

# Price Discrimination, Search, and Negotiation in an Oligopoly: A Field Experiment in Retail Electricity\*

David P. Byrne<sup>†</sup>      Leslie A. Martin<sup>†</sup>      Jia Sheen Nah<sup>†</sup>

December 21, 2019

## Abstract

We use a field experiment to study price discrimination in a market with price posting and negotiation. Motivated by concerns that low-income consumers do poorly in markets with privately-negotiated prices, we built a call center staffed with actors armed with bargaining scripts to reveal the determinants of negotiated prices. By experimentally manipulating how information is revealed within a sequential bargaining game, we identify price discrimination based on perceived search costs at the start of negotiations, which can be overcome if consumers reveal that they are informed. Combining posted and negotiated prices, we document important asymmetries between incumbents' and entrants' pricing structures that segment consumers based on their willingness to search and bargain. Finally, we show that incomplete subsidy pass-through for low-income households observed in our market is not due to discriminatory targeting; it can be explained by variation in consumers' willingness and ability to search and bargain.

**JEL Classification:** D83, L13, Q41

**Keywords:** Price discrimination, negotiation, search, natural field experiment, electricity markets

---

\*We acknowledge support from the Australian Research Council and the Faculty of Business and Economics at The University of Melbourne. This research is governed by Ethics Approval 1648136 from The University of Melbourne. We have received helpful comments and suggestions from Aaron Barkley, Severin Borenstein, Jeremy Bornstein, Melisa Bubonya, Zan Fairweather, Matthew Freedman, Joseph Harrington, Matthew Lewis, Simon Loertscher, Fiona Scott Morton, Helena Perrone, Michelle Sovinsky, Steve Puller, Steve Tadelis, and participants at the 2017 Asia-Pacific IO Conference, 2019 Melbourne IO and Theory Workshop, 2019 POWER Workshop, 2019 NBER Energy Markets Workshop, and 2019 MaCCI Summer Institute in Competition Policy. All errors are our own.

<sup>†</sup>Department of Economics, The University of Melbourne. 111 Barry Street, Melbourne, Victoria, 3010, Australia. Email: [byrned@unimelb.edu.au](mailto:byrned@unimelb.edu.au), [leslie.martin@unimelb.edu.au](mailto:leslie.martin@unimelb.edu.au), and [js.nah@unimelb.edu.au](mailto:js.nah@unimelb.edu.au).

# 1 Introduction

In many industries firms post one set of prices publicly and negotiate discounts with consumers privately. Prominent examples include automobiles, mortgages, healthcare, retirement savings, private schooling, telecommunications, and energy markets. In such settings, oligopolistic firms leverage their market power to price discriminate through posted and negotiated prices, which segments consumers based on their willingness and ability to search and bargain. For public policy, this naturally raises the question of who searches and bargains and whether high- or low-income consumers ultimately pay higher prices. These questions become even more policy relevant when the public sector intervenes to subsidize low-income households.

Yet despite the prevalence and policy-relevance of price posting and negotiation in oligopoly, there has been to-date relatively little research. This is in part because oligopolistic models of price discrimination are in general challenging to solve (Stole, 2007), but also because data on negotiated prices are difficult to access.

In this paper, we demonstrate the power of field experiments to recover negotiated price data, reveal how firms use price posting and negotiation to price discriminate, identify channels through which discrimination-based price dispersion arises (namely, search and bargaining frictions), and illustrate potential distributional consequences of public price posting and private negotiations. Our approach is based on audit studies, which have been used extensively in studying labor market discrimination,<sup>1</sup> but have been overlooked for their potential applications to oligopolistic industries until now.

Our audit study is implemented in a retail electricity market with asymmetrically-sized firms. We created fictitious customers with randomly-allocated combinations of characteristics, including stated and revealed willingness and ability to search, while holding other characteristics related to demand and cost of service fixed. We hired actors to represent these customers and provided them with scripts, effectively creating a call center that we used to negotiate with firms' call centers. These calls yielded multiple price quotes that vary with perceived customer characteristics across calls and within calls, as our customers gradually revealed individual characteristics, recording price offers as new information was revealed. We describe our industry context in Section 2 and the experimental design in Section 3.

By embedding this field experiment with sequential bargaining within an oligopoly, we are able to uncover pricing structures involving price posting and negotiation. These struc-

---

<sup>1</sup>Bertrand and Mullainathan (2004) is perhaps the most well-known audit study that examines labor market discrimination based on perceived race through fictitious resumes that vary whether job applicants have African-American and White-sounding names. See Bertrand and Duflo (2017) for an extensive overview of audit studies and discrimination.

tures are described in Section 4. Existing oligopoly models of price discrimination provide little guidance as to the form such pricing structures should take because they abstract from search frictions and private negotiation (Stole, 2007).<sup>2</sup> We uncover asymmetric pricing structures among large incumbents, mid-sized entrants, and fringe competitors. Specifically, we find that large incumbents post high prices and are willing to negotiate modest discounts, mid-sized firms post very low prices but are unwilling to negotiate, while small firms post moderately-low prices and aggressively discount. Supported by auxiliary evidence from the market, we highlight how these pricing structures give rise to consumer segmentation based on willingness to search and bargain.

To our knowledge, this analysis yields the first empirical characterization of oligopolistic price posting and negotiation. Our results complement the recent structural analysis of Allen et al. (2019) who also study oligopolistic pricing in a setting with private price negotiation and search frictions. Allen et al. (2019) leverage administrative mortgage data with prices and quantities to provide an equilibrium analysis that abstracts from price-posting, whereas we combine posted price data with an experiment that reveals negotiated prices and their determinants, but not quantities.

One benefit to our approach is that it allows us to further unpack how search frictions affect negotiated price outcomes within a sequential bargaining environment. Section 5 describes the results of this analysis. In the first stage of negotiations, we randomly assign whether prospective customers reveal they are either new to the market or already in the market looking to switch from a rival firm. We show that new customers are initially offered substantially higher prices in negotiations, which aligns with new customers having higher perceived search costs from firms' perspectives and firms engaging in search-based price discrimination.

In the second stage of negotiations, prospective customers reveal their search strategy and knowledge of either a high or low reference price, both of which are lower than posted retailer offers. Customers with low reference prices obtain larger price discounts. We further demonstrate that new customers who ex-post reveal that they are in fact informed about low reference prices are able to overcome ex-ante price discrimination; otherwise they face higher prices throughout negotiations.

These results add to existing empirical research that documents real world bargaining in competitive markets, which includes Jindal and Newberry (2018), Chandra et al. (2017), Busse et al. (2017), Shelegia and Sherman (2017), Castillo et al. (2013), Gneezy et al. (2012),

---

<sup>2</sup>Recently, Fabra and Reguant (2019) propose the first oligopolistic model of search-based price discrimination, while Anderson et al. (2019) develop a novel model of price discrimination involving price posting and personalized discounts. For tractability, both of these frameworks focus on equilibria with symmetric pricing strategies. This contrasts with the asymmetric pricing structures that we uncover.

List (2004), Scott Morton et al. (2003), and Ayres and Siegelman (1995). Our paper is closely related to Backus et al. (2018) who use high-frequency eBay price offer data to also study sequential bargaining. A key difference relative to Backus et al. (2018) is that our experiment manipulates how and what type of information is revealed within each negotiation.<sup>3</sup>

Finally, in the latter part of Section 5, we exploit our field experiment to test channels that give rise to incomplete subsidy pass-through. In our setting, the government offsets a fraction of bills faced by low-income consumers. But when subsidies are targeted and firms have market power, it can be profitable to charge subsidy recipients higher base rates (Akerlof, 1978), leading to a fraction of the subsidy going to the supplier and not benefitting the intended consumer. A burgeoning empirical literature documents incomplete pass-through of targeted government subsidies across a range of contexts: housing (Collinson and Ganong, 2015), ethanol-based fuel (Lade and Bushnell, 2016), tuition (Turner, 2017), hybrid electric vehicles (Gulati et al., 2017), childcare (Rodgers, 2018), and private Medicare Advantage plans (Cabral et al., 2018).

Documenting subsidy capture is difficult because subsidy recipients paying higher prices does not, on its own, imply targeted discrimination. Subsidy recipients could be more costly to serve or less likely to search, for many reasons including the subsidy itself (Gulati et al., 2017). To overcome this identification problem, we randomly assign subsidy eligibility to our actor-consumers and use this variation to test for whether firms target subsidy recipients with higher negotiated prices. Despite the public concern over this issue, our experimental results provide evidence that the incomplete subsidy pass-through observed in this market (ACCC, 2018) is not due to specific targeting by retailers. Rather, our results suggest that it is based on differences in low-income consumers’ willingness or ability to search and haggle.

Section 6 summarizes and concludes the paper. Here, we elaborate on the policy implications, focusing on two issues. First, our results, together with recent studies of customers’ willingness to engage in search and bargaining, point to a potentially undesirable regressive form of price dispersion in markets with price posting and negotiation. Second, we discuss implications for energy market design, contributing to on-going policy debates worldwide as to whether regulated monopolies in utility markets should be deregulated.

---

<sup>3</sup>Ours results also relate to findings from Gneezy et al. (2012) who document statistical discrimination on perceived search differences in a non-sequential bargaining experiment, and Busse et al. (2017) whose bargaining experiment reveals gender-based differences in the value of price information in negotiations. We also connect to structural analyses of bargaining with incomplete information from Larsen (2019) and Keniston (2011) that characterize the equilibrium impact of information frictions on market efficiency. Our experimental approach that exogenously varies buyers’ ex-ante perceived and ex-post revealed knowledge about prices within a sequential bargaining environment to reveal the determinants of price discrimination makes our paper distinct from these other studies.

## 2 Industry

Our research context is the electricity market of Victoria, Australia, a state with 6.3 million people, 4.4 million of which live in the city of Melbourne. The power market is split into four parts: generation, transmission, distribution, and retail. Generators bid supply into an exchange where dispatch and the marginal wholesale cost of generating electricity is determined through uniform price auctions. Transmission and distribution companies are regulated monopolists who own the electricity grid’s wires and poles and manage geographically-distinct networks. Retailers compete downstream, paying network fees upstream to buy electricity from distributors, and supplying electricity to both residential and commercial end users.<sup>4</sup>

We focus on the residential retail market, where in our 2017 sample period there are 13 firms: 3 large, 3 mid-sized, and 7 small. The large firms each have more than 1 million customers; mid-sized firms each have between 200,000 and 1 million customers; small firms each have less than 200,000 customers.<sup>5</sup> These groups of retailers have market shares of 60%, 28% and 12%, respectively, in terms of households served. The large retailers – AGL, Origin, and Energy Australia – are vertically-integrated incumbent firms that compete in both electricity generation and retailing, and who were serving the customers as price-regulated monopolists in their respective geographies before retail competition was introduced in 2009.

Retailers engage in door-to-door selling, telemarketing, online, and cable advertising to encourage customers to switch retailers. Each year 26% of customers switch firms. There is, however, considerable inertia with electricity contracts, especially among the three incumbent firms. The Australian Competition and Consumer Commission (ACCC) estimates that 35% of customers of these three large retailers have been with their electricity supplier for more than two years (ACCC, 2018). In contrast, only 18% and 20% of the customer base of mid-sized and small firms, respectively, have been with their retailer that long, revealing some market segmentation based on customer willingness to switch retailers.<sup>6</sup>

### 2.1 Retail pricing

As in many electricity markets, retail contracts in Victoria consist of a two-part tariff: a fixed daily charge and a variable per kilowatt-hour (kWh) charge. Some retailers offer variable

---

<sup>4</sup>See AEMC (2017) for a detailed description of Victoria’s electricity market design.

<sup>5</sup>All figures discussed throughout Section 2 are drawn from four major government inquiries into the retail market: Australian Competition and Consumer Commission (ACCC 2018), Australian Energy Regulator (AER 2017), Australian Energy Market Commission (AEMC 2017), and a state-level retail electricity market review by the Victorian Government (Thwaites et al. 2017).

<sup>6</sup>These institutional features are in-line with results from Hortaçsu et al. (2017) who find significant customer inertia with retail electricity contracts and an incumbency advantage for electricity suppliers who were in the retail market pre-deregulation in Texas.

rates that increase with quantity consumed or vary by time of day. Our experimental design, discussed below, focuses on the prices most commonly-offered in the market: contracts with constant per kWh charges.

Electricity contracts can be categorized into three groups: default prices, posted prices, and negotiated prices.<sup>7</sup> The energy regulator requires each retailer to offer a *default price* to ensure that customers always have a valid electricity supply contract irrespective of their level of engagement in the retail market. If a customer fails to renew or renegotiate their current retail electricity contract after it expires, they may be automatically switched to the default price of the retailer that currently supplies them electricity.

*Posted prices* are lower than default prices and are typically valid for one or two years. Firms promote these prices through online, television, and print advertising, and they are often expressed as a percentage discount relative to a retailer’s current default price. Variation in posted prices often exists, with retailers offering additional discounts for automatic payment (direct debit), on-time payments, one-time sign-up discounts or other promotions, as well as higher prices for green power commitments.<sup>8</sup> Customers can sign-up for posted prices through retailer websites or by calling their sales centers directly.

Finally, there are *negotiated prices*: customers can call their current electricity supplier or rival firms to negotiate directly. Prior to our study, there was anecdotal evidence of the potential gains from negotiating rates in the market (Johnston, 2016). But previously-reported aggregate industry statistics focused exclusively on default and posted prices, and the limited customer survey data available did not distinguish between retailers’ posted and negotiated prices. This is precisely the measurement problem that we designed our field experiment to address.

Anecdotal evidence from government and consumer advocacy reports (Thwaites et al., 2017; Johnston, 2016) suggest that the combination of electricity contract complexity and barrage of marketing campaigns leave customers feeling confused and creates large search costs that limits their engagement in finding lower prices and switching firms. To promote customer search the state and federal governments offer online price comparator websites to help customers compare electricity pricing contracts.<sup>9</sup>

---

<sup>7</sup>For the sake of brevity in language, for the remainder of the paper we use the word “price” to mean an electricity contract with two components: a fixed daily charge and per kWh charge.

<sup>8</sup>We collected all prices with and without discounts for automatic and on-time payments.

<sup>9</sup>*Energy Made Easy* is the national website (<https://www.energymadeeasy.gov.au/>). *Victorian Energy Compare* is the state-run website (<https://compare.energy.vic.gov.au/>).

## Government subsidies

Because high electricity bills can exacerbate cycles of debt for low-income customers, many governments worldwide subsidize electricity costs for vulnerable groups. Examples include social tariffs in France, the Low Income Home Energy Assistance Program and National Grid Energy Affordability Program in the US, and the Warm Home Discount in Great Britain. ([The Brattle Group, 2018](#))

In Victoria, the state government subsidizes annual electricity costs for low-income households, pensioners with moderate-to-low income, and veterans. Specifically, for eligible households the state pays 17.5% of annual electricity costs above and beyond the first \$171.60 of costs, after any solar credits have been applied. This rebate is calculated by retailers and is automatically deducted from total nominal costs on each bill. Customers observe the nominal cost, subsidy, and net payable amount on their bills. Subsidy-eligible customers are required to provide evidence to their electricity supplier to prove their entitlement.

There is suggestive evidence that purchase subsidies may be partially captured by the retailers. The ACCC obtained proprietary data from retailers for its anti-trust investigation into the retail electricity market. In [ACCC \(2018\)](#), they show that subsidy recipients indeed pay higher prices in all Australian states. In Victoria the average price of electricity, in cents per kWh, variable charges and all fixed charges averaged over level of use, is 31.4 cents for regular customers and 32.7 cents per kWh for subsidy recipients. This difference implies that 24% of the 5.5 cent subsidy per kWh goes to retailers in the form of higher prices.

Of course, there are many reasons why subsidy recipients could pay higher prices. Subsidy recipients may be more expensive to serve if they have different ratios of fixed to variable costs or are more likely to default on electricity bill payments. If more costly to serve, there is a clear efficiency case for higher prices. Alternatively, subsidy recipients could search less for good deals. [Gulati et al. \(2017\)](#) provide a simple theoretical framework that explains why, when bargaining is costly to customers, subsidy-status may in itself lower the amount of search and negotiation that occurs. In this case, there are potential efficiency and distributional gains from reducing search costs.

Separate from cost-to-serve or search and bargaining cost based explanations, higher prices could also be due to retailers explicitly targeting subsidy recipients. In this case, there is a strong argument for regulatory action. By exogenously varying customer characteristics and collecting prices for combinations of characteristics that may be infrequently observed in practice, our experimental design allows us to disentangle some of these different factors that potentially explain why subsidy recipients pay higher prices.



### 3 The experiment

We designed a natural field experiment (Harrison and List, 2004) to provide a novel characterization of oligopolistic price posting and negotiation, and to identify channels through which negotiated price dispersion arises. Our experimental approach targets four channels: (1) firms’ ex-ante perception of a customer’s search cost; (2) customers’ ex-post revelation of their knowledge of rivals’ prices; (3) the source of customers’ price information; and (4) whether a customer is eligible for low-income subsidies. In what follows, we first describe our experiment and develop hypotheses regarding the channels that generate negotiated price dispersion. We then describe the call center that we created to implement our experiment and the dataset that we generated on posted and negotiated prices.

#### 3.1 Design

Our experiment is an audit study whereby fictitious customers call electricity retailers under different experimental conditions to negotiate prices. To identify the channels that give rise to price dispersion, we created 28 unique customer types, where each type is a combination of one of four characteristics:

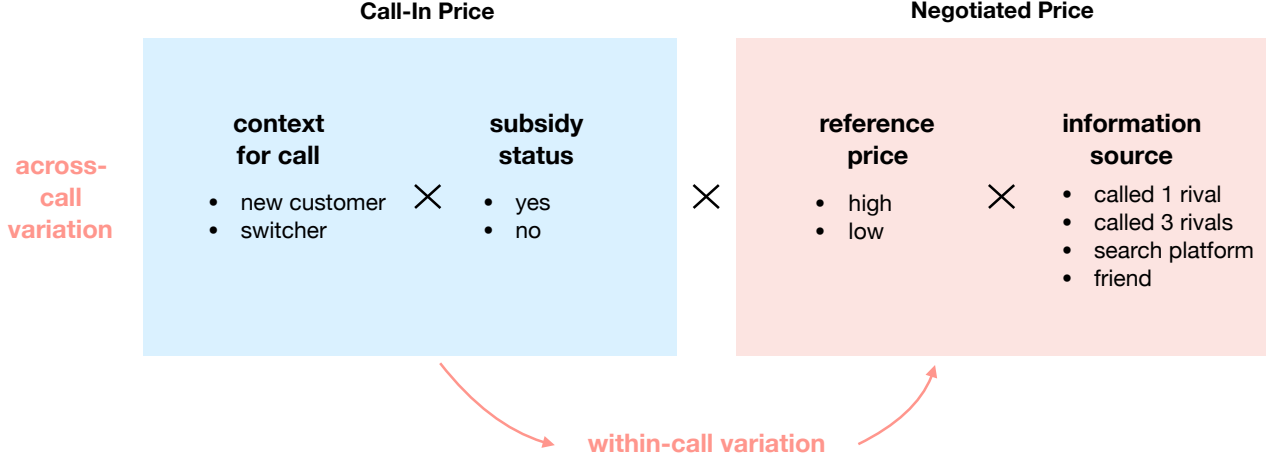
- *context for call*: a new customer in the market who just moved to Melbourne and is currently without a retailer *vs.* an existing customer in the market who already lives in Melbourne, is with a rival retailer, and is considering switching retailers
- *subsidy status*: eligible for 17.5% electricity bill subsidy *vs.* not eligible for the subsidy
- *reference price*: high reference price *vs.* low reference price. The “high” reference price was the lowest price displayed on the Victorian Energy Compare online search platform prior to the experiment. The “low” reference price was the lowest price obtained via negotiation during our pilot calls. By construction the “high” reference price was lower than (or, in one case, equal to) all posted retailer prices.
- *information source*: one of four information sources for the reference price: previously called 1 rival *vs.* previously called 3 rivals *vs.* Victorian Energy Compare government search platform *vs.* chatted with a friend.

#### Negotiation and information revelation

Figure 1 depicts the experimental design, highlighting that each call consisted of two stages. In the first stage, which we label **call-in**, callers reveal their *context for call* and *subsidy*



Figure 1: Experimental Design



*status*, along with contract standardizations common to all calls that we describe below. They then ask for a price quote and record the initial daily fixed price and per kWh variable price offered by the retailer.

In the second stage of each call, which we label **negotiate**, actors reveal their *reference price* and *information source*. There are two reference prices possible for every information source except for, by construction, the online search platform. which is always the “high” reference price. Therefore, in total, our experimental design entails  $2 \times 2 \times (2 \times 3 + 1 \times 1) = 28$  unique customer types.

## 3.2 Hypotheses

### Context for call

In our experiment we address perceived willingness to search in two ways. Our *context for call* treatment varies the situation a customer is in at the call-in stage. From the firms’ perspective, we anticipate that the perceived search costs of a *new customer* will be relatively higher than that of switchers. Getting power turned on is one of many pressing things that needs to immediately be taken care of when moving to a new city. Making the call reveals nothing for a new customer, but reveals willingness to search for existing customers of rival firms. Holding other factors fixed, new customers may also be time-constrained relative to existing customers, which could limit their ability to search among electricity retailers. They may also have higher costs of search due to more limited knowledge of

what is available in the local market.<sup>10</sup> As firms are in a quasi-monopoly position with our customers during negotiations, we expect that they will offer prices that leave customers indifferent between accepting their current offer and continuing to undertake costly search.<sup>11</sup> In this case, customers with higher perceived search costs will be offered higher prices. This leads us to our first hypothesis regarding price discrimination based on perceived search costs:

**Hypothesis H1:** *New customers* will be offered higher prices than *switchers* during the call-in stage.

## Reference price

After obtaining a call-in price quote, customers reveal whether they are informed about either a *high* or *low reference price* during the negotiate stage of the call. Within our sequential bargaining environment (Rubinstein, 1982), we expect customers who are more informed about low market price offers to obtain a greater share of surplus in the negotiation, particularly if negotiations exhibit Coasian dynamics whereby final prices converge to a point within customers' and retailers' initial offers (Fudenberg et al., 1985; Gul et al., 1986).<sup>12</sup> Alternatively, the reference price could create a framing effect that drives the final price due to psychological anchoring, as described in and documented empirically in Busse et al. (2017). Either explanation yields our second hypothesis:

**Hypothesis H2:** Customers with *low reference prices* will be offered lower prices than those with *high reference prices* during the negotiate stage.

Considering the *context* and *reference price* conditions together, a further question of interest arises: if firms initially price discriminate based on perceived high search cost (e.g., new customers in the call-in stage), does subsequently revealing that a customer in fact has a relatively low search cost and is informed about best prices (e.g., has low reference price in the negotiate stage) allow them to overcome any initial price discrimination? The answer depends on the degree of ex-ante discrimination based on perceived search cost, and the

---

<sup>10</sup>See Kennan and Walker (2011) for a structural analysis of sunk search costs in becoming informed about local price distributions in the context of labor market migration decisions.

<sup>11</sup>Conceptually, this notion of a quasi-monopoly is consistent with the search and matching frameworks of Postel-Vinay and Robin (2002) and Allen et al. (2019) whereby firms offer wages to workers (former paper) or prices to customers (latter paper) to leave them indifferent between staying with their current employer/firm and searching for another match. A key distinction between our environment and theirs is that in their respective models another match's price is determined by simultaneous price competition between firms, whereas our setting involves sequential search and price offers by firms.

<sup>12</sup>Using alternating price offer data similar to what our field experiment generates, Backus et al. (2018) find Coasian dynamics in negotiated prices are wide-spread on eBay.

degree of ex-post negotiation leverage afforded to customers who are informed about low reference prices. Our within-call experimental design allows us to characterize such search-based price discrimination and how information revelation influences outcomes within a sequential bargaining environment.

### Information source

We conduct two tests based on the four *information source* experimental conditions. The first examines on differences in negotiate stage outcomes from having *called 1 rival* versus *called 3 rivals*. Through the lens of a standard sequential search model (e.g. McCall, 1970), a customer who has called 1 rival has more firms to obtain lower price quotes from through continued search than a customer who has already called 3 rivals. If firms in a quasi-monopoly position with a customer offer prices to keep them indifferent between accepting their current offer and continuing to search, we would expect customers earlier in a sequential search to obtain lower price quotes as firms try to preempt further search.

However, given that our bargaining environment likely involves incomplete information over consumers' willingness to search, having called *called 3 rivals* versus *called 1 rival* may signal to a firm that a consumer has relatively lower search costs and are hence willing to continue searching if a sufficiently low price is not offered. If this signaling channel dominates the aforementioned preemption channel in firms' pricing decisions, then we might instead find that customers that *called 3 rivals* obtain relatively lower prices.

The second information source-based test compares negotiation outcomes between customers who cite the government *search platform* versus having *asked a friend* as their information source. These conditions vary the degree of credibility of information in negotiations, with *asked a friend* being the less credible of the two. Holding other factors such as reference price fixed, we expect that less credible signals are downweighted in cheap talk bargaining environments (Farrell and Gibbons, 1989). Our third hypothesis is therefore:

**Hypothesis H3:** During the negotiate stage customers who used the *search platform* will be offered lower prices than those who *asked a friend*.

This test is important for policy because it explores a potential role filled by government-created search platforms: they could provide customers with a credible source of price information in negotiations. The potential ability of search platforms to improve privately-negotiated outcomes would represent a separate, pro-consumer impact above and beyond their role in helping consumers rank posted-price options.

## Subsidy status

Our final hypothesis is based on *subsidy status*. Through our initial pilot calls, we confirmed that firms immediately ask whether customers are eligible for low-income subsidies for electricity costs. With this experimental condition, we test whether firms price discriminate on subsidy status, exercising market power to capture part of the subsidy. As discussed above, identifying the causes of incomplete subsidy passthrough is challenging with observational data because ability to search can be correlated with subsidy eligibility and willingness to search can be driven by subsidy eligibility. Through our experimental design we are able to hold search behavior fixed. This leads us to our final hypothesis:

**Hypothesis H4:** During the call-in stage customers who are eligible for subsidies will be offered higher prices than customers who are not.

## 3.3 Implementation

Negotiating retail prices involves calling front-line employees at retailer call centers who are the first point of contact for customers. The challenge in implementing an audit study in this environment is to produce conversations that flow naturally and are also consistent across calls. Callers need to sound spontaneous while simultaneously following a carefully-scripted conversation. Calls can neither leave out nor add key elements that could bias the negotiations. They also need to have enough irrelevant variation in case our callers reach the same call centre employee more than once.<sup>13</sup>

To assemble our team of callers, we held a casting call at The University of Melbourne where we auditioned both actors and economics students using hypothetical bargaining scripts. Actors were much better at adding extraneous and important detail in a natural way. We hired 18 different actors for the experiment, 9 of which were female. Each actor played a variety of customer types; no actor called the same retailer call center twice.

All successful recruits participated in a four-hour training session where we informed them about the study and provided background on the Victorian retail electricity market. We had the actors practice negotiating electricity contracts with each other using our bargaining scripts where one acted as the electricity retailer and the other was the customer. During the mock calls, we encouraged actors to develop their own voice in a prescribed way. We finished training by having actors engage in pilot negotiations with actual electricity retailers using different bargaining scripts. As the experiment ran, we (the authors) sat in on a large

---

<sup>13</sup>This was an ex-ante concern in our implementation strategy. To our knowledge this never happened.

number of calls, to help make sure that the different actors were indeed following the scripts in similar ways.<sup>14</sup>

## Standardizing other customer and contract characteristics

Another key component of an audit study is to credibly standardize all customer characteristics that are not being manipulated experimentally. In our context, we need to hold constant, to the best of our ability, a customer’s perceived cost of service. Because electricity bills typically have both fixed and variable components, we fixed expected level of usage. All of our customers obtained price quotes for a two-bedroom rental apartment with an average monthly energy usage of 300 kWh/month. This level corresponds to average electricity usage for a two-person household in Melbourne.

We shared usage information in all calls, being careful to not signal extreme familiarity with electricity bills in the process. All of our callers were holding a copy of “their” last bill, with a level of use of “about 300” (kWh/month). Although callers wrote down both daily fixed charges and per kWh variable charges for each price quote, we encouraged them to negotiate using total annual bills to facilitate comparison across offers. Because of the potential for lower variable prices to be offset by higher daily fixed prices, our empirical analyses in Sections 4 and 5 focus on total annual bills. In Appendix C.1, we show that all of our main conclusions are robust to defining price exclusively as the per kWh variable charge.

During our pilot calls, we learned that customer addresses were required to establish credibility with call center personnel to initiate negotiations. We selected and randomly assigned home addresses for our fictitious customers from 2-bedroom units available on a large online rental listing website. All home addresses were chosen from the catchment of a single Melbourne-based electricity distribution network, United Energy. This feature guaranteed that electricity network charges would also be identical across customers.

We also normalized several key contract characteristics. Our fictitious customers all negotiated one-year contracts. The properties had existing natural gas connections that, because not all retailers offer gas, our callers did not want to link at the time. Our callers were also not interested in green power plans or time-of-day plans, both of which are relatively rare in the Victorian retail market. Further, if asked, callers said that they did not know their meter type, and wanted to collect prices for the most common type.

When our customers provided a reference price, we associated the price with the same

---

<sup>14</sup>Appendix B contains the bargaining script used in negotiations and the price sheets that our callers and (silent) research assistants filled out in collecting price offer data during the call-in and negotiate phase of each call.

competitor retailer regardless of whether it was a high or low reference price. When switching from a rival, we used the same rival for all calls, a competitor that was not part of the experiment because it sells pre-paid power and displays its prices in proprietary units that make price comparisons very difficult. The choice of rival also allowed our callers to easily deflect any questions about current prices.

It is important to note that although we fixed level of use and distribution zone, there may still be perceived differences in cost of service. For example, customer subsidy status may be associated with perceived differences in likelihood of defaulting on bills, need for payment reminders, or need for customer service in relation to bills. To mitigate this issue we collected data on prices with and without discounts for automatic (direct-debit) payments and pay-on-time discounts. The logic is that automatic payment resolves many cost-of-default concerns because a bank’s penalty of insufficient funds at the time of payment is higher, and the likelihood of timely payment is considerably greater. Similarly, pay-on-time discounts are a clear commitment to timely payment. We also collected prices with and without paperless bills, again to address a similar concern that comfort with technology could signal higher value customer type.

Finally, after some pilot calls where call centre personnel appeared to strategically switch between pre- and post- sales tax prices, we insisted that callers note whether each price quote includes sales tax: 10% Value Added Tax (VAT).

## **The call center**

We called 12 of the 13 retailers in the market with every caller type, after randomly assigning actors to each of the 28 caller types. We randomly allocated addresses and actors to each retailer to ensure that a given retailer would not be called twice for the same address or by the same actor. This ultimately generated price data from the call-in and negotiate stages of our calls from  $28 \times 12 = 336$  customer-retailer combinations.

The calls took place at our call center, which consisted of private offices in the University of Melbourne’s Faculty of Business and Economics during the third week of March 2017 between 9am and 4pm. The actors were provided with disposable SIM cards that they inserted into their own mobile phones. Using mobile phones enabled us to disable caller IDs.

Armed with a bargaining script, a caller dialed each designated retailer on speaker phone. A silent research assistant sat next to each caller taking duplicate notes during the call-in and negotiate stages of the call to ensure data quality. As required by human ethics, calls were not recorded. The study’s authors also participated silently in many calls to further ensure quality control and uniformity across calls. After each call, the actor and research assistant compared notes to finalize data collected from the call. As with previous audit studies

(Bertrand and Mullainathan, 2004), our experiment involved deception: the retailers’ call center employees were not told that they were participating in a research study.

To minimize the burden on call center staff, we limited all calls to 20 minutes. We also encouraged actors to publicize good deals to friends and family after the experiment was run. The University’s ethics review board prevented us from using data on caller or call center employee gender or race in our analyses. The board also prevented us from revealing statistics based on individual firms, but we were allowed to report empirical results based upon three groups of firms – large, mid-sized, small – as defined in Section 2 above.

To learn about the call centers themselves, we combed through employment ads for call center personnel and websites where employees share their experiences. Some retailers run their call centers in-house, while others contract from specialized call center service companies. To the best of our knowledge, all centers are located within Australia: we identified several centers within the greater Melbourne area, in Geelong, and in Tasmania. Employees who work in inbound customer service and sales are paid competitively by the hour,<sup>15</sup> with financial bonuses and in-kind rewards for customer acquisitions, total sales, and, in some cases, ratings on post-call customer experience surveys. Advertisements for these jobs mention both what appear to be rewards that are linear in outcomes and bonuses for individuals and group outcomes that exceed discrete thresholds, or meet minimum expectations. According to employee posts, some rewards come in the form of intangibles like preferential scheduling. Importantly for our study, it appears that call center staff have incentives to not just close deals, but close profitable deals. The full incentive, however, is clearly not linear in retailer profits.

### 3.4 Data

Our dataset consists of default and posted prices from the field, and negotiated prices from our experiment. We scraped retail contracts from the firms’ websites to obtain default and posted prices. Each price quote is composed of a daily fixed charge and a per kWh variable charge, and any connection fees or special discounts, as per our contract and customer standardizations from Section 3.3 above. To normalize prices across retailers, we calculate a total annual bill based on average use of 300 kWh/month. Connection fees and discounts are included in the total annual bill estimate. All prices are not inclusive of the 10% VAT, as confirmed by our callers in negotiations.

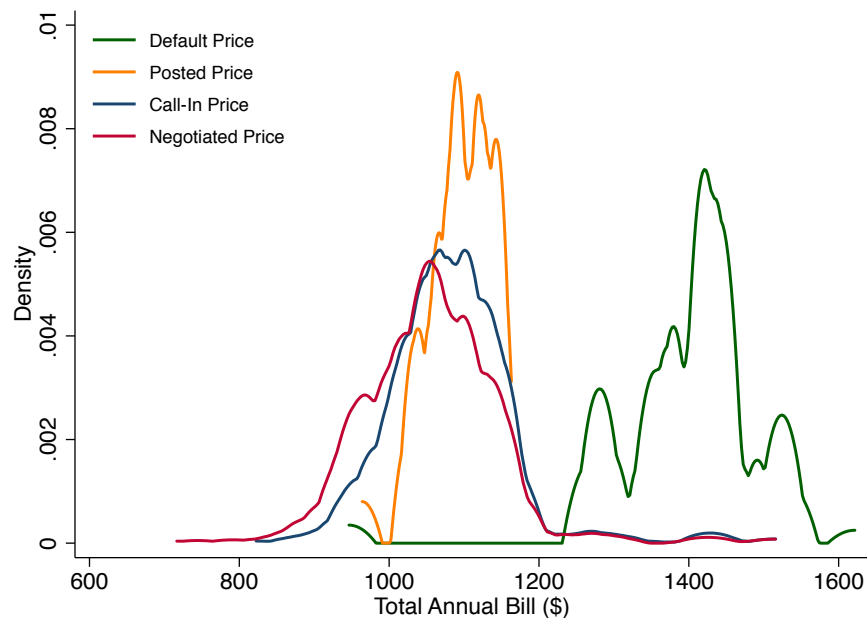
After scraping the websites and running the experiment, we obtain 12 default prices, 12 posted prices, 336 call-in prices, and 336 negotiated prices, all computed in terms of total

---

<sup>15</sup>Wages posted online range between AUD \$25-35; longer term contracts include benefits like annual leave.



Figure 2: Distribution of Annual Bills Associated with Default, Posted, Call-In, and Negotiated Electricity Contracts Assuming 300 kWh/day Usage



pre-VAT annual bills assuming 300 kWh/month electricity usage. Figure 2 presents the distribution of these annual bills implied from our dataset. In the figure, annual bills from default prices are centered near \$1400 per year, whereas annual bills based on posted and call-in prices are centered around \$1150. The distribution of bills from negotiated prices is shifted further left and is centered around \$1050 per year. The negotiated price distribution also has a mass to the left of \$1000 that is not present in the posted nor call-in distributions.

Most noticeable in Figure 2 is the range of prices for what is essentially an identical product. Annual electricity costs can be as high as \$1600 (upper end of the default price distribution) and as low as \$800 (lower end of the negotiated price distribution).

The distribution of prices in Figure 2 further highlights significant dispersion both across and within the different contract types. On average, there is a 21% reduction in annual electricity bills when moving from default prices to posted or call-in prices. Based on the raw data, once customers start negotiating with retailers on calls, they are able to obtain an additional 9% discount off of their annual electricity bills in the negotiate stage on average, and in the best case a 35% discount relative to same-retailer posted price. Below, we use fixed effects regressions to formally estimate discounting rates between posted, call-in, and negotiated prices.

## 4 Price posting and negotiation

A unique feature of our study is that we observe oligopolistic pricing structures in a market where prices are both publicly posted and privately negotiated. In this section, we characterize these pricing structures and test for asymmetric structures among asymmetrically-sized firms. To our knowledge there does not exist a theory of price discrimination involving public price posting and private, customer-specific negotiation, a common pricing structure in many oligopolistic industries.<sup>16</sup> The novel empirics presented here thus give context for our experimental analysis of information revelation and discrimination in negotiations in Section 5, and motivate the development of future theories of oligopolistic price discrimination.

### 4.1 Baseline results

Motivated by Figure 2, we develop a set of baseline results that quantify discounting rates between default, posted, call-in, and negotiated prices. Specifically, we regress the log of the total annual bill for call  $i$  from retailer  $j$ ,  $\text{Bill}_{ij}$  on the way in which the associated price was obtained:

$$\begin{aligned} \log(\text{Bill}_{ij}) = & \beta_0 + \beta_1 \text{Posted}_j + \beta_2 \text{Call-In}_j + \beta_3 \text{Negotiate}_j \\ & + \gamma_1 N\text{call}_k + \gamma_2 N\text{call}_k^2 + \alpha_k + \rho_j + \delta_t + \epsilon_{ij} \end{aligned} \quad (1)$$

where  $\text{Posted}_j$  equals 1 if  $\text{Bill}_{ij}$  corresponds to the best price posted on retailer  $j$ 's website,  $\text{Call-In}_j$  equals 1 if  $\text{Bill}_{ij}$  corresponds to the price obtained during the call-in stage of a call, and  $\text{Negotiate}_j$  equals 1 if  $\text{Bill}_{ij}$  corresponds to the negotiate stage of a call. To implement these regressions, for each call we stack four prices such that call  $i$  contains four prices for firm  $j$ : default, posted, call-in, and negotiated. The default and posted prices are common across calls for retailer  $j$ , while the call-in and negotiated prices are specific to call  $i$  and retailer  $j$ . Given our 336 combinations of customer types and firms, this implies a sample size of  $336 \times 4 = 1344$  prices for estimating (1). As the omitted category in (1) is a retailer's default price, the  $\beta$ 's in (1) correspond to percentage discounts relative to default prices.

To improve the efficiency of our coefficient estimates, our regression also includes actor  $k$ , retailer  $j$ , and date-of-call  $t$  fixed effects: respectively,  $\alpha_k$ ,  $\rho_j$ , and  $\delta_t$ . We also include the cumulative number of calls made by an actor by the time they made call  $i$  and its square,  $N\text{call}_k$  and  $N\text{call}_k^2$ , to account for any actor-experience effects on negotiated offers. To

---

<sup>16</sup>The closest theoretical analysis of price posting and negotiation in an oligopoly that we can find is [Anderson et al. \(2019\)](#). While they focus on symmetric equilibria in their theoretical analysis, our empirics below reveal important asymmetries in post and negotiate pricing structures in practice.

Table 1: Discounting Among New Customers and Switchers

	All Contracts (1)	Excluding Default Contracts (2)
Posted	-0.242*** (0.017)	
Call-In	-0.257*** (0.016)	-0.015* (0.008)
Negotiated	-0.282*** (0.018)	-0.040*** (0.010)
R-Squared	0.809	0.499
Observations	1648	1231

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. In column (1) the omitted category is the firm’s default contract. Column (2) drops the default contracts and presents call-in and negotiated price discounts relative to the posted price. Standard errors are clustered to allow for arbitrary covariance at the firm and contract type level. All regressions include actor, retailer, and date fixed effects, and the number of calls made by an actor up to that point, and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

further improve precision, we also use data from 59 pilot calls which brings our total sample size to  $(336 + 59) \times 4 = 1580$ .<sup>17</sup> Standard errors are clustered at the retailer-contract type level. This follows a similar approach to inference in audit studies used in studies of labor market discrimination (e.g. [Bertrand and Mullainathan, 2004](#)).

Table 1 presents our baseline results. In column (1) all bill reductions are shown relative to the default price as per equation (1). We find that posted prices are 24.2% lower than default contracts and that the magnitude of call-in and negotiate discounts grow further to 25.7% and 28.2%, respectively.

In column (2) of the table, and in all subsequent regressions in the paper, we focus on the tension between posted and negotiated prices. We therefore drop default prices from the sample and posted prices becomes the omitted category. In this case, the  $\beta$ ’s on  $\text{Call-In}_j$  and  $\text{Negotiate}_j$  in equation (1) quantify the percentage discounts of call-in and negotiated prices relative to posted prices. We find that customers obtain a 1.5% discount from calling to obtain a price quote. When they further negotiate during the call, this discount rises to 4.0%. These discounts are individually statistically significant, and a joint test of their equality rejects the null ( $p < 0.001$ ).

<sup>17</sup>While including pilot calls that are identical in terms of execution help improve the precision of our regression model estimates, they have no impact on any of our coefficient estimates. Results that exclude pilot calls are available upon request.

## Economic magnitudes

The call-in and negotiated price reductions are statistically-different from zero, but are they economically-meaningful? The following back-of-the-envelope calculations suggest that they are.

On the consumer side, an average annual savings of \$90 represents almost 7 hours of minimum wage work.<sup>18</sup> We obtained price quotes for a two-person household living in an apartment. A household with children, or with older less energy-efficient appliances is likely to consume more electricity, and hence leave more money on the table if they fail to negotiate. Although we did not vary expected consumption levels in our experiment, we also note in Appendix C that negotiating leads disproportionately to reductions in variable rates, so the above estimate is likely to be a lower bound on the potential savings for larger electricity users.

On the firm side, we translate the price reductions to changes in margins. Through the federal government’s unique access to customer-level contract data and firm cost data, the ACCC estimates that Victorian retailers earn an 11% profit margin on average. (ACCC, 2018) In dollar terms, this implies that \$160 of a customer’s \$1457 annual before-tax electricity bill is retailer profit. Moreover, historical data from the ACCC reveals that the average retail margin was also 11% in 2009 when the retail market was first deregulated. That is, market power has persisted over time despite the introduction of retail competition and the entry of mid-sized and smaller competitors to compete with the three large incumbent firms. This persistence has ultimately led to Victoria having the highest retail electricity margins in the world by 2017, as documented by the anti-trust authority.<sup>19</sup>

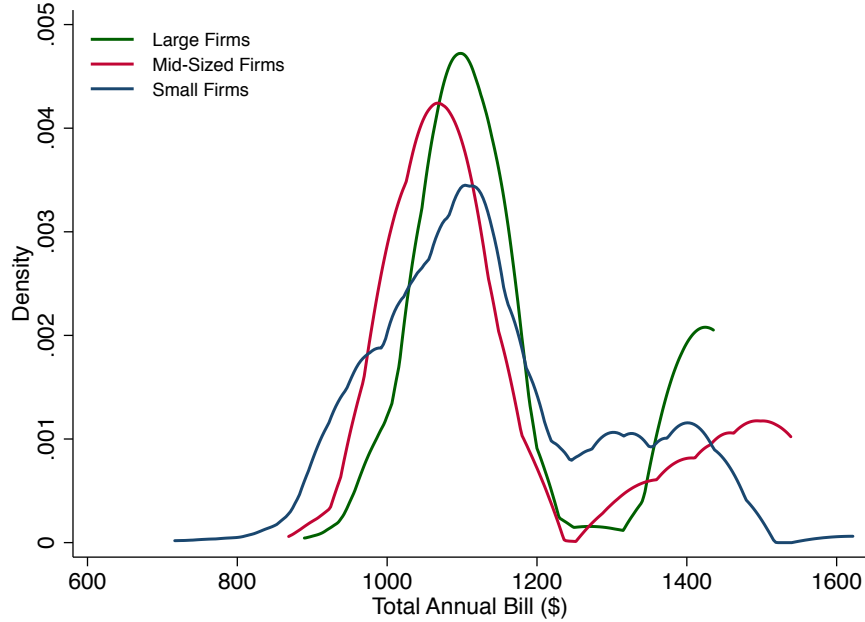
From the Lerner Index, an average annual bill of \$1457 with a retail margin of 11 percentage points (pps) implies an annual cost to serve of \$1297 per customer. Applying our estimates of negotiation effects on electricity costs, a 4 pp bill reduction relative to average usage yields average annual bill of \$1399. This implies a reduction in profit margin from negotiation to 8 pps. In other words, retail profit margins decrease from 11 to 8 pps, or by 27%, when customers negotiate. In this sense, our estimated negotiated price discounts are economically significant.

---

<sup>18</sup>Calculated based on 2017 federal minimum wage of \$18.29, or \$13.10 per hour after-tax assuming a 38-hour work week and no tax-free threshold.

<sup>19</sup>All margin figures correspond to earnings before interest, taxes, depreciation and amortization. See ACCC (2018) (Fig 1.22) and calculations therein for world rankings of retail electricity market margins.

Figure 3: Distribution of Annual Energy Bills Across Firm Types, Pooling Contracts



## 4.2 Pricing structures of large and small firms

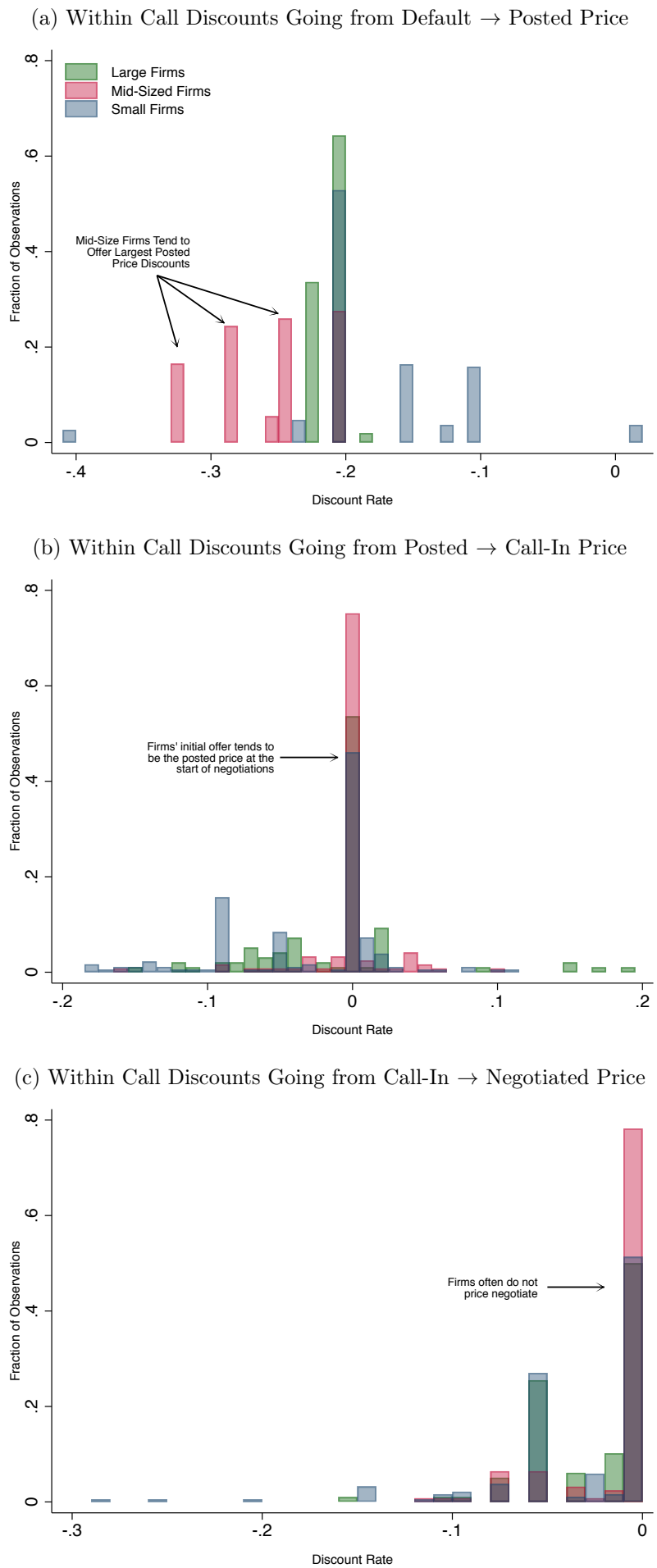
Our discussion of customer demand in Section 2 emphasized differences in customer switching rates and inertia between large incumbent firms and mid-sized and small entrants, pointing to market segmentation based on customers' willingness to search for prices and switch firms. This asymmetry in firm size and customer inertia motivates us to see whether firms adopt different pricing structures in terms of price posting and negotiation.

Figure 3 plots the distributions of prices for each firm type, pooling default, posted, call-in, and negotiated prices.<sup>20</sup> For each firm type we find a bi-modal distribution, where the right-most mass corresponds to default prices. The distribution of prices around the left-most modes is not clearly ordered by firm size. Ignoring default prices, we find that the median annual energy bill for large and small firms (\$1108 and \$1109) is higher than for mid-sized firms (\$1074). But small firms have a larger mass of prices with highly discounted annual bills below \$950, suggesting that they also offer the most competitive prices.

Figure 4 further summarizes differences in discounting across the firm types. Here, we plot the distribution of within-call discounts when going from default to posted prices (Panel (a)), posted to call-in prices (Panel (b)), and call-in to negotiated prices (Panel (c)).

<sup>20</sup>Recall firm types are defined as: Large: > 1,000,000 customers (3 firms, 60% share); Mid-sized: 200,000 – 1,000,000 customers (3 firms, 28% share); Small: < 200,000 customers (6 firms, 12% share). We omit one small firm due to its idiosyncratic pricing structure (pre-pay, created its own non-per kWh units for pricing).

Figure 4: Distribution of Discounting Rates by Firm Type



Panel (a) shows that mid-sized firms systematically offer larger discounts off of posted prices relative to default prices. Indeed, mid-sized firms’ discounts range between 25% and 32%, whereas the majority of large and small firms’ discounts range between 20% and 23%. These differences in discounting are partly driven by the fact that mid-sized firms offer higher default prices, as shown in Figure 3 above. This practice allows mid-sized firms to advertise larger “discounted” prices since, as mentioned in Section 2, it is the percentage discounts of posted prices relative to default prices that are commonly used in print, online, and television-based advertising in the market (ACCC, 2018).

Panel (b) of Figure 4, which compares posted and call-in prices, contains a large mass around 0 for each firm type. This mass at 0 implies that firms’ initial price offer during the call-in stage of a call is often anchored to the posted price. There are, however, important asymmetries. Mid-sized firms’ posted and call-in prices are the same more than 75% of the time, while this is true only 50% of the time for large and small firms. These patterns highlight a first source of asymmetry in firms’ pricing structures: mid-sized firms advertise lower prices (Panel (a)) and are less willing to immediately offer private discounts when a customer calls in to obtain a price quote (Panel (b)).

Panel (c) reveals two additional key patterns in the way in which firms discount negotiated prices relative to call-in prices. First, for all firm types, we find a mass around 0 which implies that firms sometimes do not engage in further negotiation at all after the call-in price is offered. Second, there is important asymmetry in firms’ willingness to discount: whereas small and large firms are willing to negotiate in more than 50% of calls, mid-sized firms are only willing to negotiate in 20% of calls.<sup>21</sup>

### Estimating firm-specific discounts

To formally investigate asymmetry in firms’ price posting and negotiation behavior, we augment our baseline regression as follows:

$$\begin{aligned}
\log(\text{Bill}_{ij}) = & \beta_0 + \beta_1 \text{Mid-sized}_j + \beta_2 \text{Small}_j \\
& + \beta_3 \text{Call-In}_j + \beta_4 \text{Call-In}_j \times \text{Mid-sized}_j + \beta_5 \text{Call-In}_j \times \text{Small}_j \\
& + \beta_6 \text{Negotiated}_j + \beta_7 \text{Negotiated}_j \times \text{Mid-sized}_j + \beta_8 \text{Negotiated}_j \times \text{Small}_j \\
& + \gamma_1 N\text{Call}_k + \gamma_2 N\text{Call}_k^2 + \alpha_k + \delta_t + \epsilon_{ij}
\end{aligned} \tag{2}$$

where  $\text{Mid-sized}_j$  equals 1 if firm  $j$  is a mid-sized firm, and  $\text{Small}_j$  equals 1 if firm  $j$  is a small firm. All other regressors are the same as those in our baseline regression with the exception

---

<sup>21</sup>Linear probability models confirm mid-sized firms are indeed statistically different from the large and small firms in terms of their propensity to offer discounts on negotiated prices relative to call-in prices.



that we do not include firm fixed effects to simplify interpretation of the coefficients on  $\text{Mid-sized}_j$  and  $\text{Small}_j$ . All of our results are robust to including firm fixed effects.

We estimate (2) using the sample of posted, call-in, and negotiated prices, with the base category being large firms' posted prices. The coefficients  $\beta_1$  and  $\beta_2$  therefore capture the degree to which mid-sized and small firms' posted prices are, respectively, discounted relative to large firms' posted prices. Similarly, the coefficients  $\beta_3$  and  $\beta_6$  represent call-in and negotiated price discounts for large firms relative to large firms' posted prices. The other  $\beta$ 's in the regression capture differences in call-in and posted price discounting among mid-sized and small firms relative to large firms.

We graphically present our regression results in Figure 5, with the individual coefficient estimates from (2) being presented in Appendix Table A.1. The figure plots the estimated cumulative discount of posted, call-in, negotiated prices by firm size, along with 90% confidence intervals.<sup>22</sup> Graphing the regression results in this way helps visualize across the firm types the relative magnitudes of discounts as well as the relative rates at which discounts grow across posted, call-in, and negotiated price offers.

Three main results emerge from the figure. First, cumulative negotiated discounts order by firm size: large, mid-sized, and small firms respectively offer 3.6%, 5.1%, and 8.1% negotiated price discounts relative to large firms' posted prices. Each of these discounts is statistically significantly different from 0. Economically, these differences in negotiated discounts are large; however, a joint test of equality reveals that the cumulative negotiated discounts across the three firm types are not significantly different ( $p = 0.43$ ), which in part reflects our sample size and variability in negotiated prices among small firms from Figure 3.

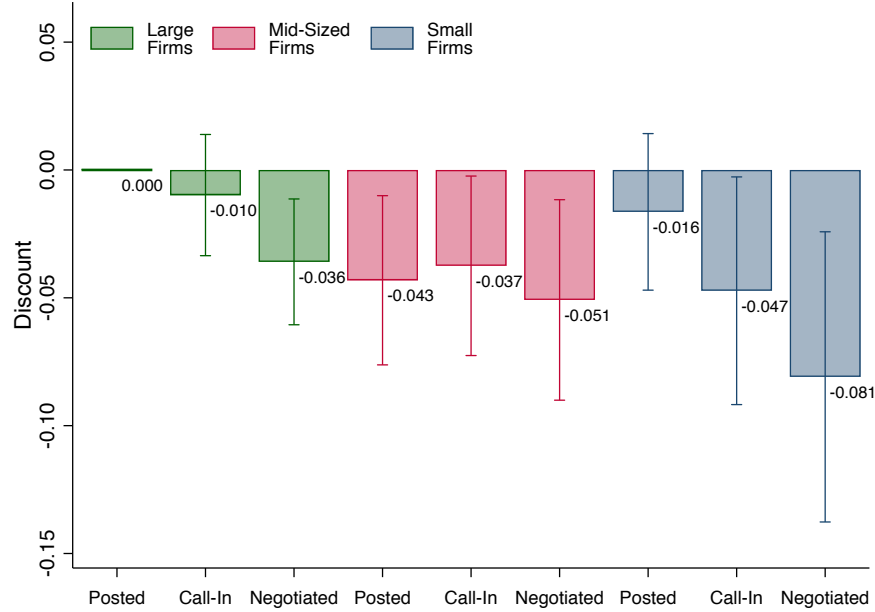
The second key finding relates to the relative discounting rates across contracts within each firm type. Both large and small firms' cumulative negotiated price discounts of 3.6% and 8.1% are statistically significantly different from their respective posted price discounts of 0.0% (base group) and 1.6%. In contrast, there are no statistical differences in mid-size firms' posted, call-in, and negotiated discounts of 4.3%, 3.7%, and 5.1%. In short, while large and small firms negotiate discounts off of their posted prices, mid-sized firms do not.

Finally, comparing posted price levels across firms, we find that relative to large firms' posted prices, mid-sized and small firms discount their posted prices by 4.3% and 1.6%, respectively. However, only the mid-sized firms' discount has a statistically significant difference ( $p = 0.034$ ).

---

<sup>22</sup>For example, the middle three red bars for mid-sized firms' posted, call-in, and negotiated price discounts relative to large firms' posted prices (the base category) are computed from (2) as  $\hat{\beta}_1$ ,  $(\hat{\beta}_1 + \hat{\beta}_3 + \hat{\beta}_4)$ , and  $(\hat{\beta}_1 + \hat{\beta}_3 + \hat{\beta}_4 + \hat{\beta}_6 + \hat{\beta}_7)$ , respectively.

Figure 5: Price Posting and Negotiation Among Large, Mid-sized, and Small Firms



Taken together, these results establish asymmetric pricing structures in terms of price posting and negotiation. Large firms post relatively high prices, but are willing to negotiate. Mid-size firms post relatively low prices but are unwilling to negotiate further from their posted price levels. Small firms post at similar levels to large and mid-sized firms, but are willing to provide substantially larger negotiated price discounts.

We believe that these asymmetric pricing structures relate back to customer segmentation based on willingness to search and switch retailers from (ACCC, 2018). Large incumbent firms are able to exploit their captive base of customers by posting high prices, but are willing to negotiate with rival firms' customers to steal them. Mid-sized firms mainly compete through their relatively low posted prices, and as such target customers whose search costs are sufficiently low that they are willing to search among retailers online, but whose bargaining costs<sup>23</sup> prevent them from going further in obtaining negotiated price discounts.<sup>24</sup> Small firms, through their willingness to negotiate steep discounts, compete for the segment of customers whose search and bargaining costs are sufficiently low that they are willing to fully engage in price negotiation.

<sup>23</sup>Jindal and Newberry (2018) identify and estimate household-level bargaining costs in a retail market.

<sup>24</sup>Summary statistics from Section 3.4 are in-line with this form of customer segmentation. In particular, the fact that mid-sized firms offer the highest posted price discount relative to default prices combined with the fact that this is the headline discount advertised in online, television, and print media allows mid-sized firms to most aggressively compete for customers who are influenced by these forms of advertising or who primarily search for electricity prices using the internet.

## 5 Bargaining, Information Revelation, and Discrimination

In light of our Section 4 findings, we can summarize firms' pricing structures as involving two interrelated forms of price discrimination:

- 2<sup>nd</sup>-degree (indirect) price discrimination: posted and negotiated prices screen customers based on their (private) willingness to call-in and negotiate and;
- 1<sup>st</sup>-degree (direct) price discrimination: among customers who negotiate, firms offer personalized discounts, potentially based on their individual characteristics.

In this section, we examine the latter form of price discrimination by showing how four of our different experimental conditions, *context for call*, *reference price*, *information source*, and *subsidy status*, give rise to negotiated price dispersion. In particular, we test hypotheses **H1-H4** from Section 3.2 above.

### 5.1 Context for call

To examine the impact on negotiated prices from a customer being new to the market vs. looking to switch from a rival (*context for call*), we adapt our regression equation as follows:

$$\begin{aligned} \log(\text{Bill}_{ij}) = & \beta_0 + \beta_1 \text{Call-In}_j + \beta_2 \text{Call-In}_j \times \text{Switcher}_i \\ & + \beta_3 \text{Negotiate}_j + \beta_4 \text{Negotiate}_j \times \text{Switcher}_i \\ & + \gamma_1 N\text{call}_k + \gamma_2 N\text{call}_k^2 + \alpha_k + \rho_j + \delta_t + \epsilon_{ij} \end{aligned} \quad (3)$$

where  $\text{Switcher}_i$  equals one if caller  $i$  is assigned to the switching customer experimental condition, and all discounts are expressed relative to posted prices. OLS estimates of  $\beta_2$  and  $\beta_4$  therefore reveal whether firms price discriminate against new customers. From **H1**, we hypothesize that relative to existing switchers in the market, new customers have higher perceived search costs and will be offered higher prices during the call-in stage. Under **H1** we therefore expect that  $\beta_2 < 0$  in (3). Moreover, if subsequent negotiations on the calls are unable to overcome any initial search-based price discrimination, we would further find that  $\beta_4 < 0$ .

Table 2 presents our results. For comparison, we reproduce our baseline estimates in column (1); the coefficient estimates from (3) are presented in column (2). Overall, our results are in-line with **H1** and search-based price discrimination. Switchers receive an additional 1.3% call-in discount above and beyond the (statistically insignificant) 0.9% call-in discount

Table 2: Discounting Among New Customers and Switchers

	(1)	(2)
Call-In	-0.015* (0.008)	-0.009 (0.009)
Call-In $\times$ Switcher		-0.013 (0.009)
Negotiated	-0.040*** (0.010)	-0.032*** (0.011)
Negotiated $\times$ Switcher		-0.018* (0.010)
R-Squared	0.499	0.504
Observations	1231	1231

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered at the firm and contract type level. All regressions include actor, retailer, and date fixed effects, and the number of calls made by an actor up to that point, and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

offered to new customers. The total call-in discount for switchers of 2.3% is statistically significant ( $p = 0.016$ ), though the 1.3% additional discount they receive relative to new customers is marginally insignificant with  $p = 0.11$ . In sum, during the call-in phase of negotiations, firms discriminate against new customers.

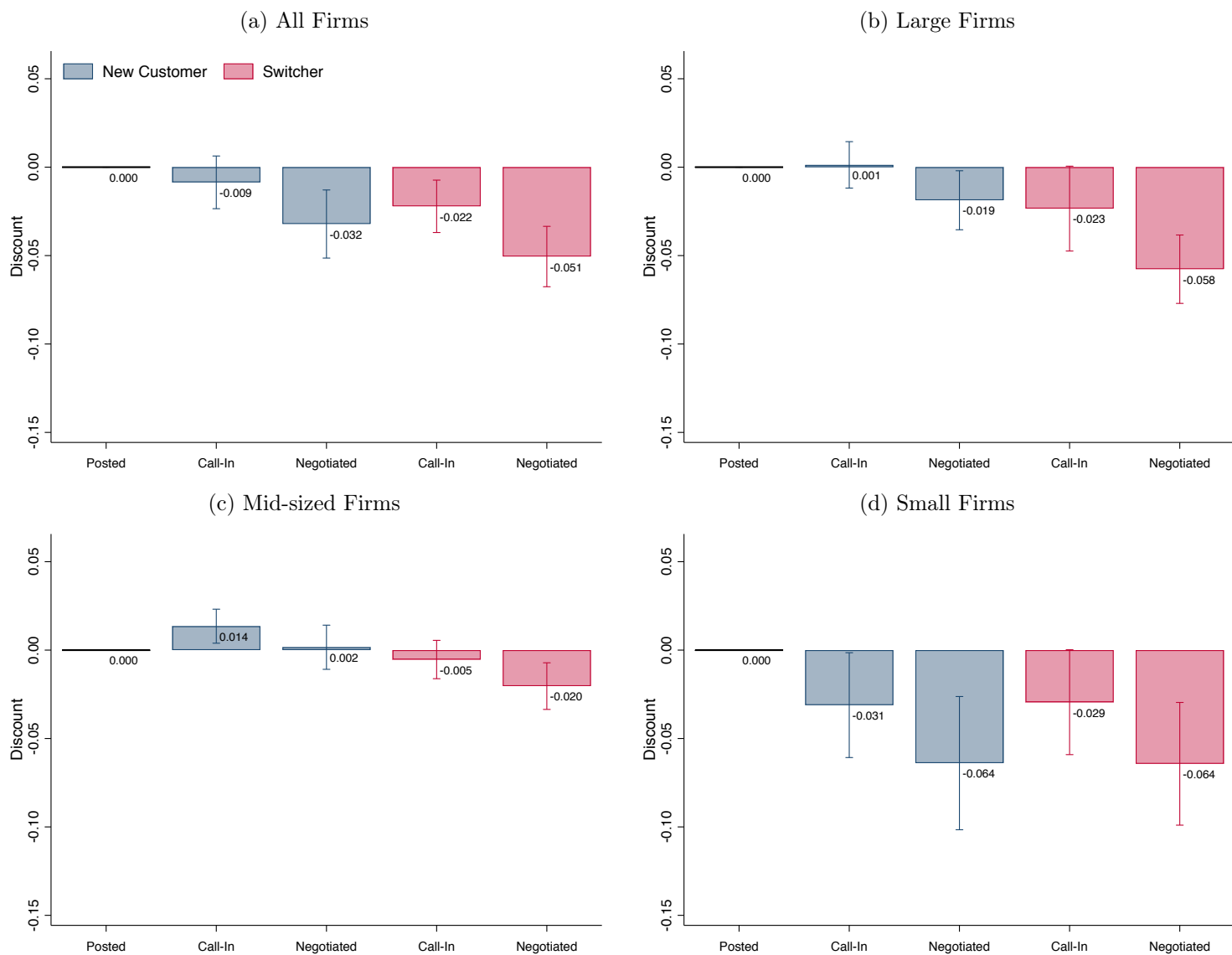
Turning to negotiated prices, we find that new customers and switchers respectively realize 3.2% and 5.0% negotiated price discounts, both of which are statistically significant with  $p < 0.001$ . Moreover, the 1.8% additional discount realized by switchers is statistically significant ( $p = 0.06$ ) and large in relative magnitude. That is, price discrimination against new customers persists through negotiations. This highlights a connection between search-based price discrimination and negotiation: firms' strategy of initially offering higher prices to customers with higher perceived search costs establishes a benchmark price from which firms are ultimately able obtain higher prices within a sequential bargaining environment with Coasian dynamics.

### Asymmetry in price discrimination

Figure 6 visualizes the regression estimates from Table 2 and presents discounting rates across call-in and negotiated prices for new customers and switchers among large, mid-sized, and small firms. Panel (a) presents results for all firms, which corresponds to column (2) of Table 2, while panels (b)-(d), presents discounting rates for the respective firm types.<sup>25</sup>

<sup>25</sup>Table A.2 in the Appendix presents the regression coefficient estimates for panels (b)-(d) of Figure 6.

Figure 6: Differences in Discounting Among New Customers and Switchers by Large, Mid-sized, and Small Firms



Large firms' discounting in panel (b) mirrors the patterns in panel (a): switchers are offered large and statistically significant call-in discounts of 2.3% relative to posted prices, which compare to an insignificant discount of 0.1% for new customers, with both new customers and switchers being offered statistically significant negotiated price discounts of 1.9% and 5.8%, respectively. The additional 3.9% discount in negotiated prices received by switchers relative to new customers is also statistically significant ( $p = 0.07$ ), implying that price discrimination persists through negotiations among the large firms.

Mid-sized firms discriminate against new customers in a different manner. They begin calls by offering new customers 1.4% *higher* prices relative to switchers, a significant difference with  $p = 0.09$ . In contrast, switchers are not offered a call-in premium nor discount relative to posted prices. From there, negotiated price discounts are only offered to switchers and the magnitude of this discount is 2.0% ( $p = 0.09$ ). Again, price discrimination emerges at the start of calls and persists throughout negotiations for mid-sized firms.

Small firms offer the lowest call-in and negotiated price discounts to both new customers and switchers. Moreover, in contrast to large and mid-sized firms, small firms do not engage in search-based price discrimination. This is consistent with smaller firms offering low prices to everyone to steal customers from their rivals. Related to our discussion from Section 4, this potentially reflects the willing-to-negotiate customer segment small firms tend to attract regardless of call context, causing them to not put any weight on whether a customer is new to the market in making their pricing decisions.

## 5.2 Reference prices

Having found evidence of price discrimination related to perceived search costs during the call-in stage, we now investigate how ex-post revelation of a customers' informedness about the *reference price*, and hence their revealed level of search cost, affects negotiations. Our analysis is based on the following regression:

$$\begin{aligned} \log(\text{Bill}_{ij}) = & \beta_0 + \beta_1 \text{Call-In}_j + \beta_2 \text{Call-In}_j \times \text{Switcher}_i \\ & + \beta_3 \text{Negotiate}_j + \beta_4 \text{Negotiate}_j \times \text{Switcher}_i \\ & + \beta_5 \text{Negotiate}_j \times \text{LowRef}_i + \beta_6 \text{Negotiate}_j \times \text{Switcher}_i \times \text{LowRef}_i \\ & + \gamma_1 \text{Ncall}_k + \gamma_2 \text{Ncall}_k^2 + \alpha_k + \rho_j + \delta_t + \epsilon_{ij} \end{aligned} \quad (4)$$

where  $\text{LowRef}_i$  equals one if household  $i$  negotiates with a low reference price. Hypothesis H2 says that, holding all else equal, relatively informed customers who negotiate with lower reference prices in a sequential bargaining game will obtain lower negotiated prices.

Table 3: Impact of Reference Prices on Negotiation Outcomes

	(1)	(2)	(3)
Call-In	-0.015*	-0.015*	-0.009
	(0.008)	(0.008)	(0.009)
Call-In $\times$ Switcher			-0.014
			(0.008)
Negotiated	-0.040***	-0.034***	-0.022*
	(0.010)	(0.010)	(0.012)
Negotiated $\times$ Switcher			-0.025*
			(0.014)
Negotiated $\times$ Low Reference Price		-0.014**	-0.021*
		(0.006)	(0.011)
Negotiated $\times$ Switcher $\times$ Low Reference Price			0.013
			(0.015)
R-Squared	0.499	0.502	0.507
Observations	1231	1231	1231

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered at the firm and contract type level. All regressions include actor, retailer, and date fixed effects, and the number of calls made by an actor up to that point, and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

Therefore, we expect that  $\beta_5 < 0$  in the regression equation. A related question of interest is whether new customers can overcome call-in stage price discrimination by subsequently revealing that they are informed during the negotiate stage and have a low reference price. Empirically, this is the case if negotiated price discounts are the same for new customers and switchers who reveal low reference prices, that is if  $\beta_6 = 0$ .

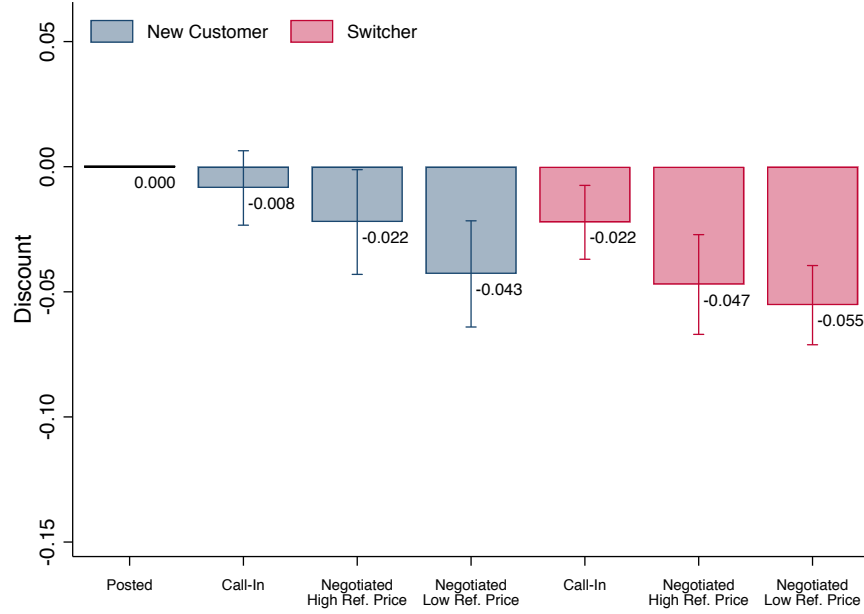
Table 3 presents our results. The column (2) estimates confirm **H2**: households who negotiate with a high reference price realize a 3.4% discount while those with low reference prices earn a 4.8% discount, with the 1.4 percentage point difference in the discounts being both statistically and economically significant. Being informed about market prices to form a reference price matters in negotiations with alternating offers.

Column (3) of Table 3 presents the full set of coefficient estimates from (4). We complement these results with Figure 7 which visualizes the implied total call-in and negotiated discounts among new customers and switchers. We obtain two results. First, new customers are indeed able to overcome call-in price discrimination if they negotiate with low reference prices. This is most clearly seen in the Figure 7, where the 4.3% and 5.5% negotiated discounts among new customers and switchers with low reference prices have a statistically insignificant difference ( $p = 0.18$ ).

Our second result is that negotiating with low reference prices is more important for new



Figure 7: Impact of Reference Prices on Negotiation



customers than for switchers. Returning to Figure 7, new customers realize 2.2% and 4.3% discounts when negotiating with high and low reference prices, respectively. This 1.9 percentage point difference in discounts is both large and statistically significant. In contrast, switchers realize 4.7% and 5.5% discounts when negotiating with high and low reference prices. In this case, the 0.8 percentage point difference in discounting is statistically insignificant. That is, firms are more responsive to information revelation over low reference prices for customers who *a priori* have higher perceived search costs. This further underscores our central finding of search-based price discrimination, particularly when firms use negotiation as a pricing mechanism in markets with consumer search frictions.<sup>26</sup>

<sup>26</sup>We obtain similar results regarding ex-ante price discrimination and ex-post information revelation among large, mid-sized, and small firms. See Table A.3 and Figure A.1 in the Appendix.

### 5.3 Information source

Does the *information source* for reference prices matter in negotiations? We use the following regression to examine this:

$$\begin{aligned} \log(\text{Bill}_{ij}) = & \beta_0 + \beta_1 \text{Call-In}_j + \beta_2 \text{Negotiate}_j + \beta_3 \text{Negotiate}_j \times \text{Called } 1_i \\ & + \beta_4 \text{Negotiate}_j \times \text{Called } 3_i + \beta_5 \text{Negotiate}_j \times \text{Platform}_i \\ & + \gamma_1 \text{Ncall}_k + \gamma_2 \text{Ncall}_k^2 + \alpha_k + \rho_j + \delta_t + \epsilon_{ij} \end{aligned} \quad (5)$$

where  $\text{Called } 1_i$ ,  $\text{Called } 3_i$ ,  $\text{Platform}_i$ , and  $\text{Friend}_i$  are dummy variables that respectively equal one the information source for the reference price in call  $i$  is called one rival firm, called three rival firms, or searched on the online government platform. The information source for the base group is having asked a friend.

From our discussion in Section 3.2 above, we might expect that  $\beta_3 < \beta_4$  if firms offer lower prices to customers who are earlier in a sequential search process to preempt them from obtaining lower prices from further search. Alternatively, if firms perceive customers who have called 3 rivals as signaling low search costs, then we would expect  $\beta_3 > \beta_4$  if firms offer low prices to compete for customers with lower perceived search costs. Whether the preemption versus signaling channel dominates will govern the relative magnitudes of  $\beta_3$  and  $\beta_4$ . Finally, from hypothesis H3, we expect  $\beta_5 < 0$  if firms put more weight on information obtained from the government search platform than simply having asked a friend.

The regression coefficient estimates from (5) are presented in column (2) of Table 4. Conditional on the reference price, we find that the information source itself has virtually no impact on negotiated prices. Column (3) of the table adds interactions with the  $\text{Switcher}_i$  dummy to allow for heterogeneity based on call context. Again, we find no meaningful impact of the information source among new customers and switchers. This is clearly seen in panel (a) of Figure 8 where, as above, we plot total discounts for new customers and switchers as a function of the information source, as implied by the regression estimates. Panel (b) of the figure similarly plots discounting rates depending on whether a customer negotiates with a high or low reference price. Again, we find little impact of the information source. All that matters is the reference price from which a customer negotiates.<sup>27</sup>

---

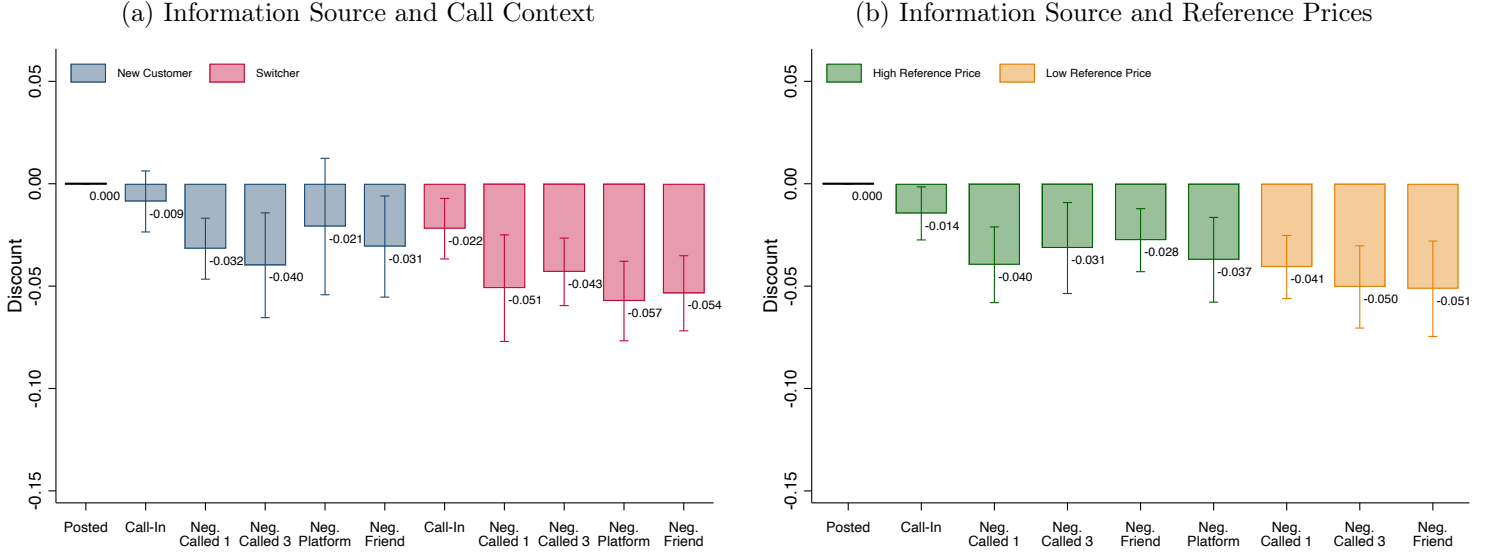
<sup>27</sup>In panel (b) of Figure 8 there is no “Negotiate (Neg.) Platform” condition for low reference prices because, as described in Section 3.1 above, all negotiations that rely on platform-based information quote high reference prices. Appendix Table A.4 contains the regression coefficient estimates used to construct panel (b) of Figure 8.

Table 4: Impact of Information Source on Negotiation Outcomes

	(1)	(2)	(3)
Call-In	-0.015*	-0.017**	-0.011
	(0.008)	(0.008)	(0.009)
Call-In $\times$ Switcher			-0.013
			(0.009)
Negotiated	-0.040***	-0.040***	-0.030**
	(0.010)	(0.011)	(0.015)
Negotiated $\times$ Switcher			-0.023
			(0.014)
Negotiated $\times$ Called 1 Rival		0.000	-0.001
		(0.008)	(0.010)
Negotiated $\times$ Called 1 Rival $\times$ Switcher			0.004
			(0.020)
Negotiated $\times$ Called 3 Rivals		-0.001	-0.010
		(0.008)	(0.011)
Negotiated $\times$ Called 3 Rivals $\times$ Switcher			0.020*
			(0.011)
Negotiated $\times$ Platform		0.001	0.007
		(0.010)	(0.019)
Negotiated $\times$ Platform $\times$ Switcher			-0.013
			(0.025)
R-Squared	0.499	0.499	0.504
Observations	1231	1231	1231

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered at the firm and contract type level. All regressions include actor, retailer, and date fixed effects, and the number of calls made by an actor up to that point, and its square. Columns (2) and (3) also control for whether a caller negotiated with a low reference price. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

Figure 8: Impact of Information Source on Negotiation Outcomes by Search Context and Reference Price



## 5.4 Subsidy status

Our last experimental condition, *subsidy status*, varies a household's subsidy status, where recall the state government offers 17.5% discounts off of total annual electricity bills for disadvantaged groups. Further recall from our discussion in Section 3.1 that we immediately reveal subsidy eligibility during the call-in stage of the calls. Given this, we estimate the impact of subsidy status on call-in and negotiated prices using the following regression:

$$\begin{aligned}
 \log(\text{Bill}_{ij}) = & \beta_0 + \beta_1 \text{Call-In}_j + \beta_2 \text{Call-In}_j \times \text{Subsidy}_i \\
 & + \beta_3 \text{Negotiate}_j + \beta_4 \text{Negotiate}_j \times \text{Subsidy}_i \\
 & + \gamma_1 N\text{call}_k + \gamma_2 N\text{call}_k^2 + \alpha_k + \rho_j + \delta_t + \epsilon_{ij}
 \end{aligned} \tag{6}$$

where  $\text{Subsidy}_i$  equals one if in call  $i$  the caller states that they are eligible for the government subsidy. Under Hypothesis H4, we would expect  $\beta_2 > 0$  and  $\beta_4 > 0$  if firms exercise market power and target higher prices to customers who receive government subsidies. As discussed above, such a supply-side response is a first-order concern for policymakers. Identifying it, however, is typically confounded by selection into subsidy eligibility. Because we are able to randomize subsidy status, we can obtain consistent estimates of  $\beta_2$  and  $\beta_4$  via OLS to identify such rent seeking.

Despite the public concern of the issue, our results in column (2) of Table 5 reveal little evidence of subsidy-based price discrimination in the market that we study. In Appendix

Table 5: Subsidy Status and Incomplete Passthrough in Negotiations

	(1)	(2)
Call-In	-0.015* (0.008)	-0.013 (0.009)
Call-In $\times$ Concession		-0.002 (0.006)
Negotiated	-0.040*** (0.010)	-0.040*** (0.011)
Negotiated $\times$ Concession		-0.000 (0.007)
R-Squared	0.499	0.498
Observations	1231	1231

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered at the firm and contract type level. All regressions include actor, retailer, and date fixed effects, and the number of calls made by an actor up to that point, and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

tables A.5–A.7, we further show that there is no evidence of subsidy-based price discrimination among new customers and switchers, the three different firm types, and customers with high or low reference prices.

## 6 Conclusion

Price posting and private negotiation characterizes pricing behavior in many important markets, yet there is little research into these pricing structures in part because of limited access to negotiated price data. Using a field experiment that borrows from audit studies typically used to study labor market discrimination, we provide a unique empirical analysis of price posting, negotiation, and discrimination in an oligopoly.

Our study delivers three important findings. First, we document substantial dispersion between posted and negotiated prices as well as characterize asymmetric pricing structures across different firm sizes and incumbency that gives rise to customer segmentation based on willingness to search and bargain. Second, we leverage a within-negotiation experimental design to study information revelation within a sequential bargaining environment. We find evidence of price discrimination based on perceived search costs that persists through negotiations if a customer is in fact uninformed about prices. Finally, we highlight the value of audit studies for delivering simple yet powerful tests of incomplete subsidy pass-through and its underlying mechanisms. Collectively, our results indicate that subsidy recipients

pay higher prices because they face higher search or bargaining costs, not because firms are explicitly targeting subsidy recipients with higher prices.

Two policy questions naturally emerge from our results. The first concerns the distributional impact of the pricing structures that we observe. Specifically, to what extent do consumers that we perceive as vulnerable benefit or suffer in a market that encourages price posting and negotiation? Which types of customers engage in search and negotiation? Are low-income, elderly, or disadvantaged consumers less able to search or haggle, perhaps due to cultural, technological, or language constraints?

Audit studies reveal offered prices and their determinants, that is, prices by consumer type, but do not reveal quantities, i.e., the distribution of types in the population. However, in our context, the consumer advocacy group Energy Consumers Australia ran a large-scale survey shortly after our experiment revealing that each additional \$20,000 in household income is associated with a 4% increase in likelihood of search.<sup>28</sup> Similarly, recent evidence from [Ofgem \(2019\)](#) documents that in the United Kingdom low-income customers are least likely to search for better residential electricity contracts. The evidence from both of these studies would imply that pricing structures like the ones that we uncovered are regressive.

Our sequential bargaining results suggest that informing low-income customers about low reference prices can help mitigate this issue by strengthening their bargaining position in negotiations. However, the fact that the market we study has had a government search platform in place for more than two years when our experiment took place with low-income customers continuing to pay relatively higher prices suggests that simply making price data publicly available is, by itself, unable resolve the problem.<sup>29</sup>

This brings us to our second related policy question: should governments deregulate retail electricity markets to promote competition? We know that deregulating a geographically-based monopoly where all consumers pay the same regulated price will lead to price dispersion ([Borenstein and Rose, 1994](#)). However, is the price dispersion that we observe the one that society wants? Does deregulating electricity retailing lead to a market where consumers are segmented based on time costs, with high-income customers choosing to not invest the time, or based on confusion, unfamiliarity, and discomfort? This suggests a trade-off between a single regulated price and the dispersed prices achieved under competition with potentially regressive discrimination.

---

<sup>28</sup>Authors’ calculation based on raw data provided in [ECA \(2017\)](#). Income data collected in \$20,000 categories, with last category representing “\$150,000 or more”.

<sup>29</sup>In fact, the government is now paying customers to search on the platform, which is revealing of the perceived hurdle to using such technologies to navigate a market with price posting and private negotiation. See <https://compare.energy.vic.gov.au/> which offers a \$50 “Power Saving Bonus” simply for searching for the first time on the platform.

To the extent that search and bargaining costs are insurmountable for low-income customers, if governments want to avoid regressive pricing structures in energy markets, they may need to consider alternative market designs. One example may be the creation of centralized exchanges where firms periodically bid to be the lowest-cost supplier among a set of contract bids in the exchange where customers are defaulted to switch to the lowest cost contract each time the exchange is run. Offering low-income customers the opportunity to opt-out of a decentralized market with price posting and negotiation by opting into a centralized exchange with automatic switching to the lowest bidder may be more effective in moving low-income customers to more competitive prices in markets with search frictions, price posting, and negotiation.

In summary, our results, combined with the government's finding that lower-income customers tend to pay higher electricity prices, aligns with the notion that frictions related to search and bargaining costs are creating undesirable distributional impacts. Our findings are revealing of how market power manifests itself through search and bargaining frictions, which offsets potential gains from deregulation.



## References

- ACCC. “Restoring Electricity Affordability and Australia’s Competitive Advantage.” Technical report, Commonwealth of Australia, 2018.
- AEMC. “Retail Energy Competition Review.” Technical report, Commonwealth of Australia, 2017.
- AER. “State of the Energy Market, May 2017.” Technical report, Commonwealth of Australia, 2017.
- Akerlof, George A. “The economics of “tagging” as applied to the optimal income tax, welfare programs, and manpower planning.” *The American Economic Review* 68, 1: (1978) 8–19.
- Allen, Jason, Robert Clark, and Jean-François Houde. “Search frictions and market power in negotiated price markets.” *Journal of Political Economy* 108, 4: (2019) 833–850.
- Anderson, Simon, Alicia Baik, and Nathan Larson. “Price Discrimination in the Information Age: Prices, Poaching, and Privacy with Personalized Targeted Discounts.”, 2019. Working Paper, University of Virginia.
- Ayres, Ian, and Peter Siegelman. “Race and Gender Discrimination in Bargaining for a New Car.” *American Economic Review* 85, 3: (1995) 304–321.
- Backus, Matt, Tom Blake, Brad Larsen, and Steve Tadelis. “Sequential Bargaining in the Field: Evidence from Millions of Online Bargaining Interactions.”, 2018. NBER Working Paper No. 24306.
- Bertrand, Marianne, and Esther Dufo. “Field experiments on discrimination.” *Handbook of Economic Field Experiments* 1: (2017) 309–393.
- Bertrand, Marianne, and Sendhil Mullainathan. “Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination.” *American Economic Review* 94, 3: (2004) 991–1013.
- Borenstein, Severin, and Nancy L Rose. “Competition and price dispersion in the US airline industry.” *Journal of Political Economy* 102, 4: (1994) 653–683.
- Busse, Meghan R, Ayelet Israeli, and Florian Zettelmeyer. “Repairing the Damage: The Effect of Price Knowledge and Gender on Auto Repair Price Quotes.” *Journal of Marketing Research* 54, 1: (2017) 75–95.

- Cabral, Marika, Michael Geruso, and Neale Mahoney. “Do larger health insurance subsidies benefit patients or producers? Evidence from Medicare Advantage.” *American Economic Review* 108, 8: (2018) 2048–87.
- Castillo, Marco, Ragan Petrie, Maximo Torero, and Lise Vesterlund. “Gender differences in bargaining outcomes: A field experiment on discrimination.” *Journal of Public Economics* 99: (2013) 35–48.
- Chandra, Ambarish, Sumeet Gulati, and James M. Sallee. “Who Loses When New Prices Are Negotiated? An Analysis of the New Car Market.” *Journal of Industrial Economics* 65, 2: (2017) 235–274.
- Collinson, Robert, and Peter Ganong. “The incidence of housing voucher generosity.” *Available at SSRN* 2255799.
- ECA. “Energy Consumer Sentiment Survey June 2017.” Technical report, Energy Consumers Australia, 2017.
- Fabra, Natalia, and Mar Reguant. “A Model of Search with Price Discrimination.”, 2019. Working Paper, UCM III.
- Farrell, Joseph, and Robert Gibbons. “Cheap Talk Can Matter in Bargaining.” *Journal of Economic Theory* 48, 1: (1989) 221–237.
- Fudenberg, Drew, David Levine, and Jean Tirole. “Infinite horizon models of bargaining with one-sided uncertainty.” In *Game Theoretic Models of Bargaining*, Cambridge University Press, 1985, volume 73, 79.
- Gneezy, Uri, John List, and Michael K Price. “Toward an understanding of why people discriminate: Evidence from a series of natural field experiments.” Technical report, National Bureau of Economic Research, 2012.
- Gul, Faruk, Hugo Sonnenschein, and Robert Wilson. “Foundations of Dynamic Monopoly and the Coase Conjecture.” *Journal of Economic Theory* 39, 39: (1986) 155–190.
- Gulati, Sumeet, Carol McAusland, and James M. Sallee. “Tax incidence with endogenous quality and costly bargaining: Theory and evidence from hybrid vehicle subsidies.” *Journal of Public Economics* 155: (2017) 93 – 107. <http://www.sciencedirect.com/science/article/pii/S0047272717301469>.
- Harrison, Glenn W., and John A. List. “Field Experiments.” *Journal of Economic Literature* 42, 4: (2004) 1009–1055.

- Hortaçsu, Ali, Seyed Ali Madanizadeh, and Steven L Puller. “Power to choose? An analysis of consumer inertia in the residential electricity market.” *American Economic Journal: Economic Policy* 9, 4: (2017) 192–226.
- Jindal, Pranav, and Peter Newberry. “To Bargain or Not to Bargain: The Role of Fixed Costs in Price Negotiations.” *Journal of Marketing Research* 55, 6: (2018) 832–851.
- Johnston, May Mauseth. “Victorian Energy Prices 2016.” Technical report, St Vincent de Paul Society and Alvis Consulting Pty Ltd, 2016.
- Keniston, Daniel. “Bargaining and Welfare: A Dynamic Structural Analysis of the Autorickshaw Market.”, 2011. Working paper, Louisiana State University.
- Kenman, John, and James R. Walker. “The Effect of Expected Income on Individual Migration Decisions.” *Econometrica* 79, 1: (2011) 211–251.
- Lade, Gabriel, and James Bushnell. “Fuel Subsidy Pass-Through and Market Structure: Evidence from the Renewable Fuel Standard.” *Mimeo* .
- Larsen, Bradley J. “The Efficiency of Real-World Bargaining: Evidence from Wholesale Used-Auto Auctions.”, 2019. NBER Working Paper 20431.
- List, John A. “The Nature and Extent of Discrimination in the Marketplace: Evidence from the Field.” *Quarterly Journal of Economics* 119, 1: (2004) 49–89.
- McCall, John J. “Economics of Information and Job Search.” *Quarterly Journal of Economics* 84, 1: (1970) 113–126.
- Ofgem. “State of the Market Report.” Technical report, GfK UK SocialResearch, 2019.
- Postel-Vinay, Fabien, and Jean-Marc Robin. “Equilibrium Wage Dispersion with Worker and Employer Heterogeneity.” *Econometrica* 70, 6: (2002) 2295–2350.
- Rodgers, Luke P. “Give credit where? The incidence of child care tax credits.” *Journal of Urban Economics* 108: (2018) 51 – 71. <http://www.sciencedirect.com/science/article/pii/S0094119018300792>.
- Rubinstein, Ariel. “Perfect Equilibrium in a Bargaining Model.” *Econometrica* 50, 1: (1982) 97–109.
- Scott Morton, Fiona, Florian Zettelmeyer, and Jorge Silve-Risso. “Consumer Information and Discrimination: Does the Internet Affect the Pricing of New Cars to Women and Minorities?” *Quantitative Marketing and Economics* 1, 1: (2003) 65–92.

Shelegia, Sandro, and Joshua Sherman. “Bargaining at Retail Stores: Evidence from Vienna.”, 2017. CEPR DP 14113.

Stole, Lars A. “Price Discrimination and Competition.”, 2007.

The Brattle Group. “International Experiences in Retail Electricity Markets, Consumer Issues.” Technical report, Australian Competition and Consumer Commission, 2018.

Thwaites, John, Terry Mulder, and Patricia Faulkner. “Review of Electricity and Gas Retail Markets.” Technical report, Report to the Minister for Energy, Environment and Climate Change, 2017.

Turner, Lesley J. “The economic incidence of federal student grant aid.” *University of Maryland, College Park, MD* .

# Appendix

## A Supplemental Tables and Figures

Table A.1: Price Posting and Negotiation Among Large, mid-sized, and Small Firms

	(1)	(2)
Mid-Sized Firm		-0.043** (0.020)
Small Firm		-0.016 (0.018)
Call-In	-0.015 (0.017)	-0.010 (0.014)
Call-In $\times$ Mid-Sized Firm		0.015 (0.029)
Call-In $\times$ Small Firm		-0.021 (0.033)
Negotiated	-0.040** (0.020)	-0.036** (0.015)
Negotiated $\times$ Mid-Sized Firm		0.028 (0.031)
Negotiated $\times$ Small Firm		-0.029 (0.039)
R-Squared	0.058	0.108
Observations	1231	1231

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices, and the omitted category is large firms' posted prices. Standard errors are clustered at the firm and quote type level. All regressions include actor, date, and the number of calls made by an actor to date and its square.

\*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

Table A.2: Price Posting and Negotiation Among Large, mid-sized, and Small Firms

	All Firms (1)	All Firms (2)	Large Firms (3)	Mid-Sized Firms (4)	Small Firms (5)
Call-In	-0.015* (0.008)	-0.009 (0.009)	0.001 (0.007)	0.014** (0.005)	-0.031* (0.017)
Call-In $\times$ Switcher		-0.013 (0.009)	-0.025 (0.019)	-0.018* (0.010)	0.002 (0.015)
Negotiated	-0.040*** (0.010)	-0.032*** (0.011)	-0.019* (0.009)	0.002 (0.007)	-0.064*** (0.022)
Negotiated $\times$ Switcher		-0.018* (0.010)	-0.039* (0.018)	-0.021 (0.012)	-0.000 (0.016)
R-Squared	0.499	0.504	0.281	0.447	0.590
Observations	1231	1231	297	375	559

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices, and the omitted category is large firms' posted prices. Standard errors are clustered at the firm and quote type level. All regressions include actor, date, and the number of calls made by an actor to date and its square.

\*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

Table A.3: Impact of Reference Prices on Negotiation Among Large, mid-sized, and Small Firms

	All Firms (1)	Large Firms (2)	Mid-Sized Firms (3)	Small Firms (4)
Call-In	-0.009 (0.009)	0.002 (0.007)	0.013** (0.005)	-0.031* (0.017)
Call-In $\times$ Switcher	-0.014 (0.008)	-0.025 (0.019)	-0.018* (0.010)	0.002 (0.015)
Negotiated	-0.022* (0.012)	-0.015 (0.009)	0.017 (0.015)	-0.052** (0.023)
Negotiated $\times$ Switcher	-0.025* (0.014)	-0.036 (0.020)	-0.031 (0.019)	-0.014 (0.027)
Negotiated $\times$ Low Reference Price	-0.021* (0.011)	-0.008 (0.007)	-0.033 (0.025)	-0.023 (0.015)
Negotiated $\times$ Switcher $\times$ Low Reference Price	0.013 (0.015)	-0.011* (0.005)	0.021 (0.024)	0.027 (0.028)
R-Squared	0.507	0.281	0.459	0.592
Observations	1231	297	375	559

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices, and the omitted category is large firms' posted prices. Standard errors are clustered at the firm and quote type level. All regressions include actor, date, and the number of calls made by an actor to date and its square.

\*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

Table A.4: Impact of Information Source on Negotiation Outcomes, Including Reference Price Interactions

	(1)	(2)	(3)	(4)
Call-In	-0.015*	-0.015*	-0.009	-0.014*
	(0.008)	(0.008)	(0.009)	(0.008)
Call-In $\times$ Switcher			-0.013	
			(0.009)	
Negotiated	-0.040***	-0.041***	-0.031**	-0.027***
	(0.010)	(0.011)	(0.015)	(0.009)
Negotiated $\times$ Switcher			-0.023	
			(0.014)	
Negotiated $\times$ Low Ref. Price				-0.025**
				(0.010)
Negotiated $\times$ Called 1 Rival		0.000	-0.001	-0.013
		(0.008)	(0.010)	(0.009)
Negotiated $\times$ Called 1 Rival $\times$ Switcher			0.004	
			(0.020)	
Negotiated $\times$ Called 1 Rival $\times$ Low Ref. Price				0.024**
				(0.011)
Negotiated $\times$ Called 3 Rivals		-0.000	-0.009	-0.004
		(0.008)	(0.011)	(0.009)
Negotiated $\times$ Called 3 Rivals $\times$ Switcher			0.020*	
			(0.011)	
Negotiated $\times$ Called 3 Rivals $\times$ Low Ref. Price				0.006
				(0.013)
Negotiated $\times$ Platform		0.004	0.010	-0.009
		(0.010)	(0.019)	(0.008)
Negotiated $\times$ Platform $\times$ Switcher			-0.014	
			(0.025)	
R-Squared	0.499	0.498	0.503	0.502
Observations	1231	1231	1231	1231

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered at the firm and contract type level. All regressions include actor, firm, date, and the number of calls made by an actor to date and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$



Table A.5: Discounting, Subsidy Status, and Call Context

	(1)	(2)	(3)
Call-In	-0.015*	-0.013	-0.008
	(0.008)	(0.009)	(0.011)
Call-In $\times$ Concession		-0.002	-0.001
		(0.006)	(0.009)
Call-In $\times$ Switcher			-0.011
			(0.012)
Call-In $\times$ Concession $\times$ Switcher			-0.004
			(0.012)
Negotiated	-0.040***	-0.040***	-0.035**
	(0.010)	(0.011)	(0.014)
Negotiated $\times$ Concession		-0.000	0.005
		(0.007)	(0.010)
Negotiated $\times$ Switcher			-0.012
			(0.012)
Negotiated $\times$ Concession $\times$ Switcher			-0.013
			(0.012)
R-Squared	0.499	0.498	0.503
Observations	1231	1231	1231

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered at the firm and contract type level. All regressions include actor, firm, date, and the number of calls made by an actor to date and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

Table A.6: Discounting, Subsidy Status, and Reference Price

	(1)	(2)
Call-In	-0.013 (0.009)	-0.013 (0.009)
Call-In $\times$ Concession	-0.002 (0.006)	-0.002 (0.006)
Negotiated	-0.040*** (0.011)	-0.036*** (0.012)
Negotiated $\times$ Concession	-0.000 (0.007)	0.005 (0.009)
Negotiated $\times$ Low Reference Price		-0.008 (0.008)
Negotiated $\times$ Concession $\times$ Low Reference Price		-0.012 (0.009)
R-Squared	0.498	0.502
Observations	1231	1231

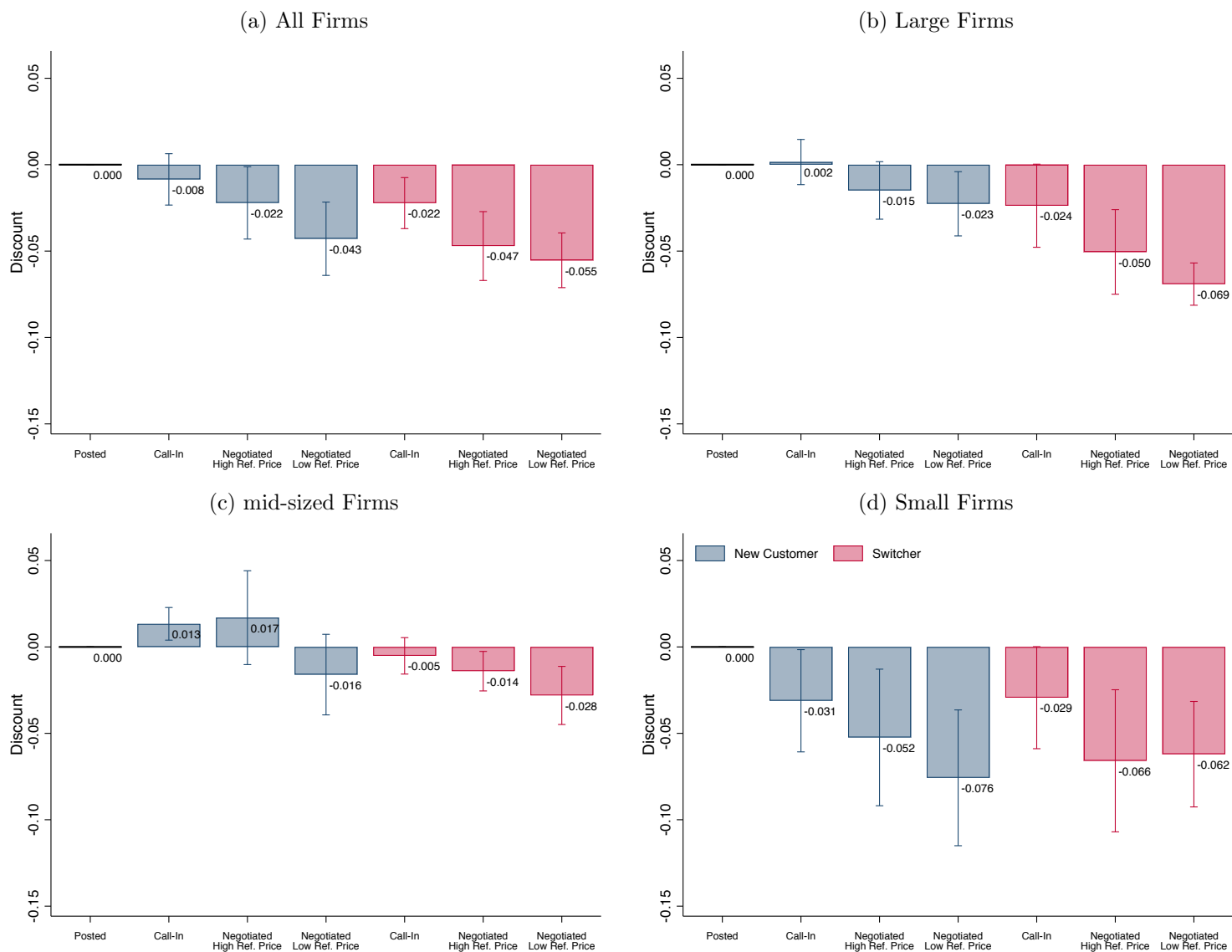
**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered at the firm and contract type level. All regressions include actor, firm, date, and the number of calls made by an actor to date and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

Table A.7: Discounting, Subsidy Status, and Firm Type

	All Firms (1)	Large Firms (2)	Mid-Sized Firms (3)	Small Firms (4)
Call-In	-0.013 (0.009)	-0.010*** (0.003)	0.007 (0.009)	-0.029* (0.017)
Call-In $\times$ Concession	-0.002 (0.006)	0.002 (0.004)	-0.006 (0.019)	-0.003 (0.007)
Negotiated	-0.040*** (0.011)	-0.032*** (0.004)	-0.006 (0.012)	-0.067*** (0.020)
Negotiated $\times$ Concession	-0.001 (0.007)	-0.006 (0.007)	-0.006 (0.021)	0.006 (0.006)
R-Squared	0.499	0.242	0.438	0.591
Observations	1229	297	373	559

**Notes:** Dependent variable is logarithm of total annual electricity bill assuming 300 kWh/month usage. The sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered at the firm and contract type level. All regressions include actor, firm, date, and the number of calls made by an actor to date and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

Figure A.1: Impact of Reference Prices on Negotiation Among Large, mid-sized, and Small Firms



## B Example Bargaining Scripts

This Appendix provides details on the bargaining scripts used in implementing our experiment. It contains two documents:

- **Bargaining Script:** this contains the structure and order of the script the actors used in obtaining call-in and negotiated prices. It highlights how the call is to be introduced, information on address is to be provided, and then how the first price quote (call-in) is to be obtained. It then shows how the second price quote (negotiated) is obtained through the revelation of search method and reference price. Finally, it describes how the conversation is to be ended promptly. Notice that the example bargaining script is for a customer who has “called around” to 1 or 3 other companies in obtaining a price quote. Slight variations on this script are made for information sources of having used the government search platform or asked a friend.
- **Price Sheet:** this is the sheet that both the caller and the student research assistant silently listening in on the call filled out during the call-in and negotiate stages of the call. It is from these price sheets that we constructed our dataset on call-in and negotiated prices.

## Bargaining Script C (Called Around)

You are now about to call **retailer X**. Please note that you have a 20-minute time limit to complete this call. If you run out of time, please conclude the call.

Introduce yourself based on your role description. Please bear in mind that they may ask more questions than the ones on this script and to answer them you should refer to Document A. **Important: Not all questions will be asked of you. Please do not provide answers not asked of you unless prompted on the script.**

### SECTION 1: DO NOT REVEAL SEARCH METHOD

Introduction	
RETAILER:	Hi, you are calling <b>retailer X</b> . My name is (sales agent's name). How can I help you?
YOU:	Hi. I want to have electricity connected to my new place. I am moving from interstate. What are your rates?  <b>I'm also eligible for an Energy Concession</b> (if applicable, else say nothing unless asked)  Only if asked: <ul style="list-style-type: none"><li>• I'm looking for a one year contract</li><li>• We use about 10kWh per day <u>or</u> 300kWh per month</li></ul> (Note: They may ask if you're interested in signing up online, in which case just say you haven't decided but ask if there's a discount for that. Also ask if discount can be applied over the phone.)
Address	
RETAILER:	Sure, may I have your address or NMI please?
YOU:	We will be moving to <b>address</b> .  Only if asked:
RETAILER:	Do you have solar panels at your new property?
YOU:	No
RETAILER:	Is there a pool at your new property?
YOU:	No
RETAILER:	Are you interested in gas as well?
YOU:	No
RETAILER:	Green energy?
YOU:	No

First Price Quote	
RETAILER:	OK. We can offer you our (name of electricity plan). It's XXXXX cents/kWh along with a XXXXX cents/day supply charge.
YOU:	Does that include GST?

RETAILER:	No, that is ex-GST.
YOU:	Is there a discount for direct debit?
RETAILER:	That plan already includes a discount for direct debit.
YOU:	How much would I have to pay without direct debit?
RETAILER:	XXXXXX% more
YOU:	So both the supply and variable charges would be that much more?
RETAILER:	Yes/No.
YOU:	<i>Confirm all of the following:</i> <ul style="list-style-type: none"> <li>• 12 month contract</li> <li>• Monthly bills</li> <li>• Bills sent via email</li> <li>• No/any penalty or exit fee if I end the contract early?</li> </ul>
YOU:	Does that price only apply if I pay my bill on time? If I don't, how much would I need to pay?
RETAILER:	Yes/No. If you don't pay on time, your total bill will be XXXX% higher.
YOU:	Does my rate increase at the end of my contract?
RETAILER:	No. Rates only increase with inflation and when we have to pass on annual increases in network charges.

## SECTION 2: REVEAL PRIOR SEARCH METHOD

Second Price Quote	
YOU:	Is this your best price? I have called <b>one company/three other companies</b> before you and I have been offered a better deal.
RETAILER:	Which company is offering you this price?
YOU:	XXXXXXXX
RETAILER:	And what did they offer?
YOU:	XXXXXX per day and XXXXXX per kWh.
RETAILER:	<i>(Retailer either provides lower new price or refuses to lower price)</i>
YOU:	Is this new plan also valid for 12 months? Are there any penalty fees?
YOU:	Can I also ask if there is a discount for direct debit payment? This is a pay-on-time price, right? How much would I pay without direct debit/without pay-on-time? <i>(record any price revisions and new plan details)</i>

### Ending the Conversation

YOU: Thank you for your help today. I'll talk with my partner and get back to you. Have a good day. Bye.

*You should decline any offer to call you back. They are likely to insist, and you should just end the conversation by asking for an ID number that you can quote if you decide to call back later followed by "Thank you for your help today. I'll talk with my partner and get back to you. Have a good day. Bye."*

--End of Conversation--

### Important:

All conversations must be kept to a maximum of **20 minutes**. The research assistant sitting beside you will notify you at the 15th-minute and 19th-minute mark. At the **second prompt, you should wrap up the conversation**. If you do not manage to complete all the stages of the bargaining script, kindly inform the researcher in-charge.

In the event that this happens, you may end the conversation by saying "Sorry, I'm afraid I need to go now. I have an appointment in a few minutes. Thank you for your help. Bye."

## Price Sheet

Name: \_\_\_\_\_

Date: \_\_\_\_\_

Company Name: \_\_\_\_\_ (e.g. Origin)

Please fill in this section before making the phone call:

<b>Variation ID:</b> _____  <b>Address:</b> _____ _____  <b>Concession:</b> Eligible / Not Eligible	<b>Search Method:</b>  Called One / Called Many / Website / Friend   <b>Price-to-Beat:</b> _____ Usage      Supply      Annual (300kWh/mo)
--	--

Price #1 – price obtained after revealing address and/or concession		
<b>Non-direct debit offer</b>  <b>1. Usage charge</b> (cents <b>per kWh</b> , incl. GST):   Pay-on-time/Not pay-on-time  <b>2. Supply charge</b> (cents <b>per day</b> , incl. GST):   Pay-on-time/Not pay-on-time  <b>3. Rate if pay-on-time/not pay-on-time:</b>	<b>Direct debit offer</b>  <b>1. Usage charge:</b>   Pay-on-time/Not pay-on-time  <b>2. Supply charge:</b>   Pay-on-time/Not pay-on-time  <b>3. Rate if pay-on-time/not pay-on-time:</b>	<div style="border: 1px solid black; padding: 5px; margin: 10px auto; width: 80%;"> <b>Direct Debit discount:</b> </div>
Other Discounts and offers (e.g. One-off rebates, movie tickets):   <hr style="border-top: 1px dashed black;"/> Exit Fee:   Price after 12 months (if different):		

Please ensure that the call only proceeds to the next stage after you have acquired the details for the current stage.





Price #2 – price obtained after revealing search method	
<b>Non-direct debit offer</b>  <b>1. Usage charge</b> (cents <b>per kWh</b> , incl. GST):  Pay-on-time/Not pay-on-time  <b>2. Supply charge</b> (cents <b>per day</b> , incl. GST):  Pay-on-time/Not pay-on-time  <b>3. Rate if pay-on-time/not pay-on-time:</b>	<b>Direct debit offer</b>  <b>1. Usage charge:</b>  Pay-on-time/Not pay-on-time  <b>2. Supply charge:</b>  Pay-on-time/Not pay-on-time  <b>3. Rate if pay-on-time/not pay-on-time:</b>
<div style="border: 1px solid black; padding: 5px; width: fit-content; margin: 10px auto;">Direct Debit discount:</div>	
Other Discounts and offers (e.g. One-off rebates, movie tickets):  	
Exit Fee:  	
Price after 12 months (if different):  	



Price #3 – price obtained after friend's very low price or threatening to search more		
<b>Non-direct debit offer</b>		<b>Direct debit offer</b>
<b>1. Usage charge</b> (cents <b>per kWh</b> , incl. GST):		<b>1. Variable charge:</b>
Pay-on-time/Not pay-on-time		Pay-on-time/Not pay-on-time
<b>2. Supply charge</b> (cents <b>per day</b> , incl. GST):		<b>2. Supply charge:</b>
Pay-on-time/Not pay-on-time		Pay-on-time/Not pay-on-time
<b>3. Rate if pay-on-time/not pay-on-time:</b>		<b>3. Rate if pay-on-time/not pay-on-time:</b>
Other Discounts and offers (e.g. One-off rebates, movie tickets):		
Exit Fee:		
Price after 12 months (if different):		

**Other Notes:**

## C Extra Tables

Table C.1: Robustness to Defining Price Exclusively as Variable Charge

Panel (a): Discounting Among New Customers and Switchers

	All Contracts (1)	Excluding Default Contracts (2)
Posted	-0.320*** (0.024)	
Call-In	-0.329*** (0.023)	-0.009 (0.007)
Negotiated	-0.345*** (0.024)	-0.026*** (0.007)
R-Squared	0.804	0.457
Observations	1648	1231

Panel (b): Subsidy Status and Incomplete Passthrough in Negotiations

	(1)	(2)
Call-In	-0.009 (0.007)	-0.009 (0.008)
Call-In $\times$ Concession		0.001 (0.008)
Negotiated	-0.026*** (0.007)	-0.027*** (0.009)
Negotiated $\times$ Concession		0.002 (0.007)
R-Squared	0.457	0.456
Observations	1231	1231

**Notes:** Dependent variable is logarithm of per kWh variable charge. In Panel (a) column (1) the omitted category is the firm's default contract. Column (2) drops the default contracts and presents call-in and negotiated price discounts relative to the posted price. In Panel (b) the sample includes posted, call-in, and negotiated prices. The omitted category is posted prices. Standard errors are clustered to allow for arbitrary covariance at the firm and contract type level. All regressions include actor, retailer, date, and the number of calls made by an actor to date and its square. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$