Effect (\$/mo) in Jan '04	\$113.31	\$51.51	\$266.78	\$47.10	\$45.70	\$86.41
Incumbent Brand Effect (\$/mo) in April '06	\$23.47	\$13.13	\$17.08	\$19.89	\$16.04	\$17.05

Notes: This table reports results of estimating the benchmark model (Column 1 of Table 2) split by the demographic characteristics of the household's Census block group. A household is classified by whether its Census block group is above or below the median among all Census block groups. "Education" is defined by the fraction of the population with a BS degree or above.

Table 5: Policy Counterfactuals: Annual Changes in Consumer Surplus Per Household

		Entrant Brand Effect Relative to Incumbent				
		0%	25%	50%	75%	100%
Fraction Searching						
2%	\$0 (Status Quo)	\$1	\$3	\$6	\$8	
25%		\$32	\$50	\$73	\$101	\$133
50%		\$67	\$103	\$149	\$205	\$268
75%		\$101	\$155	\$225	\$309	\$404
100%		\$136	\$208	\$301	\$412	\$539

Notes: This table shows the average annual change in consumer surplus per household under the counterfactual experiment described in section 6. The status quo is that 2% of the incumbent’s customers search for alternative retailers in a given month and that new entrant retailers enjoy none of the incumbent’s brand effect. Under each counterfactual, we simultaneously change two characteristics of high inertia customers, i.e. those who are still purchasing from the incumbent after two years of retail choice. First, we increase the fraction of incumbent customers who search in a given month (displayed down the rows). Second, we endow the new entrant retailers with a fraction of the incumbent brand effect (displayed across the columns). The dollar figures are the estimated yearly increases in consumer surplus for each incumbent customer, calculated as discussed in section 6.

A Appendix

For Online Publication

Demographic Differences in Potential Savings that are Achieved

Here we provide descriptive evidence that retail choice disproportionately benefits specific demographic groups. These correlations are consistent with the findings of our structural model in section 5.4.

We calculate metrics of the fraction of potential savings that were realized by switching, as compared to a benchmark of purchasing from the incumbent at the price-to-beat for the entire sample period. Our “upper bound” measure of electricity expenditures is the bill size if the household had purchased from the incumbent for the entire sample period. Our “lower bound” of expenditures is the monthly bill size if the household had purchased from the lowest price retailer each month. Finally, we calculate the actual monthly bill under the observed retail choice by the household and compare it to these bounds.

For each household-month, we define a metric of the amount of potential savings that are realized. “Percent achieved” is the percent of possible gains realized and is defined as: $Percent\ Achieved \equiv \frac{Actual\ Bill - Incumbent\ Bill}{Lowest\ Possible\ Bill - Incumbent\ bill}$. The mean “Percent achieved” across all household-months is 11.0%.²⁴ This relatively low figure should not be surprising because nearly 60% of households purchase from the incumbent at the end of the sample period.

We characterize correlations between “Percent achieved” and demographic characteristics of the household’s neighborhood. Note that we do not have demographic data on the occupants of each household; rather we have characteristics of the household’s Census block group. Thus, we interpret these regressions as correlations between realized gains of retail choice and demographics of the *neighborhood* rather than demographics of individuals.²⁵

Table 6 shows the mean of “Percent achieved” for households in Census block groups above and below the median of three demographic characteristics – income, education, and fraction of senior citizens. Specifically, we compute if each Census block group is above or below the median Census block group when ordered by household income, fraction of the population with at least a bachelor’s degree, and the fraction of the population that is over age 65. The mean “Percent achieved” is nearly twice as large in high income versus low income neighborhoods – 14.2% in wealthier neighborhoods and 7.5% in less wealthy neighborhoods. Similar trends are present when comparing neighborhoods by education and senior citizens. Households realize more of the potential savings of switching in neighborhoods with higher education and fewer senior citizens.

²⁴In calculating this figure, we do not include months in which there were no potential savings from switching away from the incumbent, which primarily includes only the first few months of the sample period.

²⁵Borenstein [2010] documents the heterogeneity within Census block groups and the shortcomings of using such metrics for distributional analyses in some settings.

Table 6: Direct Measures of Potential Savings that are Achieved by Switching

Characteristic of Block Group	High	Low
Income	14.2%	7.5%
Fraction Senior	8.1%	13.8%
Fraction with Education Bachelor or More	14.3%	7.4%

Notes: This table contains the mean “Percent Achieved” of possible savings from switching to the lowest price retailer, as compared to remaining with incumbent. We calculate the monthly bill size under three scenarios: 1) purchasing from the incumbent, 2) purchasing from the lowest-price retailer, and 3) the household’s actual choice. “Percent achieved” is the percent of possible gains realized $((\text{actual bill} - \text{incumbent bill}) / (\text{lowest possible bill} - \text{incumbent bill}))$. Households are grouped by the characteristics of their Census block group into categories of above or below the median for the sample.

Search Criteria

Zip Code:

TDU Service Areas:

- CENTERPOINT ENERGY
- TEXAS-NEW MEXICO POWER COMPANY

Rate Type:

Renewable Content:

Price (cents per kWh):
From: To:

Contract Term (months):
From: To:

REP Company:

Or check boxes to compare offers

Click the column headings to sort offers

List of electric offers

<input type="checkbox"/>	Retail Electric Provider	Avg. Price/kWh (1,000 kWh)	Cost per 1,000 kWh	Rate Type	Renewable Energy Content	Term (Mo.) Cancellation Fee
<input type="checkbox"/>	Bounce Energy <i>Express Move - \$50 Macy's OR Home Depot GC, Same Day Turn-On Offered, PLUS 4 Moving Services</i> Terms of Service Facts Label Sign Up Special Terms	11.7¢	\$117.00	Variable	3%	1 \$0.00
<input type="checkbox"/>	Texas Power <i>Texas Power Plan</i> Terms of Service Facts Label Sign Up Special Terms	10.3¢	\$103.00	Variable	1%	1 \$0.00
<input type="checkbox"/>	Gexa Energy <i>Gexa Guaranteed 12</i> Terms of Service Facts Label	10.7¢	\$107.00	Fixed	1%	12 \$150.00

Figure 5: Web Portal to Search and Switch Retailers

Notes: This displays a screenshot of the website *www.powertochoose.com* where households can search for alternative retailers and switch on-line. A customer enters her zipcode and then is able to observe a list that displays the average price per kwh at a usage level of 1000kwh/month. If she finds a plan she wishes to switch to, she clicks on “Sign Up” and then goes through a brief on-line process to switch the retailer.

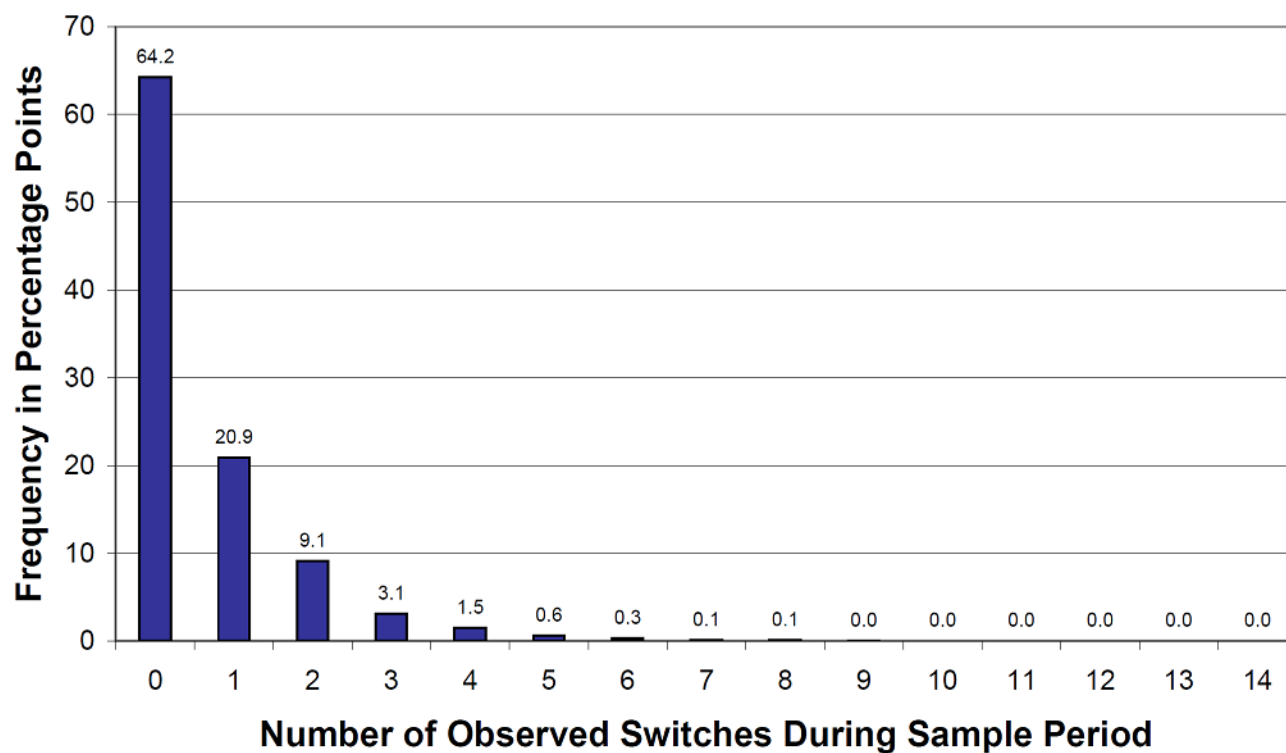


Figure 6: Frequency of Switches Per Household

Notes: This figure displays the frequency of the number of switches in retailer by a household over the sample period of January 2002-April 2006. This indicates that 64% of households never switched, and for those that did switch retailers, most switched only once or twice.