

# Essays on Energy Economics and Industrial Organization

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Dissertation submitted in partial fulfillment of the requirements for the degree of  
Doctor of Philosophy in the Department of Economics  
in the Graduate School of Duke University  
2016

ABSTRACT

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# Abstract

The dissertation consists of three chapters related to the low-price guarantee marketing strategy and energy efficiency analysis. The low-price guarantee is a marketing strategy in which firms promise to charge consumers the lowest price among their competitors. Chapter 1 addresses the research question “Does a Low-Price Guarantee Induce Lower Prices” by looking into the retail gasoline industry in Quebec where there was a major branded firm which started a low-price guarantee back in 1996. Chapter 2 does a consumer welfare analysis of low-price guarantees to drive policy indications and offers a new explanation of the firms’ incentives to adopt a low-price guarantee. Chapter 3 develops the energy performance indicators (EPIs) to measure energy efficiency of the manufacturing plants in pulp, paper and paperboard industry.

Chapter 1 revisits the traditional view that a low-price guarantee results in higher prices by facilitating collusion. Using accurate market definitions and station-level data from the retail gasoline industry in Quebec, I conducted a descriptive analysis based on stations and price zones to compare the price and sales movement before and after the guarantee was adopted. I find that, contrary to the traditional view, the stores that offered the guarantee significantly decreased their prices and increased their sales. I also build a difference-in-difference model to quantify the decrease in posted price of the stores that offered the guarantee to be 0.7 cents per liter. While this change is significant, I do not find the response in competitors’ prices to be signif-

icant. The sales of the stores that offered the guarantee increased significantly while the competitors' sales decreased significantly. However, the significance vanishes if I use the station clustered standard errors. Comparing my observations and the predictions of different theories of modeling low-price guarantees, I conclude the empirical evidence here supports that the low-price guarantee is a simple commitment device and induces lower prices.

Chapter 2 conducts a consumer welfare analysis of low-price guarantees to address the antitrust concerns and potential regulations from the government; explains the firms' potential incentives to adopt a low-price guarantee. Using station-level data from the retail gasoline industry in Quebec, I estimated consumers' demand of gasoline by a structural model with spatial competition incorporating the low-price guarantee as a commitment device, which allows firms to pre-commit to charge the lowest price among their competitors. The counterfactual analysis under the Bertrand competition setting shows that the stores that offered the guarantee attracted a lot more consumers and decreased their posted price by 0.6 cents per liter. Although the matching stores suffered a decrease in profits from gasoline sales, they are incentivized to adopt the low-price guarantee to attract more consumers to visit the store likely increasing profits at attached convenience stores. Firms have strong incentives to adopt a low-price guarantee on the product that their consumers are most price-sensitive about, while earning a profit from the products that are not covered in the guarantee. I estimate that consumers earn about 0.3% more surplus when the low-price guarantee is in place, which suggests that the authorities should not be concerned and regulate low-price guarantees. In Appendix B, I also propose an empirical model to look into how low-price guarantees would change consumer search behavior and whether consumer search plays an important role in estimating consumer surplus accurately.

Chapter 3, joint with Gale Boyd, describes work with the pulp, paper, and pa-

perboard (PP&PB) industry to provide a plant-level indicator of energy efficiency for facilities that produce various types of paper products in the United States. Organizations that implement strategic energy management programs undertake a set of activities that, if carried out properly, have the potential to deliver sustained energy savings. Energy performance benchmarking is a key activity of strategic energy management and one way to enable companies to set energy efficiency targets for manufacturing facilities. The opportunity to assess plant energy performance through a comparison with similar plants in its industry is a highly desirable and strategic method of benchmarking for industrial energy managers. However, access to energy performance data for conducting industry benchmarking is usually unavailable to most industrial energy managers. The U.S. Environmental Protection Agency (EPA), through its ENERGY STAR program, seeks to overcome this barrier through the development of manufacturing sector-based plant energy performance indicators (EPIs) that encourage U.S. industries to use energy more efficiently. In the development of the energy performance indicator tools, consideration is given to the role that performance-based indicators play in motivating change; the steps necessary for indicator development, from interacting with an industry in securing adequate data for the indicator; and actual application and use of an indicator when complete. How indicators are employed in EPA's efforts to encourage industries to voluntarily improve their use of energy is discussed as well. The chapter describes the data and statistical methods used to construct the EPI for plants within selected segments of the pulp, paper, and paperboard industry: specifically pulp mills and integrated paper & paperboard mills. The individual equations are presented, as are the instructions for using those equations as implemented in an associated Microsoft Excel-based spreadsheet tool.

This dissertation is dedicated to my beloved parents.

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# Acknowledgements

First and foremost, I would like to express my deepest gratitude to my co-advisors, Professor Daniel Yi Xu and Professor Christopher Timmins, for their invaluable guidance, and tremendous support and encouragement throughout my doctoral studies. They have been very helpful in leading me to the research areas that I am interested in; and in offering every possible resource to support my learning process when exploring new areas and picking up new skills. I am really grateful that my committee member, Professor Andrew Sweeting, remains responsive and offers helpful advice after moving from Duke to Maryland. I benefited greatly from the guidance and support from my committee members, Professor Wilfred Amaldoss and Professor Gale Boyd. I really appreciate the opportunities Professor Wilfred Amaldoss offered me to learn from him on both research and teaching. I am also grateful for the opportunity to work with Professor Gale Boyd on developing the energy performance indicator (EPI), which constitutes one chapter of this dissertation. My working experience with Professor Gale Boyd has been always enjoyable.

I wish to thank the people who helped me to have the opportunity to pursue my doctoral studies. I am very fortunate to have Professor Charlie Becker as my mentor. He admitted me into Duke Economics Program and has been always there for me. I am also grateful for Professor Huseyin Yildirim's recommendation for me to Duke Economics Ph.D. program, which enables me to start my Ph.D. studies after one year in our terminal master's program. My professors in my undergraduate studies

- Professor Baomin Dong, Professor Weixing Wu, Professor Yiping Xu, Professor Zhihong Chen and Professor Pingyao Lai - play important roles in shaping my goal to pursue an Economics Ph.D. degree in U.S. I am always grateful for their guidance and support.

My research has also benefited from the comments of Professor Joe Mazur, Professor Jimmy Roberts, Professor Pat Bayer and other seminar participants at Duke Economics Department. Part of the data used in this dissertation was obtained with the help of an anonymous manager from Ultramar. I would like to thank him for sharing their price zone maps with me.

In addition, the funding and administrative support from the Duke Economics Department was crucial to the completion of this dissertation.

Finally, I would like to thank my parents for their unconditional support and love.

I am solely responsible for any errors.

Disclaimer for Chapter 3: The research was conducted at Duke University with funding from the U.S. Environmental Protection Agency's Office of Atmospheric Programs, while the authors were special sworn status research associates at the Triangle Census Research Data Center. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. The authors thank the participants in the ENERGY STAR Focus on the pulp, paper and paperboard industry. Their willingness to provide guidance and review on issues affecting energy use was invaluable.

# Does a Low-Price Guarantee Induce Lower Prices?

## 1.1 Introduction

The low-price guarantee is a marketing strategy in which firms promise to charge consumers the lowest price among their competitors. When a lower price is found, they will match or offer an even lower price. It is used widely in various industries. Yet whether it indeed induces low prices for everyone and what role it plays are still far from well-understood.

Existing literature explains low-price guarantees from three main perspectives. First, the dominant economic and antitrust view of low-price guarantees is as a collusive device. Salop (1986), Logan and Lutter (1989), and Hviid and Shaffer (1994, 1999) argue that such a guarantee eliminates rivals' incentives to cut prices because undercutting cannot erode their market share. Some empirical evidence was found that low-price guarantees are associated with higher prices, as shown in Hess and Gerstner (1991) and Arbatskaya et al., (2000, 2004, 2006). Second, when firms only match to consumers who find lower prices, it encourages consumers to search and serves as a means of price discrimination. From this perspective, Corts

(1997) and Chen et al. (2001) find that whether the guarantee is pro-competitive or anti-competitive depends on consumer types and the proportion of different types in the market. Empirically, Moorthy and Zhang (2006) find that the actual frequency of redemption is generally relatively low, which indicates that price discrimination may not play a major role. Third, Jain and Srivastava (2000) and Moorthy and Winter (2006) argue that the guarantee can serve as a low-price signal to attract uninformed consumers. Their experimental data and survey data support the notion that consumers expect matching stores<sup>1</sup> to have lower prices and the stores with the lowest prices are more likely to adopt the guarantee.

To examine the role of the guarantee, I start with a descriptive analysis by looking into the movement of matching stores' market share and their volume sold weighted prices; and by comparing the volume sold weighted average prices at the price zone level. I then quantify the difference-in-difference changes in prices and volume sold before and after the guarantee's implementation. I find that posted prices significantly decrease by 0.71 cents per liter and volume sold significantly increases by 6.5% for the stores that have the guarantee. While their direct competitors did not change their prices significantly as a response, the volume sold decreased significantly by 3.4%. Mañez (2006) also finds evidence showing the matching firms decreased prices; however, my data is much richer, which enables me to estimate the effects of the low-price guarantee on sales.

This chapter overcomes the common data shortcoming of previous empirical literature by obtaining the actual price zone information from the stores that offer the low-price guarantee. Existing empirical literature is scarce and suffers from a common criticism that their results are highly dependent on getting the market definition right.

The retail gasoline industry provides an attractive context in which to study the

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<sup>1</sup> Matching stores are referred to the stores that have the low-price guarantees.

effects of low-price guarantees because the product space is much simpler than in the retail grocery industry, where the guarantee is frequently observed. The message that gas stations deliver to consumers is subsequently clearer. The econometric analysis is based on Quebec's retail gasoline industry from 1995 to 1997. This data is well suited to address my research question because a leading company announced a low-price guarantee in 1996. In this market, only one leading company named Ultramar had the full control of their retail prices, which makes the strategic moves among the market players much simpler.

This chapter is organized as follows: I will discuss the existing literature on low-price guarantees in more detail in the next section; Section 1.3 introduces the industry background and presents my data; Section 1.4 illustrates the descriptive analysis; Section 1.5 describes the model I build in the difference-in-difference regression analysis; Section 1.6 presents the regression results and I conclude in Section 1.7.

## 1.2 Literature Review

Low-price guarantees take different forms in real life. For example, some stores agree to refund the difference if a better price is available in their competitor stores, which is the most commonly observed price matching guarantee. When stores agree to refund more than the difference, they have the price beating guarantee. Some stores promise to match their own price and/or their competitors' prices within a time frame after purchase. While some stores promise to change their posted price once a lower price is found, other stores just match the price for the customers who have the proof of a lower price and trigger the guarantee. Given the various forms that the low-price guarantee can take, the literature can be divided into several branches that tell different stories. Whether the low-price guarantee is anti-competitive or pro-competitive is still not conclusive in both the theoretical and empirical literatures. In

this literature review, I will introduce each story one by one and list both theoretical reasoning and empirical evidence.

### *1.2.1 Collusive Device*

Since Salop (1986), low-price guarantees have been mainly discussed as a cartel-facilitating collusive device. Salop argues that a price matching policy removes the rivals' incentives to undercut their competitors, because charging a lower price cannot erode any share from competitors if the lower price is automatically matched. When all firms in the market adopt a price matching policy and post the prices that maximize joint profit, no firm will have the incentive to deviate.

Logan and Lutter (1989) and Hviid and Shaffer (1994, 1999) extend the analysis to markets with asymmetric firms. The asymmetry can either come from cost differences or demand advantages. They show that when the asymmetry is small, price-matching can still sustain a collusive price, but it loses the ability to do so when the asymmetry becomes large. On the other hand, requiring all firms to adopt price-matching is not necessary to maintain supra-competitive prices, which can also be supported when only higher-priced firms adopt price-matching. Hviid and Shaffer (1999) also point out that when price-matching is costly for consumers, the ability to raise prices using price-matching is limited.

Some empirical evidence supports the anti-competitive collusive story of the low-price guarantee. Arbatskaya et al. (2000) analyze the effects of low-price guarantees on advertised tire prices, based on P185/75R14 retail tire prices collected from U.S. Sunday newspapers. They find that although a tire retailer's own price-matching guarantee has no significant effect on the retailer's advertised tire price, an increase in the percentage of firms in the market announcing low-price guarantees tends to raise the firm's advertised tire price. Hess and Gerstner (1991) also find that low-price guarantees lead to higher prices, in this case within the context of grocery stores in a

market where several stores announced the guarantee; and Arbatskaya et al. (2006) find matching firms tend to have weakly higher advertised prices than non-matching firms when they looked at paired observations on tire prices. However, Arbatskaya et al. (2004) cast doubt on the guarantee facilitating high prices after documenting 515 low-price guarantees from newspaper ads. They claim that most guarantees promise to match rivals' advertised prices instead of selling prices, and hassle costs might not be low as there are usually restrictions to redeem the guarantee.

### *1.2.2 Price Discrimination*

When the store does not change its posted price but instead just matches the price to the consumers who activate the guarantee, low-price guarantees can be used as price discrimination devices. Corts (1997) looked into the competitive effects of the low-price guarantee when it is used as a price discrimination device in a market with sophisticated consumers and unsophisticated consumers. Sophisticated consumers take advantage of the guarantee, whereas unsophisticated consumers only consider posted prices and never activate the guarantee. He assumed the same marginal cost for the firms but optimal prices have complete dispersion. Whether a low-price guarantee is pro-competitive or anti-competitive depends on the relative elasticities of sophisticated and unsophisticated consumers at appropriate prices. When the sophisticated consumers' demand is relatively elastic, prices of all firms will increase after the guarantee is allowed in the market; when the sophisticated consumers' demand is relatively inelastic, prices of all firms will decrease. In equilibrium, either all firms or all except the lowest-priced firm adopt a low-price guarantee. By segmenting consumers into four types based on loyalty and search cost, Chen et al. (2001) find that both anti-competitive and pro-competitive equilibria exist for a scenario with two symmetric firms, depending on consumer heterogeneity. Equilibria include all possible cases from where both stores match to where neither matches and all

possible pricing movements after the guarantee expect for one case<sup>2</sup>.

A possible indicator for price discrimination in empirical studies is the redemption rate of the low-price guarantee. Consistent with other empirical studies, Moorthy and Zhang (2006) find that the frequency of redemption is generally relatively small, which may be inconsistent with the price discrimination story.

### *1.2.3 Low-Price Signals*

Jain and Srivastava (2000) and Moorthy and Winter (2006) argue for possible pro-competitive effects of price-matching from the prospective of signaling low prices. While Jain and Srivastava (2000) assumed the same cost and asymmetric demand of firms, Moorthy and Winter (2006) assumed identical product but different location and cost of firms. In both of their models, they assume the market includes both informed and uninformed consumers. In Jain and Srivastava (2000), experimental data shows consumers' price expectations of matching stores are lower. The guarantee in their models is used as a signal of low price to attract uninformed consumers. When both the share of informed consumers and firm asymmetries are large, it will be not profitable for higher-priced firms to adopt price-matching, and thus the guarantee can be a credible signal of low-price to the uninformed consumers. When the lowest-priced firm adopts price-matching, it sells to more uninformed consumers. As a result, the lowest-priced firm faces a more inelastic demand after the guarantee and its optimal price to maximize profit increases. On the other hand, the non-matching higher-priced firms will decrease their prices to keep their informed consumers.

Along with their theoretical model, Moorthy and Winter (2006) also find lowest-priced stores are more likely to adopt the guarantee in their survey data from 46 retailers in the United States and Canada in five categories. Using collected data

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<sup>2</sup> In this particular impossible case, one store adopts the low-price guarantee and posts a lower price in the equilibrium, whereas the other store does not adopt the low-price guarantee and posts a higher price

from three superstores, including prices of a basket of matching goods and non-matching goods before and after low-price guarantee was introduced, Mañez (2006) finds that the guarantee is offered by the firm with the lowest price. In his data sample, the low-price guarantee causes a reduction in the prices of all products, regardless of whether the products are included in the guarantee. He concludes that his observations most closely align to the predictions of the low-price signaling story. In Mañez (2006), the data indicate that the low-price guarantee is pro-competitive.

#### *1.2.4 Consumer Search*

If low-price guarantees can alter consumers' beliefs about prices, they can also change consumers' searching behavior. Srivastava and Lurie (2001) conducted several survey studies to find out the effects of the guarantee on consumer search behavior. Their study shows that consumers perceive price-matching policies as signals of low store prices and that the presence of a refund increases the likelihood of discontinuing the price search. On the other hand, they find that search cost plays an important role. When search costs are low, consumers search a greater number of stores if any store offers a price-matching policy. When search costs are high, consumers appear to accept the price-matching signal at face value and search less in the presence of a refund.

In the studies above, we see different theoretical perspectives with regard to the competitive effects of a low-price guarantee, some of which also have empirical implications. While theoretical insights are abundant, the empirical literature is still scarce. Note that both the theoretical and empirical literatures do not have conclusive results. This chapter will enlarge the empirical literature with better data of accurate market definitions.

## 1.3 Background and Data

This section introduces the industry background and describes the data I used. The data description provides the available information I use to address my research question, including gas station level data, price zone data.

### *1.3.1 Industry Background*

Specifically, I will investigate Ultramar’s value plus program, which is essentially a low-price guarantee. In the Quebec city area, Ultramar is one of the five major brands in the retail gas station industry, which also includes Irving, Petro-Canada, Shell and Esso. On June 18th, 1996, Ultramar introduced its value plus program<sup>3</sup>. Their website announced, “At Ultramar, our goal is clear: to offer our customers high quality gasoline products at unbeatable prices. And if a competitor initiates a drop in prices, we will quickly adjust our prices. In short, our objective is that customers will not find a lower price in the zone than that offered at this station.” As you can see, the value plus program is essentially a low-price guarantee.

The low-price guarantee here is not likely to be a price discrimination device, because it promises to adjust the posted prices instead of offering a refund to those consumers who found a lower price. In order to make their promise convincing, Ultramar claims to conduct a price survey at least daily. Moreover, they also offer a toll-free line for consumers to report lower prices found inside the price zone with Ultramar. According to a manager from Ultramar, most of the time, they learn about a competitor’s a price change from Ultramar store operators. The station has to call the pricing center first to obtain an authorization number before changing the price. From this perspective, it seems that the hassle cost for consumers discussed in previous literature would be very small. The store operators would have a strong

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<sup>3</sup> More details on <http://www.ultramarcst.ca/en/quebec/service-stations/services/value-plus/>

incentive to call in and get the price adjusted to the lowest, because they are on commission based contracts. The more they sell, the more commissions they can earn. Therefore, we can conclude Ultramar did not intend to use the guarantee to discriminate amongst consumers.

It is not obvious whether the guarantee was used as a collusive device, because Ultramar is the only company who can adopt the guarantee due to its unique vertical structure. All the branded gas stations are operated by the upstream oil company or under lessee-dealer contracts. Ultramar offers a commission based lessee contract, where Ultramar keeps the ownership of the gasoline and is responsible for setting the retail price. Other brands offer a traditional type of lessee contract, where the lessee-station owner sets the retail price of gasoline and pays a whole sale price to the upstream oil company at delivery. Therefore, unlike other brands, Ultramar, the leading chain, has the full control of the retail prices of all their gas stations. Thus, the decision of Ultramar adopting a low-price guarantee is unilateral and cannot be collusive in the traditional sense. However, using 2005 data, Clark and Houde (2013) document the collusive pricing behavior in the retail gasoline industry. They find Ultramar usually was the first to cut prices and the last to increase prices. Specifically, there were fewer conversations when prices decreased in the market than when prices increased. They argue that Ultramar's low-price guarantee potentially serves as a coordination device to help Ultramar organize price decreases in a cartel. I argue that the guarantee is not necessarily the reason why market players communicate less when prices decrease. Even without the guarantee, you could still expect that more conversations are needed to increase the price, as whoever increases the price first will very likely lose a lot of their customers. When they have to increase price to keep their margin, they would prefer all players adjust their prices at the same time or at least within a very short time horizon. On the other hand, when the market price decreases, the first movers will have an advantage to win customers when

other players in the market have not adjusted their prices accordingly. Therefore, the incentive to communicate with other players in the market has vanished when the market price decreases. In fact, I compare the prices of Ultramar a year before and after the guarantee was introduced and find that Ultramar indeed decreased their posted prices and effective prices after adopting the low-price guarantee. Therefore, I argue that the guarantee here is unlikely to be a collusive device.

### *1.3.2 Data Description*

I use two main sets of data. The gasoline station level data provides necessary information to looking into price and sales movements before and after the guarantee. The price zone data provides accurate information on which stations are included in Ultramar's low-price guarantee.

#### *Gasoline*

The gasoline station data were collected by Kent Marketing, a leading survey company for the Canadian gasoline market. The data includes station characteristics, price, and volume sold for every gasoline station in the Quebec market every two months from 1995 to 1997. The observed characteristics of gasoline stations include location, the type of convenience store (small, medium, or large), a car-repair shop indicator, the number of service islands and pumps, opening hours, brand name, type of service, and an indicator for the availability of car wash. For the analysis, I focus on regular gasoline. The sample has 5778 observations, including 357 different gasoline station sites, among which 83% of the gasoline stations survive the whole time span in this sample.

Table 1.1 summarizes the key variables in the data. As we can see, gasoline station level heterogeneity was significant, considering either volume sold per day or capacity and other characteristics. Also notice that over a half of the gasoline

Table 1.1: Summary Statistics of the Gasoline Station Data

	Mean	Std. Dev.	Min	Max
Volume (liter/day)	4578	2801	39.18	20768
Posted price (cents/liter)	57.36	3.71	35.88	67.67
Number of pumps	6.27	4.37	1	24
Number of islands	2.31	1.39	1	8
Convenience store	53.08%	0.50	0	1
Full service	39.98%	0.49	0	1
24 hours	40.60%	0.49	0	1
Carwash	20.11%	0.40	0	1
Repair shop	19.04%	0.40	0	1
Major brands	63.01%	0.48	0	1

stations sell major branded gasoline.

The total number of gas stations dropped from 341 at the beginning of 1995 to 310 at the end of 1997. The number of gasoline stations that sold non major branded or unbranded gasoline dropped steadily from 126 at the beginning of 1995 to 117 at the end of 1997. The number of gasoline stations that sold major branded gasoline dropped steadily from 215 at the beginning of 1995 to 193 at the end of 1997. However, the market share of major branded gasoline stations increased from 71% to 74%.

### *Price Zone*

Notice that in Ultramar's value plus program, "each of the Value Plus stations is placed in a price zone". The promise to have the lowest price only applies to the stations in the same price zones with Ultramar stations. I obtained the price zones in the Quebec city area from Ultramar.<sup>4</sup> Figure 1.1 illustrates one of Ultramar's price zones. As you can see, this particular price zone has 8 stations, one of which is Ultramar. According to Ultramar, price zones are defined by their needs in volume and margins. Normally, important road axes act as limits. The zones also aim to

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<sup>4</sup> The data obtained from Ultramar are the price zones they use currently. They said there were not many changes of the price zones over the decade.

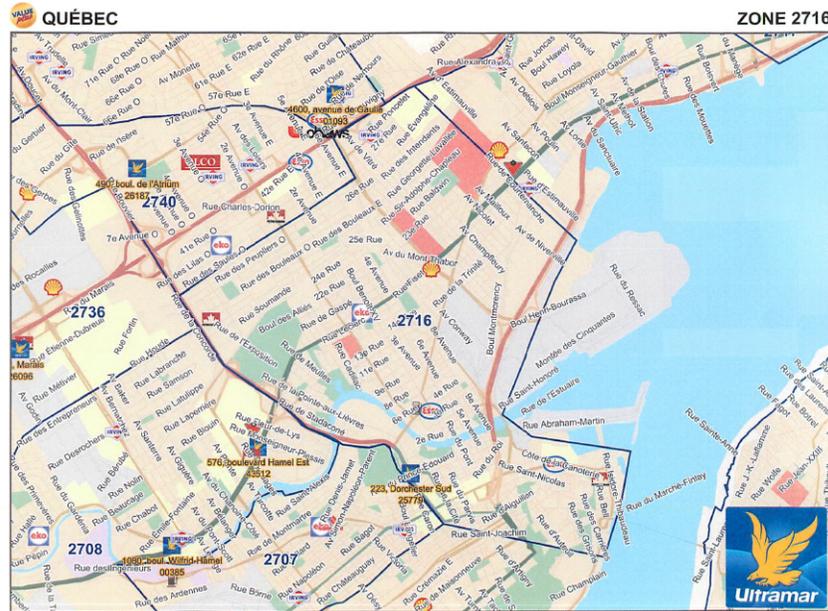


FIGURE 1.1: Ultramar Price Zone 2716

reflect a traffic pattern to make sure competitors with similar traffic patterns are included. There are 30 price zones in total with 23 including at least one Ultramar station.<sup>5</sup>The 23 Ultramar price zones cover about 90% of the stations in my sample. Among all the price zones, the number of gas stations within a zone varies from 1 to 32. The median number of gas stations within a zone is 13. The number of Ultramar gas stations in a price zone varies from 0 to 6 and the median number is 2. The median ratio of the number of Ultramar stations to the total number of stations within the same zone is 17%.

#### 1.4 Descriptive Analysis

This section presents a descriptive analysis of how effective the low-price guarantee was and how the market share and prices changed after the guarantee was adopted.

Table 1.2 investigates the effectiveness of the low-price guarantee. The t-test

<sup>5</sup> Ultramar's price zones look very similar to the territorial divisions used in the original destination survey conducted by the Quebec Ministry of Transportation. Thus, I generate the other 7 price zones following the pattern to cover the stations that are not in Ultramar's price zones.

Table 1.2: Comparing Ultramar’s Posted Price Being Lowest Before and After

Ultramar’s Posted Price	median			mean			ttest p-value	
	before	after	after1	before	after	after1	after-before	after1-before
Difference to the lowest (cpl)	.49	0	0	.86	.38	.34	.0014	.0001
Probability being the lowest	.37	.69	.67	.38	.66	.66	.0002	.0002

(Note: after1 is for robusiness check where the after periods do not start until two months after the adoption of the guarantee)

p-values are for the one side hypotheses. Results show that the differences between Ultramar’s posted prices and the minimum prices within the price zones are significantly lower after the guarantee than before; the probability of an Ultramar station posting the lowest price within the price zone significantly increased after the guarantee. To test the first hypothesis, I allow correlation between different observations from the same gasoline station by using clustered standard errors.<sup>6</sup> As is shown, the difference between Ultramar’s posted prices and the lowest prices within their corresponding price zones significantly decreased by 0.48<sup>7</sup> cents per liter, while the probability of Ultramar posting the lowest price within its corresponding price zone significantly increased by 28% after adopting the guarantee. Since the data collection may not happen at the exact same time for all stations, I cannot be precise about the frequencies of Ultramar posting the lowest price within a zone every day. At least, generally speaking, Ultramar was quite effective in carrying out their promise to charge the lowest price. As an additional check, among those cases where Ultramar posted the lowest price in the price zone, almost all cases were price matches, meaning there was at least one other non-Ultramar station in the price zone posting the same lowest price.

Figure 1.2 shows that Ultramar increased its market share successfully both in terms of volume sold and the dollar amount after the guarantee. There is a high peak for both volume sold and the dollar amount of sales right after the introduction

<sup>6</sup> The p-value for the first hypothesis drops to zero when using the usual standard errors.

<sup>7</sup> If we compare the data 2 months before the guarantee and the data 2 months after the guarantee, this number increases to 0.52 cents per liter.

of the guarantee. This is not because of massive entries of Ultramar or exits of competitors. In fact, before the guarantee was adopted, there were consistently 50 Ultramar stations. The upward trend of the share is due to exits of other stations in the market. After the guarantee was adopted, the fluctuation of the share of number of stations is mainly due to 1 or 2 shut-down Ultramar stations along with market change. As a result, the high peak may be from consumers' welcoming reaction to the guarantee. After a few months, consumers cooled down, maybe because they learned that Ultramar just matched the lowest price instead of beating their competitors most of the time, or maybe because other stations also made their own adjustments. Even after the cooling down, the market share of Ultramar's volume sold and sales are still higher than before. Moreover, the volume sold line lies above the dollar amount line after the guarantee was adopted. This means the revenue did not increase as much as the volume sold, which makes sense given that Ultramar's prices were lower.

Ultramar kept their promises to post the lowest price, and the guarantee itself boosted Ultramar's market share effectively. Just how much lower were Ultramar's prices compared to its competitors? Figure 1.3 compares the volume weighted posted prices of Ultramar stations with other stations within their price zones. As you can see, after the value plus program was introduced, Ultramar on average charged lower prices than their competitors within their zones all the time. Especially right after they introduced the value plus program, their prices were about 2 cents lower per liter on average than their competitors, the biggest difference in the time span of my sample. Ultramar may have had the strongest incentive to make their low price guarantee convincing during the first few months after the introduction of the value plus program. The consumers seemed to be convinced, as the market share of Ultramar in the next period was even higher, as shown in Figure 1.2. It may also have been easier for Ultramar to undercut their competitors' prices at the beginning of the value plus program, as their competitors may still not have figured out how

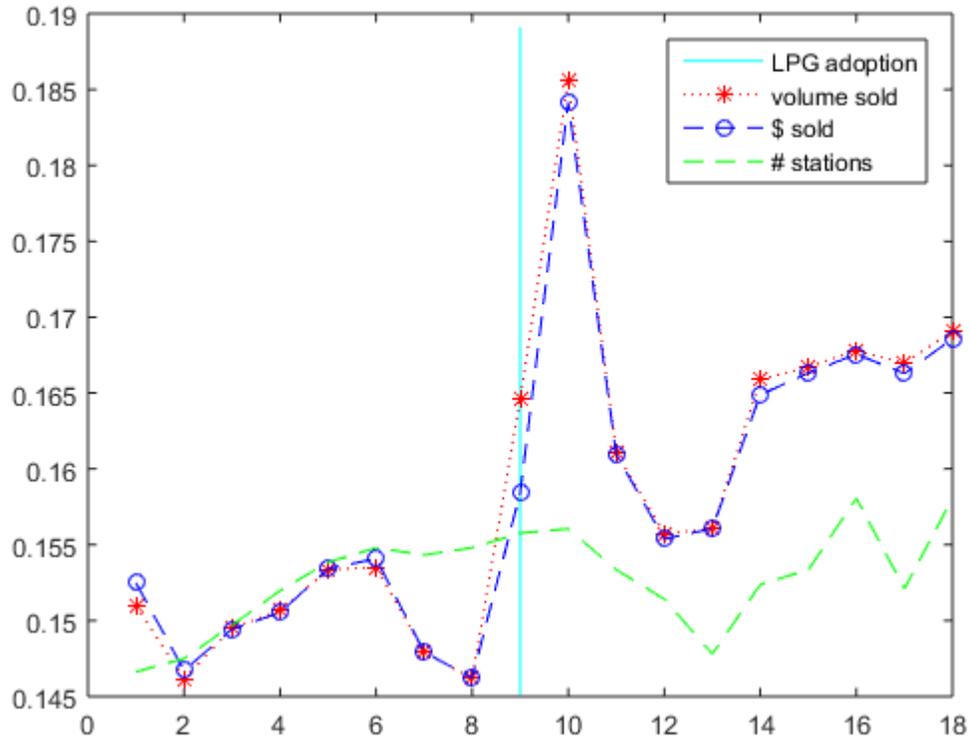


FIGURE 1.2: Ultramar's Market Share Over Time

to best respond strategically.

Comparing Figure 1.2 and Figure 1.3, before the guarantee, the market share of volume sold and dollar amount sales almost always moved in the opposite direction to the movements of the differences of volume weighted posted prices between Ultramar and its competitors. However, after the guarantee, the negative correlation between the movement of market share of relative price is much weaker and sometimes even positive. This means that besides the relative prices, the low-price guarantee must have played some role in driving the market share.

Ultramar's low-price guarantee is pro-competitive since it induces lower average market prices. Table 1.3 compares the average posted price weighted by quantity sold between price zones with and without the guarantee. The hypotheses I test are

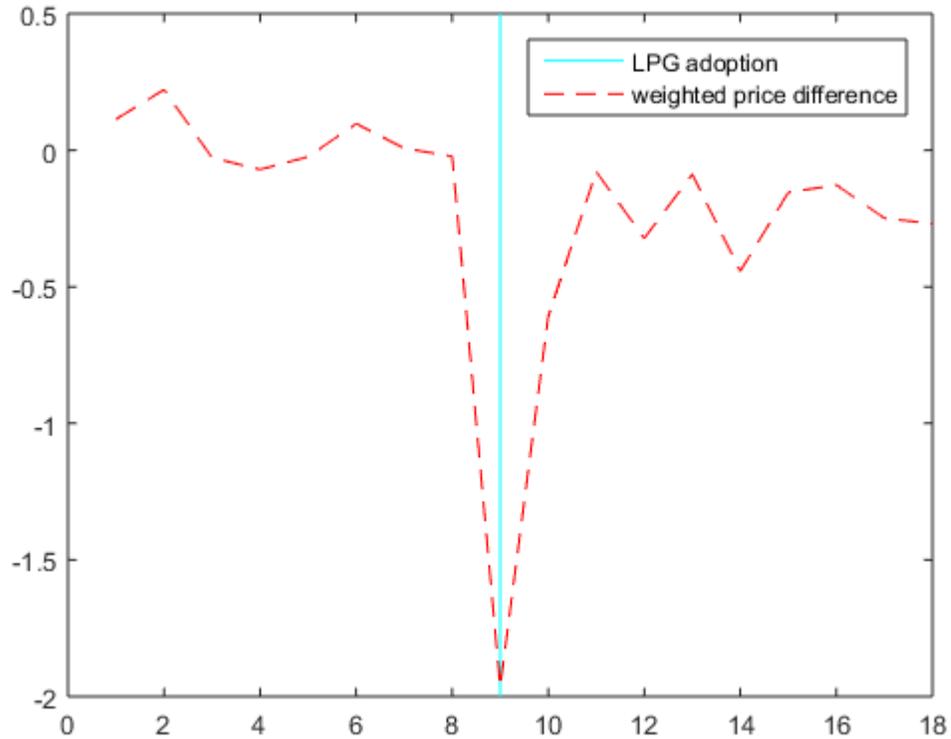


FIGURE 1.3: Difference of Weighted Posted Prices between Ultramar and Its Competitors

as follows: the volume weighted average prices of the price zones with at least one Ultramar station decreased significantly after the guarantee; the volume weighted average prices of the price zones with no Ultramar stations did not change significantly after the guarantee; before the guarantee, there were no significant difference of the volume weighted average prices between the price zones with Ultramar stations and those with no Ultramar stations; after the guarantee, the volume weighted prices of the price zones with Ultramar stations are significantly lower than those of the zones with no Ultramar stations. I allow the volume weighted zone-level average prices to be correlated for the same price zone when observed from different time periods by using clustered standard errors. As is shown, only the first hypothesis cannot be rejected at the 10% significance level. Therefore, although we observe some decrease

Table 1.3: Comparison of Zone-Level Volume Weighted Average Prices

hypothesis	difference	t-statistics	p-value
The volume weighted average prices of the price zones with at least one Ultramar station decreased significantly after the guarantee	-0.6551*	-1.5283	0.0669
The volume weighted average prices of the price zones with no Ultramar station did not change significantly after the guarantee	-0.3978	-0.5108	0.6169
Before the guarantee, there were no significant difference of the volume weighted average prices between the price zones with Ultramar stations and those with no Ultramarstations	-0.1609	-0.3840	0.7038
After the guarantee, the volume weighted prices of the price zones with Ultramar stations are significantly lower than those of the zones with no Ultramar stations	-0.4181	-0.7390	0.2328

(Note: \* –significant under 10% level; \*\* –significant under 5% level; \*\*\* –significant under 1% level. )

in the volume weighted average prices for the price zones where the guarantee was presented, most of the decreases at the price zone level are not very significant. Moreover, when we drop the period where the guarantee was adopted and compare data for two months before and after the guarantee, none of the differences are significant.

Overall, the descriptive analysis shows that Ultramar is pretty effective in posting the lowest price among their competitors after adopting the low-price guarantee. Their market share increased after the guarantee and the volume sold weighted average prices seems to be lower for those price zones that have the guarantee.

## 1.5 The Model

In order to look into the different effects that the low-price guarantee may have had on matching stations and non-matching stations, I use a difference-in-difference comparison. This section describes the model for the difference-in-different regression.

$$Y_{it} = X_{it}\beta + \sum_{k=1}^5 I_{it}^k \alpha_k + FE_i + FE_t + \epsilon_{it}$$

where  $X_{it}$  is a vector of control variables including the station characteristics and price zone characteristics;  $I_{it}^k$  is the group indicator.

I estimate fixed-effects regressions to quantify changes on price, volume sold, and dollar sales for different groups of stations. Control variables  $X_{it}$  include the characteristics of gas stations and price zones, such as whether the station is company-

owned or independent, where the station has a convenience store, whether the convenience store is large, whether the station offers car wash service, the number of pumps in the station, the number of islands in the station, whether the station operates 24 hours, whether the station has repair service, whether the station has rental service, whether the station is full service, the number of all gas stations within the price zone, the number of company-owned gas stations within the price zone, and the number of independent gas stations within the price zone. In addition, both gas station fixed effects and time fixed effects are included.

The Wald test is used to calculate the significance of the difference between coefficients of different groups: *Ultr* denotes Ultramar stations, *Comp* denotes competitors' stations whose prices Ultramar promised to match, and *Ctrl* denotes stations whose prices Ultramar never offered to match. *Before* indicates a station before the low-price guarantee, and *After* (*After1*) denotes a station (two months) after the guarantee took effect. (For example, *UltrBefore* denotes Ultramar stations before the guarantee, while *UltrAfter* denotes Ultramar stations after.) Note that I treat *Ctrl* as the control group and normalize *CtrlBefore* to be zero.

## 1.6 Results

This section presents the difference-in-difference regression results.

According to the difference-in-difference results, the matching stations decreased their prices significantly after the guarantee. Specifically, Table 1.4 shows that Ultramar's posted price significantly decreased by 0.71 cents per liter. The difference decreases to 0.39 cents per liter if we drop off the period where the guarantee was adopted. I include both p-values using the station clustered standard errors and the usual non-clustered standard errors. To be conservative, the significance levels on the table are indicated according to the clustered p-value. When no correlation between the observations from the same station is assumed, Ultramar's average volume sold

per day significantly increased by 6.52% due to the guarantee, while dollar amount of sales significantly increased by 5.13%. However, when we use the station clustered standard errors, those become insignificant. The effective price of Ultramar is generated by replacing the minimum price of the corresponding price zone to Ultramar's price, if it is not already the minimum.<sup>8</sup> We noticed that the effective price of Ultramar significantly decreased by 1.10 cents per liter. If we drop off the period where the guarantee was adopted, the difference decreased to 0.73 cents per liter.

Ultramar's competitors may not have made a significant response in their pricing strategy, as the difference-in-difference change of the prices of the stations that Ultramar offered to match is not significant.

To sum up, consistent with what we observed from the descriptive analysis, the difference-in-difference regression analysis suggests that the matching stores decreased their posted prices significantly by 0.7 cents per liter if we include the period right after the guarantee was adopted or 0.39 cents per liter if we exclude that period. Usually, the price signs outside the gas stations have one decimal place. Therefore, this change would be reflected obviously to consumers on the price signs. The significance level of sales change are not robust to the station clustered standard errors. The matching stores sold more gasoline while their competitors suffered after the guarantee was adopted.

## 1.7 Conclusion

This chapter answers the research question concerning whether the guarantee induces lower prices. Using retail gasoline station level data before and after the guarantee and clear definition of competitors in the guarantee, I find that the matching company increased their market share after the guarantee and the price zones that has

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<sup>8</sup> The posted price is different from the effective price for 162 out of the 438 observations of Ultramar stations after the guarantee.

Table 1.4: Difference-in-Difference Change of The Low-Price Guarantee

	Wald Test	difference	p (clustered)	p
posted price	$(UltrAfter - UltrBefore) - (CtrlAfter - CtrlBefore) = 0$	-0.7067***	0.0001	0.0003
	$(CompAfter - CompBefore) - (CtrlAfter - CtrlBefore) = 0$	-0.1253	0.3738	0.4399
	$UltrAfter - CompAfter = 0$	-0.0063	0.9768	0.9894
	$UltrBefore - CompBefore = 0$	0.5750**	0.0149	0.2360
effective price	$(UltrAfter - UltrBefore) - (CtrlAfter - CtrlBefore) = 0$	-1.0988***	0.0000	0.0000
	$(CompAfter - CompBefore) - (CtrlAfter - CtrlBefore) = 0$	-0.1370	0.3323	0.4007
	$UltrAfter - CompAfter = 0$	-0.5164	0.2358	0.2787
	$UltrBefore - CompBefore = 0$	0.4455	0.3091	0.3607
logvolume	$(UltrAfter - UltrBefore) - (CtrlAfter - CtrlBefore) = 0$	0.0652	0.2017	0.0027
	$(CompAfter - CompBefore) - (CtrlAfter - CtrlBefore) = 0$	-0.0340	0.4795	0.0603
	$UltrAfter - CompAfter = 0$	0.1209	0.3705	0.0225
	$UltrBefore - CompBefore = 0$	0.0216	0.8733	0.6898
logsales	$(UltrAfter - UltrBefore) - (CtrlAfter - CtrlBefore) = 0$	0.0513	0.3067	0.0181
	$(CompAfter - CompBefore) - (CtrlAfter - CtrlBefore) = 0$	-0.0365	0.4428	0.0437
	$UltrAfter - CompAfter = 0$	0.1214	0.3619	0.0217
	$UltrBefore - CompBefore = 0$	0.0336	0.8008	0.5338

	Wald Test	difference	p (clustered)	p
posted price	$(UltrAfter1 - UltrBefore) - (CtrlAfter1 - CtrlBefore) = 0$	-0.3887***	0.0089	0.0066
	$(CompAfter1 - CompBefore) - (CtrlAfter1 - CtrlBefore) = 0$	-0.1266	0.2939	0.2887
	$UltrAfter1 - CompAfter1 = 0$	-0.0770	0.7247	0.8220
	$UltrBefore - CompBefore = 0$	0.1851	0.4355	0.5968
effective price	$(UltrAfter1 - UltrBefore) - (CtrlAfter1 - CtrlBefore) = 0$	-0.7324***	0.0000	0.0000
	$(CompAfter1 - CompBefore) - (CtrlAfter1 - CtrlBefore) = 0$	-0.1378	0.2591	0.2493
	$UltrAfter1 - CompAfter1 = 0$	-0.5974	0.1456	0.0819
	$UltrBefore - CompBefore = 0$	-0.0029	0.9945	0.9935
logvolume	$(UltrAfter1 - UltrBefore) - (CtrlAfter1 - CtrlBefore) = 0$	0.0633	0.2461	0.0048
	$(CompAfter1 - CompBefore) - (CtrlAfter1 - CtrlBefore) = 0$	-0.0336	0.5099	0.0733
	$UltrAfter1 - CompAfter1 = 0$	0.1253	0.3582	0.0198
	$UltrBefore - CompBefore = 0$	0.0284	0.8357	0.6050
logsales	$(UltrAfter1 - UltrBefore) - (ControlAfter1 - ControlBefore) = 0$	0.0564	0.2980	0.0116
	$(CompAfter1 - CompBefore) - (CtrlAfter1 - CtrlBefore) = 0$	-0.0359	0.4795	0.0546
	$UltrAfter1 - CompAfter1 = 0$	0.1239	0.3592	0.0207
	$UltrBefore - CompBefore = 0$	0.0316	0.8159	0.5634

(Note: \* -significant under 10% level; \*\* -significant under 5% level; \*\*\* -significant under 1% level. After1 is for robustness check where the after periods do not start until two months after the adoption of the guarantee)

the low-price guarantee tend to have lower volume sold weighted average prices. My difference-in-difference regression estimates show that the matching company decreased their posted prices by 0.7 cents per liter and effective price by 1.1 cents per liter. These numbers becomes smaller if I exclude the period right after the guarantee was adopted in my difference-in-difference regression analysis but they remain to be significant. On the other hand, I did not find strong evidence showing significant reaction from the non matching stores or nearby stores which were not affected directly by the guarantee. Overall, I conclude the low-price guarantee is pro-competitive by inducing matching stores to decrease prices and increase volume sold.

The conclusion of this chapter can safely be generalized to low-price guarantees where the matching companies promise to change their posted price for all their consumers. When the matching companies only promise to apply the guarantee to their consumers who have found a lower price, i.e. price discrimination is involved, we need to be careful about extending the conclusion from this chapter. It would be interesting to see future empirical work on the competitive effects of low-price guarantees with potential price discrimination.

## Consumer Welfare Analysis of a Low-Price Guarantee and the Firms' Incentives

### 2.1 Introduction

The low-price guarantee is a marketing strategy in which firms promise to charge consumers the lowest price among their competitors. When a lower price is found, they will match or offer an even lower price. It is used widely in various industries. Yet whether authorities should regulate low-price guarantees and what are the incentives for firms to adopt the guarantee are still far from well-understood.

Existing literature have modeled low-price guarantees from different perspectives, such as collusive devices, low-price signals, price discrimination tools and so on. They have not reached a conclusion on whether the authorities should regulate the guarantees. In the real world, antitrust authorities usually think the guarantees would harm consumers. For example, in 2013, “a federal US judge ruled that the price-matching provisions in Apple Inc.’s contracts with five major book publishers was part of a conspiracy to fix e-book prices”<sup>1</sup>. Mamadehussene (2016) builds a

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<sup>1</sup> See more details at <http://www.wsj.com/articles/SB10001424127887323664204578605880157245830>

theoretical model trying to explain whether low-price guarantees benefit or harm consumers and concludes it depends on market's characteristics. He finds evidence in the tire stores in Chicago area that low-price guarantees harm consumers.

From Chapter 1, I find the matching stores decreased their posted price significantly after adopting the low-price guarantee. This conforms to the predictions of theoretical models viewing it as either a price discrimination tool or a simple commitment device. Since the low-price guarantee from my data takes the term to adjust posted prices to all of their consumers after a lower price is found, this chapter treats the low-price guarantee as a commitment device. Belton (1987) considers a price-setting theoretical model in a duopoly market with differentiated products in which firms have the option to pre-commit to a low-price guarantee. Under different conditions, the guarantee can perform different functions. It may facilitate oligopoly coordination, lead to price discrimination or promote competition. Which role the guarantee actually plays depends on the demand structure in the market.

Given my data include volume sold, prices, other store characteristics and clear definition of the competitors defined in the guarantee, which are much richer than most of the existing scarce empirical literature, this enables me to estimate the effects of the low-price guarantee on sales and consumer surplus. In order to get an idea of how a low-price guarantee affects the consumer surplus, I use structural estimation to conduct counterfactual analysis. In particular, I use a similar demand estimation model to the one proposed by Berry et al. (1995). Using counterfactual analysis, I find that with the guarantee, the matching stores significantly decreased their effective prices by 0.6 cents, and increased their market share by 16%. While the estimated decrease in effective prices is 1.1 cents per liter from difference-in-difference regression analysis in Chapter 1, which is larger than the estimates from my structural model, the percentage increase in sales are larger from my structural estimates. My difference-in-difference results include the change made by any difference between the

matching stores and the control group in the summer of 1996, while my structural estimation explicitly models how the guarantee would change the market equilibrium. From my structural estimation results, the matching stations suffer a minor decrease in the profit from gasoline sales, but the increase in the consumer visits could turn into profits from their other on-site services or convenience stores, which can easily cover the decrease in the gasoline profit caused by the guarantee. Therefore, I conclude firms have strong incentives to adopt a low-price guarantee on the product that their consumers are most price-sensitive about, in the hope of earning more profits from their other products that are not included in the guarantee.

This chapter fills two gaps in the literature. First, this paper is the first to empirically estimate the difference that a low-price guarantee makes on sales and consumer surplus. It is still unclear whether the authorities should be concerned about this marketing strategy or not. Using counterfactual analysis with my structural model, it helps to understand firms' incentives to adopt a low-price guarantee and speaks to the debate about whether low-price guarantees should be regulated or not. In fact, the company who adopted a low-price guarantee in my data had to drop this policy in one of the markets recently due to government regulations. Second, this chapter overcomes the common data shortcoming of previous empirical literature by obtaining the actual price zone information from the stores that offer the low-price guarantee. Existing empirical literature is scarce and suffers from a common criticism that their results are highly dependent on getting the market definition right. This chapter will enlarge the empirical literature using structural estimation with better data of accurate market definitions and meanwhile offer a unique observation of the firm's incentive to adopt a low-price guarantee.

This chapter is organized as follows: Section 2.2 introduces the industry background and presents my data; Section 2.3 discusses the model; Section 2.4 states the estimation strategy; Section 2.5 discusses identification; Section 2.6 presents my

estimation results; Section 2.7 shows my counterfactual analysis, and I conclude in Section 2.8. Appendix A is attached to explain how I simulate the consumers and the inversion algorithm that I used.

## 2.2 Background and Data

This section introduces the industry background and describes the data I used. The data description provides the available information I use to address my research question, including gas station level data, price zone data and consumer demographic data.

### *2.2.1 Industry Background*

Starting from June 18th 1996, one of the major retail gasoline company in Quebec, Ultramar, has launched their value plus program, which is essentially a low-price guarantee. They promise to charge the lowest price in their corresponding price zones by conducting daily surveys of prices from their competitors. They also established a toll-free line for consumers to call in to report lower prices found from their competitors. The descriptive analysis in Chapter 1 shows they are quite effective in posting the lowest prices after the guarantee was adopted.

Given I find that the low-price guarantee is not a collusive device and induces lower prices from Ultramar in Chapter 1, one suspects that the real reason for Ultramar to adopt the low-price guarantee was to attract more consumers to visit their sites, some of which have convenience stores. A manager from Ultramar who has started working there since 1995 conjectured that the value plus program may be a result of their “Corner Store” program. In 1995, Ultramar started the “Corner Store” program with the goal of opening a whole chain of convenience stores in a company-operated network of stations.<sup>2</sup> The value plus program was born to bring

<sup>2</sup> The main focus was to transfer the existing convenience stores into a chain. Few new convenience

people to these locations and to increase Ultramar's market shares in the provinces of Eastern Canada.

For people who are familiar with the background, I have ruled out other ongoing events to be possible reasons. First, Ultramar's acquisition of Sunoco stations in Quebec in 1996 is not the reason. All the acquired Sunoco stations took several years to rebrand to Ultramar. Although the ownership of those Sunoco stations changed, they were not covered by the value plus program while the brand was still Sunoco. Moreover, the Ultramar manager assured me that Sunoco had nothing to do with the introduction of the value plus program. Second, Ultramar introduced the unit train called "Ultratrain" in the summer of 1996. Unit train is a train in which all wagons carry the same commodity and are shipped from the same origin to the same destination, without been splitted up or stored en route. Ultratrain was advertised as a more cost efficient mode of transportation. However, the route of the newly constructed unit train was only within the Quebec Province, while the value plus program was applicable for all Ultramar stations in Eastern Canada, which includes Quebec, Ontario and Atlantic provinces.<sup>3</sup> Therefore, the introduction of the unit train could not be the reason for Ultramar to adopt the guarantee.

Given all the above background, I model the guarantee as a commitment device of Ultramar's low price. The model assumes full information of prices. I also develop an empirical model in Appendix B where I relax this assumption and allow consumers to search.

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stores were opened.

<sup>3</sup> There are some recent updates regarding to the value plus program. Quebec is the only province where Ultramar still offers the value plus program now. Ultramar had to cancel the program in Atlantic provinces due to government regulations. Ultramar was evaluating the relevance to keep the value plus program in Ontario back in 2014. As of Sep 1st 2015, we can see that Ontario is now excluded from the program.

### *2.2.2 Data Description*

I use three main sets of data. The gasoline station level data provides necessary information to estimate demand for differentiated products. The price zone data provides accurate information on which stations are included in Ultramar's low-price guarantee, while the transportation and census data, which includes consumer commute patterns and income, enable me to look into demand from heterogeneous consumers.

Chapter 1 discusses the details of the gasoline station level data and the price zone data. Therefore, I mainly focus on the description of consumer demographics, which is the new piece of information for this chapter.

#### *Consumer Demographics*

For consumer demographics, I consider income and transportation routes. I use the empirical distribution of consumer transportation routes to estimate demand with multiple destinations. The multiple destination model considers the consumers' choice set as the gasoline stations along their commute routes instead of only those located near their house. Since Houde (2012) points out that multiple destinations play a very important role in accurately estimating the demand of gasoline, this paper takes this variable into account by using data from Quebec City Metropolitan Area (CMA) to define the geography of the market.

Starting from 2001, Canadian Census has introduced a new geographic definition, Dissemination Area (DA), the smallest census agglomeration for which data is publicly available. There are about 1200 DAs in Quebec City alone. For Quebec CMA, the average population of each DA is around 500. Dissemination Area (DA) boundaries respect the boundaries of census subdivisions and census tracts. DAs remain stable over time, to the extent that census subdivisions and census tracts can. I assume the relative distribution of population is stable over time, so that it is

possible for me to disaggregate census data from previous years, which are based on census tracts, to DAs.

In order to construct the empirical distribution of commuters across different geographies of the market, additional data from the monthly Canadian Labor Force survey are used, which reports estimates of the adult population and the number of workers for the main Census Metropolitan Areas. Empirical distribution of income conditional on the DA where people live are available from the Census.

Commuters may choose different transportation for various trips of different purposes. The 1996 Origin-Destination survey performed by the Quebec Ministry of Transportation for the Quebec CMA collected individual level data of mode of transportation used and destination for four trip purposes: work, leisure, study, and shopping. The 2001 OD survey provides additional information of transportation used by different groups according to the trip purposes. Since the variation is small across these two years, I assume that the traffic pattern was stable and the transportation mode usage stayed proportionally the same. Combining this piece of information, I can finally compute the number of commuters for each origin destination pairs. Moreover, the usage data derived from the OD survey is used to back up the total potential market size.

Given the defined geography of the market, commuters' route choices are derived using a version of the Dijkstra's Shortest Path Tree (SPT) algorithm. Information on the Quebec CMA street network was obtained from the CanMap RouteLogistics database DMTI-Spatial (2004), the leading road data provider in Canada. The database includes more than 30,000 segments and the average travel time per segment is less than 30 seconds. Therefore, the commute routes should be quite accurate.

## 2.3 The Model

This section aims to estimate the change in consumer surplus after the low-price guarantee was adopted. In order to achieve this, I solve the market equilibrium in a Bertrand competition setting. I incorporate the effective price under the guarantee into my demand estimation and the lowest price constraint facing by Ultramar stations into my supply side.

The difference-in-difference comparison in Chapter 1 of changes on prices, volume sold, and sales of different groups of stations before and after the guarantee hints at how to build the structural model that captures the role that the guarantee played. My results show that the low-price guarantee is pro-competitive in the retail gasoline industry, and that it may be a price commitment or low price signaling device. Given Ultramar promises to adjust their posted price to all their consumers when a lower price is found from their competitor, price discrimination is not possible here. Therefore, I model it as a simple commitment device.

### *2.3.1 Demand*

In order to estimate demand, I use the random coefficient discrete choice model with multiple destinations similar to Houde (2012). Consumers do not necessarily just shop at places near their house but are also likely to fill up their tanks at the gas stations near their daily commute routes from home to work. The travel cost is the time that consumers travel to the station deviating from their commute routes. Taking into account station characteristics, prices, and travel costs, consumers end up choosing whichever station gives them the highest utility.

I assume complete information in the market, so that all consumers know the prices in the market perfectly well. I also include my work in progress in the appendix where I relax this assumption and allow consumers to search to get the price

information. Given previous preliminary evidence showing that Ultramar kept posting the lowest price quite effectively, I assume that the effective price charged by Ultramar is the lowest within the price zone. This assumption is quite reasonable in the complete information set up. Moreover, even if prices are not perfectly known by consumers, the matching stations will still choose the lowest price within a price zone in equilibrium. Meanwhile, since the value plus program from Ultramar was well advertised and corresponding price zones were posted near the counter of each station, I treat the price zones as public information. Only the effective prices affect consumers' demand.

Consumers have  $J + 1$  choices, where  $J$  is the number of gas stations in the market and plus one is the outside option where consumers end up not purchasing any gasoline. Each period, consumers pick the choice that gives them the maximum utility level. The utility function is assumed to take the following functional form (subscript  $t$  is omitted in this section for notation convenience):

$$U_{ij} = \begin{cases} X_j b - (\bar{\alpha} + \alpha y_i) p_j - \kappa_1 D(r(o_i, d_i), l_j) + \xi_j + \varepsilon_{ij} & \text{if } j \neq 0 \\ -\kappa_0 I(o_i, d_i) + \varepsilon_{i0} & \text{otherwise} \end{cases}$$

where  $X_j$  is a vector of observed characteristics of station  $j$ , including number of pumps, islands, service type (self service, full service, or both), convenience store scale (no convenience store, small, medium or large), whether repair service is available, whether carwash is offered, operation hours (12 hours, 24 hours or extended hours), brand dummies, time dummies;  $y_i$  is consumer  $i$ 's log hourly income;  $p_j$  is the effective price of station  $j$ ;  $D(r(o_i, d_i), l_j)$  is the minutes of consumer  $i$ 's traveling time for deviating from his daily commute route  $r(o_i, d_i)$  to station  $j$ ; and  $I(o_i, d_i)$  is an indicator for long commuters who do not live and work in the same neighborhood.  $\xi_j$  represents the characteristics of station  $j$  that are observed by consumers but not

by the econometrician.  $\varepsilon_{ij}$  is the utility shock which is assumed to independently identically follow the Type-I extreme distribution, where  $\varepsilon_{i0}$  is normalized to zero. Notice that I include the dummy variable for long commuters to capture the fact that the outside option (i.e. taking public transportation) seems less attractive to them. The parameter  $\alpha$  allows me to capture different price sensitivities for consumers with different income levels.

Given the above utility function form, a consumer  $i$ , whose commute route is  $r(o_i, d_i)$  and earns income  $y_i$ , has the following probability of purchasing gasoline at station  $j$ :

$$P_j(r(o_i, d_i), y_i) = \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum_l \exp(\delta_l + \mu_{il})}$$

where  $\delta_j = X_j b - \bar{\alpha} p_j + \xi_j$  is the mean utility term which is independent of consumers' characteristics, while  $\mu_{ij} = -\alpha y_i p_j - \kappa_1 D(r(o_i, d_i), l_j) + \kappa_0 I(o_i, d_i)$ .

The demand for gasoline of each individual can vary. I assume that the average daily demand for gasoline of consumers on commute route  $r(o, d)$  takes the form  $\bar{q}(r(o, d)) = c_0 + c_1 m(o, d)$ , where  $m(o, d)$  is the kilometers one needs to travel for a round trip of the commute route  $r(o, d)$ . I fix  $c_1 = 0.1$  liter/kilometer<sup>4</sup> and I will estimate  $c_0$  which captures the gasoline consumption on shopping trips. Therefore, the total market size can be represented as

$$M = \sum_{o,d} \bar{q}(r(o, d)) T_{o,d}$$

where  $T_{o,d}$  is the population whose commute route is  $r(o, d)$ . The demand for gasoline from station  $j$  would be

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<sup>4</sup> This is about 0.0425 gallons per mile, which is around 23.5 miles per gallon.

$$Q_j(\mathbf{p}) = \sum_o \sum_d \int \bar{q}(r(o, d)) P_j(r(o_i, d_i), y_i) dF(y|o) T_{o,d}$$

where  $F(y|o)$  is the empirical distribution of income conditional on the neighborhood where consumers live.

### 2.3.2 Supply

I model the supply side in a Bertrand competition environment. Following the argument of the retail gasoline market structure in Hastings (2009) and Houde (2012), I model stations' pricing behavior under the retail-price maintenance structure. It is believed that the upstream suppliers can control the retail price of most of their gasoline indirectly, so branded gas stations act as a vertically integrated firm. In my case, Ultramar is the only supplier who can set the retail price of all their gas stations directly using commission based contracts. Other branded suppliers operate their retail gas stations under a mix of company-operated and lessee-dealer contracts. Of all the branded stations in my sample, 67% are controlled directly by their upstream suppliers. So I consider it reasonable to use the retail-price maintenance structure.

Before the low-price guarantee was introduced, firms maximized profit as follows:

$$\max_{p_f} \sum_{j \in \mathcal{J}_f} (p_j - mc_j) Q_j(\mathbf{p}_f, \mathbf{p}_{-f})$$

First order condition:

$$\mathbf{Q}(\mathbf{p}) + (\mathbf{\Omega} .* \Delta(\mathbf{p}))(\mathbf{p} - \mathbf{mc}) = 0$$

where  $.*$  denotes the element-by-element operator;  $\mathcal{J}_f$  maps each station  $j$  to its upstream supplier  $f$ ;  $\mathbf{\Omega}$  is the  $J \times J$  ownership matrix with  $\Omega_{ij} = 1$  if station  $i$  and station  $j$  sell the same brand of gasoline;  $\Delta(\mathbf{p})$  is the Jacobian matrix of the demand with  $\Delta_{ij} = \partial Q_i / \partial p_j$ .

After the low-price guarantee was introduced, the matching stations would face a constraint when they set their prices. In equilibrium, the posted price should be equal to the effective price in demand estimation.

$$\max_{\mathbf{p}_f} \sum_{j \in \mathcal{J}_f} (p_j - mc_j) Q_j(\mathbf{p}_f, \mathbf{p}_{-f})$$

$$\text{s.t. } p_j \leq p_k, \quad \text{if } j \in \mathcal{J}_{\text{Ultramar}} \quad \text{and} \quad Z(j) = Z(k)$$

where  $Z(j)$  represents the corresponding price zone that station  $j$  belongs to. Given a constrained optimizing problem, we will have Kuhn-Tucker conditions as follows:

$$Q_j(\mathbf{p}_f, \mathbf{p}_{-f}) + \sum_{l \in \mathcal{J}_f} (p_l - mc_l) \frac{\partial Q_l(\mathbf{p}_f, \mathbf{p}_{-f})}{\partial p_j} = 0, \quad \text{for } j \notin \mathcal{J}_{\text{Ultramar}}$$

$$\begin{aligned} Q_j(\mathbf{p}_f, \mathbf{p}_{-f}) + \sum_{l \in \mathcal{J}_f} (p_l - mc_l) \frac{\partial Q_l(\mathbf{p}_f, \mathbf{p}_{-f})}{\partial p_j} &= 0, & \text{if } z_{(j)}^{p_j < p_k} = Z(k) \\ Q_j(\mathbf{p}_f, \mathbf{p}_{-f}) + \sum_{l \in \mathcal{J}_f} (p_l - mc_l) \frac{\partial Q_l(\mathbf{p}_f, \mathbf{p}_{-f})}{\partial p_j} &> 0, & \text{otherwise} \end{aligned}, \quad \text{for } j \in \mathcal{J}_{\text{Ultramar}}$$

I assume that the pure Bertrand Nash equilibrium in prices exists and the low-price guarantee does not change the demand structure. Those first order conditions will be used to recover the unobserved marginal cost of each station. When Ultramar's effective price is the strictly lowest within the price zone (i.e. all other stations in the same zone charge a higher price), I can recover the marginal costs using the first order conditions. When Ultramar's effective price is the matched lowest within the price zone (i.e. at least one other station in the same zone charges the same price), I predict those marginal costs from the ones I recovered from the first order conditions. I assume the cost structure did not change after the low-price guarantee was adopted.

### 2.3.3 Consumer Surplus

To get a sense of how the low-price guarantee affects consumer surplus, I compare the consumer surplus after the guarantee was adopted to my counterfactual case where I remove the guarantee and resolve the equilibrium. Using my structural model, I can easily calculate consumer surplus as follows:

$$CV_i = \frac{\ln \left[ \sum_{j=0}^J V_{ij} \right] - \ln \left[ \sum_{j=0}^J V_{ij}^{cf} \right]}{\bar{\alpha} + \alpha y_i}$$

where

$$V_{ij} = \exp(X_j b - (\bar{\alpha} + \alpha y_i) p_j - \kappa_1 D(r(o_i, d_i), l_j) + \kappa_0 I(o_i, d_i) + \xi_j)$$

and  $V_{ij}^{cf}$  represents the corresponding  $V_{ij}$  when I remove the guarantee in the counterfactual analysis. The mean compensating variation in the population is given by

$$\sum_o \sum_d \int CV_i \bar{q}(r(o_i, d_i)) dF(y|o) T_{o,d}$$

## 2.4 Estimation Strategy

To estimate my parameters  $\boldsymbol{\theta} = \{ \alpha, c_0, \kappa_0, \kappa_1, \bar{\alpha}, b \}$ , I use two groups of moments, which is similar to Petrin (2002) and Houde (2012). Only  $\alpha, c_0, \kappa_0, \kappa_1$  are the non-linear parameters. The first group of moments follow Nevo (2001):

$$\bar{g}^1(\boldsymbol{\theta}) = \frac{1}{n} \sum_{j,t} g_{jt}^1(\boldsymbol{\theta}) = \frac{1}{n} \sum_{j,t} \tilde{\xi}_{j,t}(\boldsymbol{\theta}) \tilde{\mathbf{W}}_{j,t}^1$$

where  $n$  is the number of observations,  $\tilde{\xi}_{j,t}$  is the demeaned  $\xi_{j,t}$  where station fixed effects have been taken out,  $\tilde{\mathbf{W}}_{j,t}^1$  includes both the demeaned observed station

characteristics  $\tilde{X}_{j,t}$  and the instrumental variables  $\tilde{Z}_{j,t}$ . The term  $\tilde{\xi}_{j,t}$  would capture unobserved station characteristics variation in different periods, such as temporary road constructions at the location. The second set of moments match observed usage from OD survey to the predicted usage from the demand estimation. Specifically,

$$\bar{g}^2(\boldsymbol{\theta}) = \frac{1}{n_2} \sum_{o,d} \left( U_{od}(\boldsymbol{\theta}) - \hat{U}_{od} \right) \mathbf{W}_{od}^2$$

where  $n_2$  is the number of aggregated original-destination pairs to the traffic zone in the OD survey,  $\mathbf{W}_{od}^2$  includes a constant, income, and the long commuter indicator. This moment will help to identify the outside good market share.

The GMM objective function is

$$\boldsymbol{\theta} = \underset{\boldsymbol{\theta}}{\text{arg min}} g^1(\boldsymbol{\theta})^T A_1^{-1} g^1(\boldsymbol{\theta}) + g^2(\boldsymbol{\theta})^T A_2^{-1} g^2(\boldsymbol{\theta})$$

The weighting matrix  $A_2$  is a consistent estimate of  $E \left[ g^2(\boldsymbol{\theta})^T g^2(\boldsymbol{\theta}) \right]$ , while the weighting matrix  $A_1$  is constructed following Conley (1999) and Houde (2012) to deal with spatial and time correlation between empirical moments. More weights are put on the more recent periods and the closer stations.

$$A_1 = \frac{1}{n} \sum_t \sum_{l=-3}^3 K(t, t+h) g_t^1(\hat{\boldsymbol{\theta}}^1)^T D(t, t+h) g_{t+l}^1(\hat{\boldsymbol{\theta}}^1)$$

$$D_{j,k}(t, t+h) = \begin{cases} 1 - \frac{d(j,k)}{3} & \text{if } d(j,k) \leq 3 \\ 0 & \text{Otherwise} \end{cases}$$

$$K(t, t+h) = \begin{cases} 1 - \frac{|h|}{3} & \text{if } |h| \leq 3 \\ 0 & \text{Otherwise} \end{cases}$$

where  $\hat{\boldsymbol{\theta}}^1$  is the vector of estimated parameters from the first step GMM. For the inversion of getting  $\delta_{jt}$ , I use Broyden's root-finding algorithm instead of the

traditional contraction mapping. This algorithm is proven to be much faster. Please refer to the appendix for more details.

Calculation of asymptotic variance follows Petrin (2002), i.e.  $(\Gamma'\Gamma)^{-1} \Gamma'V\Gamma (\Gamma'\Gamma)^{-1}$ , where  $\Gamma$  is the gradient of the moments with respect to the parameters evaluated at the true parameter values, and  $V$  is a block-diagonal matrix with variance from the two sets of moments.

## 2.5 Identification

Since consumers and stations observe  $\xi_{j,t}$  and observed prices are the market clearing outcome, prices are likely to be correlated to  $\xi_{j,t}$ , and cause endogeneity problems. In order to fix that, I have constructed several instruments. A valid instrument would be correlated with prices but be independent from the unobserved station characteristics after taking out the station fixed effect and time fixed effect. I mainly employ two types of instruments: the BLP type and cross-section cost variation.

As Berry et al. (1995) pointed out, the characteristics of nearby competitors would enter the first order conditions when firms make their optimal prices. Therefore, those can be related to prices. If we assume that the nearby station characteristics are independent of the unobserved station characteristics conditional on station fixed effect and time fixed effect, the BLP type instruments are valid. This assumption seems reasonable given that most station amenities involve a relatively large sunk cost. Thus, a decision of entering or exiting or changing a station characteristic is not likely to be related to some transitory unobserved station characteristic or temporary road constructions,  $\tilde{\xi}_{j,t}$ . Specifically, this set of instruments includes the number of stations on the same street but within 5 minutes drive, and the average number of pumps of those stations. It also accounts for the average number of pumps of the stations within the rings of distance smaller than 0.1 KM, between 0.1 KM and 0.33 KM, between 0.33 KM and 1KM.

Another typical instrument for price is cost shifters or cost variations. Since I have already included time fixed effects, I would need the instruments to reflect within cross-sectional cost variations. The rack price at the Quebec terminals has a very small variation, so I take advantage of this to construct the extra instruments. For gasoline retailers, independent stations are more likely to buy from the unbranded terminals at the rack price plus some wholesale discount and delivery fee. Therefore, following Houde (2012), I use the product of unbranded gasoline rack price at a Sunoco or Olco terminal and a dummy indicating the presence of a Sunoco or Olco station nearby<sup>5</sup> as instruments.

## 2.6 Estimation Results

This section presents the estimation results for demand, cross-price elasticities, and recovered marginal costs.

### 2.6.1 Demand

Table 2.1 shows the estimation results for my demand model. The average demand price elasticity is less than -20, which shows that consumers are very price sensitive. The number is close to the reported average demand price elasticity of gasoline in Houde (2012), which is -15; and to the reported median elasticity of gasoline in Rossi and Chintagunta (2015), which is -17.5. All signs of the coefficients are as expected and most of them are significant. As is indicated, consumers are willing to travel an extra minute for a savings of 2.62 cents per liter. This number is fairly close to the findings from Chan et al. (2007); i.e., consumers are willing to travel up to a mile for a savings of 3 cents per liter. If we assume consumers travel 50 kilometers per hour<sup>6</sup>, then in terms of the traveling time, their number means consumers are willing to

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<sup>5</sup> Within 1KM distance or on the same street within 5 minutes of drive time.

<sup>6</sup> This is the statutory speed limits in urban area in Quebec, which is about 31 miles per hour.

Table 2.1: Demand Estimation Result

variable	coefficient	standard error
min consumption ( $c_0$ )	5.2526	3.7509
Commuting distance ( $c_1$ )	0.1	–
Income ( $\alpha$ -log(\$/hour))	-0.0019	0.0004
Long commuters ( $\kappa_0$ )	1.4413	0.0329
Transportation cost ( $\kappa_1$ )	0.4179	0.0122
Price ( $\bar{\alpha}$ )	0.1596	0.0256
Observations	5778	

travel an extra minute to save at least 1.55 cents per liter. In my data, an average consumer's daily demand for gasoline  $\bar{q}(r(o_i, d_i))$  is estimated to be 6.1 liters. The median value of willingness to pay for a minute of travel to get their daily demand is 0.16 dollars, i.e. 9.88 dollars per hour, which is a little bit less than the median income per hour (i.e. 11.52 dollars per hour) in Quebec City. On the other hand, the median value of willingness to pay to be a long commuter (i.e.  $30^*(\bar{q}(r(o_i, d_i)) \kappa_0 / (\bar{\alpha} + \alpha y_i))$ ) is \$16 per month. This means you have to pay a representative consumer \$16 a month for him to be willing to live in a different neighborhood from work. This interpretation has not taken account that once the same consumer becomes a long commuter, his travel route changes and the set of stations that are more convenient for him to visit also changes, and so does his travel time to each station deviating from his commute route.

### 2.6.2 Elasticities

In order to better understand the competitiveness in the market and how different spatial measurements are related to cross-price elasticities, Table 2.2 presents the summary statistics of the estimated cross price elasticities of market share and consumer share, along with different measurements of spatial distance. The common traffic is defined as the percentage of the simulated consumers who travel less than 1/2 minute to get to either station. Cross price elasticity for either market share

Table 2.2: Summary Statistics of Estimated Elasticities and Control Variables In Elasticity Analysis

Variables	Avg.	SD	$p_1$	$p_{10}$	$p_{50}$	$p_{90}$	$p_{99}$	Max
estimated cross elast. market share	.0459	.1151	1.42e-5	.0002	.0100	.1157	.5418	6.987
estimated cross elast. consumer share	.0452	.1163	8.35e-6	.0001	.0091	.1141	.5448	7.023
Same zone	.0433	.2035	0	0	0	0	1	1
Common traffic	.0270	.1049	0	0	0	.0513	.6000	1
Driving time	12.71	6.603	1.235	4.861	11.74	22.42	29.48	36.10
Common street	.0255	.1577	0	0	0	0	1	1

or consumer share is around 0.05, which means when price increases by 1%, your competitor's market share goes up by 0.05%. This number is not too far away from the reported average cross price elasticity of gasoline demand in Houde (2012), which is 0.025.

The cross price elasticities should change for different pairs of stations as their relative spatial locations are different. To explore this relationship, Table 2.3 shows the regression results. As is shown, Ultramar stations on average have a small significant effect on cross price elasticity. When an Ultramar station decreases its price by 1%, the other stations on average suffer a loss of 0.0016% on market share and 0.0018% on consumer share. If two stations are in the same price zone or share some common traffic, their cross price elasticities are larger. Sharing a common street also has a small positive significant effect on cross price elasticities. On the other hand, one more minute of driving time between two stations decreases the cross price elasticities by 0.0044.

### 2.6.3 Marginal Cost

Given that in most cases Ultramar is just matching the lowest price in the zone, I cannot recover marginal costs for those cases using the first order conditions, as the constraint of the low-price guarantee is binding. Therefore, I use the following re-

Table 2.3: Regression Results of Elasticity Analysis

	Cross-elasticity market share	Cross-elasticity consumer share
Ultra_j	.0016 (.0002)	.0018 (.0002)
Same zone	.1562 (.0004)	.1611 (.0004)
Common traffic	.2825 (.0008)	.2907 (.0008)
Driving time	-.0044 ( $1.08e - 5$ )	-.0043 ( $1.09e - 5$ )
Common street	.0365 (.0005)	.0371 (.0005)
Constant	.0858 (.0002)	.0838 (.0002)
Observations	1825123	1825123
Adj. $R^2$	0.4041	0.4095

gression to estimate those unidentified marginal costs based on station characteristics and controlling supplier fixed effect and time fixed effect. The average marginal cost is around 44 cents per liter, while the average rack price is around 46 cents per liter. In order to maintain the competitiveness of their retailers, wholesalers sometimes subsidize the wholesale prices to their dealers. Therefore, the effective marginal cost could be lower than the observed posted rack price. According to Lerner (1995), little gasoline is sold at the rack in Canada, therefore, the rack prices are used as a proxy for the ex-tax refinery price. Depending on the volume bought, a wholesale discount off the rack is often provided. Typically, the discount is somewhere around 1 to 1.5 cents per liter.

As you can see, the regression results are quite intuitive. Larger stations, stations with self service, convenience stores, carwash, and fewer operating hours tend to have lower marginal costs; stations offering repair service and those under lessee dealer contracts tend to have higher marginal costs. The average mark up is 10.72%, i.e. 6.13 cents per liter. This number is very close to the Browne (1997) reported margin

level, i.e. 4 to 6 cents per liter, in the Saint John market, which is located in the province next to Quebec.

$$\begin{aligned}
mc_{jt} = & 42.1713 - 0.0248 \times pumps_{jt} - 0.0490 \times small\ conv.\ store_{jt} \\
& \quad (0.2144) \quad (0.0079) \quad (0.0915) \\
& -0.1493 \times medium\ conv.\ store_{jt} - 0.0788 \times large\ conv.\ store_{jt} \\
& \quad (0.0929) \quad (0.0890) \\
& -0.3079 \times self\ service_{jt} - 0.2679 \times split\ service_{jt} \\
& \quad (0.0844) \quad (0.1160) \\
& -0.3209 \times 12\ hours_{jt} - 0.1597 \times extended\ hours_{jt} \\
& \quad (0.1144) \quad (0.0617) \\
& +0.2208 \times repair_{jt} - 0.1867 \times carwash_{jt} \\
& \quad (0.0741) \quad (0.0673) \\
& +0.5834 \times lessee\ dealer_{jt} + FE_t + FE_{supplier}, \quad Adj. R^2 = 0.7027 \\
& \quad (0.0646)
\end{aligned}$$

## 2.7 Counterfactual Analysis

Assuming the estimated demand and recovered marginal cost stay the same if the low-price guarantee is removed, I conduct counterfactual analysis in this section to discover the difference that the guarantee has brought to station prices, volume sold, profits, revenues, and consumer surplus.

Table 2.4 presents the changes made by the guarantee for three groups of stations: Ultramar stations, which adopted the guarantee; nonultr stations, those within Ultramar's price zones; and other stations, those in a zone with no Ultramar. As shown, compared to the case where the guarantee is removed, Ultramar stations on average decreased their prices by 0.6 cents per liter (i.e. 1% decrease) when the guarantee was adopted; their competitors within their zones and the other stations that were not directly affected by the guarantee did not respond much. Ultramar's market share and consumer share increased by 16% , and their revenue increased about 13% as a result. However, Ultramar suffered a decrease of about 11% in profits.

Table 2.4: Changes Due to LPG

LPG-noLPG	ultramar	nonultr	others
price	-.6045	-.0015	-.0014
market share	$7.34e - 5$	$-7.33e - 6$	$-4.76e - 6$
consumer share	$6.91e - 5$	$-6.81e - 6$	$-4.19e - 6$
profit	-1269	-156.1	-105.8
revenue	9165	-1144	-714.9
compensating variation	$4.38e + 4$		
(LPG-noLPG)/noLPG	ultramar	nonultr	others
price	-.0116	$-3.20e - 5$	$-3.04e - 5$
market share	.1646	-.0035	-.0016
consumer share	.1645	-.0034	-.0015
profit	-.1118	-.0037	-.0017
revenue	.1274	-.0035	-.0016
compensating variation	.0028		

From those numbers, we wonder why Ultramar introduced the low-price guarantee in the first place if it cannot bring more profits. My results show that the matching firms decreased prices significantly while other firms did not respond much. However, over 80% of the Ultramar stations had at least some type of add-on services, i.e. convenience store, car wash, or repair shop. Getting more traffic to the station could potentially be more profitable than it appears for just the gasoline profit. According to a manager who has worked at Ultramar since 1995, one possible goal for low-price guarantee is to bring in more consumers in the hope that they will shop at the attached convenience stores. From my data, before the guarantee was adopted, 46% of all Ultramar stations had attached convenience stores. This number remained stable before the guarantee was adopted. After the guarantee was adopted, the percentage of Ultramar stations that had attached convenience stores steadily increased from 46% to 59%. For a station with convenience store, to compensate the decrease in profit of gasoline caused by the guarantee, it only had to make a profit of around 35 cents<sup>7</sup> for each consumer who was attracted by the guarantee to visit their stations.

<sup>7</sup> Profit/(consumer share\*population)=1269/(6.91e-5\*5.17e+5)=35

Given that the profit margin of a gallon of milk is around 49 cents<sup>8</sup>, it is very likely that the low-price guarantee is profitable if we consider the overall profit of a gas station with the attached service or convenience store.

According to NACS (2013), for a typical station, gasoline sales account for 70% of its revenue but only 30% of its profit. The daily average gasoline profit is around \$300 with 775 consumers. Then the profit from other services or convenience store should be around \$700, i.e. \$0.9 profit per consumer. Given that the guarantee attracted on average around 36 more consumers to visit the station, that would bring in \$32.4, which is larger than the decrease in the profit from gasoline sales which is about \$12.7. Although this calculation involves a lot of hand waving, the idea is to illustrate that gasoline stations have strong incentives to attract price sensitive consumers to fill their tanks.

Lastly, I compute the compensating variation that the guarantee has brought. Due to the lower prices Ultramar posted, the mean compensating variation of the population is around \$438 per day. Therefore, authorities should not be concerned that low-price guarantee would hurt consumers or competition in the market.

## 2.8 Discussions and Conclusion

This paper models the low-price guarantee as a pricing commitment device and answers the research question concerning whether the guarantee benefits consumers and what are the firms' incentives to adopt a low-price guarantee. Using retail gasoline station level data before and after the guarantee, I find that the matching company increased their market share significantly after the guarantee. My counterfactual analysis with my structural model estimates the decrease in effective prices to be 0.6 cents per liter. I did not find strong evidence showing significant reaction from the

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<sup>8</sup> According to Chernoff et al. (2013), the profit margin of dairy product in Quebec from 1995-1997 is around 15%. <http://www.1990sflashback.com/1996/economy.asp> shows that a gallon of milk is priced at \$3.3 in 1996. (Accessed 2015.09.09)

non matching stores or nearby stores which were not affected directly by the guarantee. Surprisingly, while the low-price guarantee did boost the matching stores' volume sold and revenue, the net change in the profit from gasoline alone is negative. However, given that consumers are highly price-sensitive on gasoline, a station does not have to suffer much decrease in profit to attract a lot more customers. The potential profit from its add-on service or attached convenience store can easily make up the decrease in gasoline profit. I also investigate the impact of the low-price guarantee on consumer surplus. Due to the lower prices that consumers could enjoy from the matching stations, the mean compensating variation of the population is estimated to be \$438 per day. I conclude that authorities should not have any anti-competitive concerns. Low-price guarantees should not be regulated in the market.

This paper is limited to the extent that I assumed price is complete information and only allows the guarantee to play a role through the price channel. The model I proposed in Appendix B relaxes this assumption and takes price as incomplete information and allows consumers to search before making their purchase decisions.

## Development of Energy Star<sup>®</sup> Energy Performance Indicators for Pulp, Paper, and Paperboard Mills

### 3.1 Introduction

ENERGY STAR was introduced by EPA in 1992 as a voluntary, market-based partnership to reduce air pollution associated with energy use through increased energy efficiency. This government program enables industrial and commercial businesses as well as consumers to make informed decisions that save energy, reduce costs, and protect the environment. For businesses, a key step in improving energy efficiency is to institutionalize a strategic approach to energy management. Drawing from management standards for quality and environmental performance, EPA developed the ENERGY STAR Guidelines for Energy Management that identifies the components of successful energy management practices (EPA (2003)).

These include: commitment from a senior corporate executive to manage energy across all businesses and facilities operated by the company; appointment of a corporate energy director to coordinate and direct the energy program and multi-disciplinary energy team; establishment and promotion of an energy policy; devel-

opment of a system for assessing performance of the energy management efforts including tracking energy use as well as benchmarking energy in facilities, operations, and subunits therein; conduct of audits to determine areas for improvement; setting of goals at the corporate, facility, and subunit levels; establishment of an action plan across all operations and facilities, as well as monitoring successful implementation and promoting the value to all employees; and provision of rewards for the success of the program.

Of the major steps in energy management program development, benchmarking energy performance by comparing current energy performance to a baseline or a similar entity is critical. In manufacturing, it may take the form of detailed comparisons of specific production lines or pieces of equipment, or it may be performed at a broader system level by gauging the performance of a single manufacturing plant to its industry. Regardless of the application, benchmarking enables companies to determine whether better energy performance could be expected. It empowers them to set goals and evaluate their reasonableness.

Boyd et al. (2008) describe the evolution of a statistically based plant energy performance indicator for the purpose of benchmarking manufacturing energy use for ENERGY STAR. Boyd and Dutrow (2005) describe the basic approach used in developing such an indicator, including the concept of normalization and how variables are chosen to be included in the analysis. To date, ENERGY STAR has developed statistical indicators for a wide range of industries. This report describes the basic concept of benchmarking and the statistical approach employed in developing performance-based energy indicators for several segments of the pulp, paper, and paperboard industry, the evolution of the analysis done for these segments of this industry, the final results of this analysis, and ongoing efforts by EPA to improve the energy efficiency of this industry and others.

## 3.2 Benchmarking the Energy Efficiency of Industrial Plants

Among U.S. manufacturers, few industries participate in industry-wide plant benchmarking. The petroleum and petrochemical industries each support plant-wide surveys conducted by a private company and are provided with benchmarks that address energy use and other operational parameters related to their facilities. Otherwise, most industries have not benchmarked energy use across their plants. As a result, some energy managers find it difficult to determine how well their plants might perform.

In 2000, EPA began developing a method for developing benchmarks of energy performance for plant-level energy use within a manufacturing industry. Discussions yielded a plan to use a source of data that would nationally represent manufacturing plants within a particular industry, create a statistical model of energy performance for the industry's plants based on these data along with other available sources for the industry, and establish the benchmark for the comparison of those best practices, or best-performing plants, to the industry. The primary data sources would be the Census of Manufacturing, Annual Survey of Manufacturing, and Manufacturing Energy Consumption Survey collected by the Census Bureau, or data provided by trade associations and individual companies when warranted by the specific industry circumstances and participation.

### *3.2.1 Scope of an Indicator - Experience with the Pulp, Paper, and Paperboard Industry*

In 2008, EPA initiated discussions about developing a plant-level benchmark with the pulp, paper and paperboard industry. Companies with facilities located within the United States were invited to participate in discussions. When EPA first launched the ENERGY STAR for Industry in 2001, the term “plant benchmark” was used. Companies that were first engaged in the program said that industry engineers rou-

tinely develop benchmarks at many levels of plant operation, but they expressed concern that using the word “benchmark” would be confusing and could imply a particular process or tool. For this reason, it was decided that a simple descriptive term would be clearer; thus, ENERGY STAR plant Energy Performance Indicator (EPI) was adopted and has been used ever since. The scope for the EPI is a plant-level indicator, not process-specific, and it relates plant inputs in terms of all types of energy use to plant outputs as expressed in a unit of production and/or material processed. Discussion with industry representatives helped to define the scope of the EPI.

The EPI uses a statistical model to account and normalize for major, measurable impacts that affect a plant’s energy use in order to make fairer comparisons between plants. The starting point for EPI development is Census data for industrial plants. For the pulp, paper and paperboard industry, the basic inputs included information on energy use, total production (physical), amount of material input in the form of preprocessed inputs, the total value of shipments, the shares of product types, and production labor person hours. The actual data used for each of the industry segments depended on the information available from Census and on the results of the statistical analysis. Ideally the approach to developing an EPI identifies those factors that most directly influence energy use and applies them to normalize the energy use. The most basic normalization is for production level, i.e., energy use per unit of product. Other factors may influence the level of energy use per unit of product, including specific product types, and quality and choice of materials used in production (e.g., amount of raw vs. preprocessed inputs). Including these other factors in the statistical model allows one to construct alternative “benchmarks” of the basic concept of energy use per unit of product. This ideal situation may be limited due to the availability of data, or simply by limits of the methodology’s capacity to incorporate all of the possible options. The options and data under

consideration for the analysis of pulp, paper and paperboard industry energy use are as follows.

### *Production*

The industry can be grouped into a wide range of product segments. The initial focus was stand-alone pulp mills and “integrated” mills, i.e., those that produce paper or paperboard via the on-site production of pulp. While separating plants into the two groups effectively controls for the broad differences in plant configuration, there are still issues regarding the measurement of production and differences in product type within plant type. The Census data provide total value and quantity of product shipped for each plant; physical measures of production are preferred. The different product types may have different energy requirements. The role of product types is explored for each plant type listed above.

### *Materials*

Data on the use of raw and preprocessed materials can also be included in the analysis to the extent that they have direct correlation with energy. However, the level of raw material use may not reflect what types of downstream processing different products may require. Since some plants produce products from raw instead of preprocessed materials, this is likely to have a different energy impact.

### *Capacity*

A source of industry-wide data on plant capacities was not available. If trade associations or other industry sources have this type of information, it could be incorporated in a future analysis. The book value of capital is available from the Census, but would be difficult to apply in this setting.

Table 3.1: Pulp Mill Product Categories

NAICS 10-digit	Descriptions
322110 1100	Special alpha and dissolving wood pulp
322110 3111	Sulfate, bleached and semi-bleached, including soda
322110 3121	Sulfate, unbleached
322110 5111	Sulfite, bleached and unbleached
322110 5121	Ground wood pulp (stone, refiner, and thermo-mechanical)
322110 5131	Semi-chemical
322110 5141	Other
322110 7123	Pulp, other than wood
322110 7123	Pulp, other than wood

*Utilization*

Without direct measurement of plant capacity and physical product, a simple measure of utilization is not possible. However, labor hours may provide a proxy of plant utilization. Labor data may also capture differences in downstream product processing, i.e., differences in the raw production and a fabricated final product. These data are available from Census and can be tested during model development.

The primary focus of this analysis is plants that produce pulp, paper and paperboard from raw materials in order to manufacture intermediate or final products. The U.S. Bureau of Census defines pulp, paper, and paperboard in several segments, and we draw the analysis from several different categories. The first category, Pulp Mills (NAICS 32211), comprises establishments primarily engaged in manufacturing wood pulp for further processing at non-integrated mills or finishing mills. The 10-digit NAICS product types as defined in the Census of Manufacturing are shown in Table 3.1.

The second category is Integrated Paper mills (NAICS 32212) and Paperboard Mills (NAICS 32213). Only those plants that produce a final product from primarily pulp fiber produced on-site from wood and wood chips are considered integrated mills. Mills primarily using recycled fiber were not included in the scope of the

Table 3.2: Integrated Paper and Paperboard Product Categories

NAICS 7-digit	Descriptions
3221211	Clay-coated printing and converting paper
3221213	Uncoated freesheet paper (containing not more than 10 percent mechanical fiber)
3221215	Bleached bristols (weight more than 150 g per sq meter), excluding cotton fiber index and bogus
3221217	Cotton fiber paper (containing 25 percent or more cotton or similar fibers) and thin paper
3221219	Unbleached kraft (not less than 80 percent) packaging and industrial converting paper
322121A	Packaging and industrial converting paper, except unbleached kraft
322121C	Special industrial paper, except specialty packaging, including absorbent, battery separator, electrical papers, etc.
322121E	Construction paper
322121G	Tissue paper and other machine-creped paper
322121K	Disposable diapers and similar disposable products, made in paper mills
322121N	Sanitary tissue paper products, made in paper mills
3221301	Unbleached kraft packaging and industrial converting paperboard (80 percent or more virgin woodpulp):
3221303	Bleached packaging and industrial converting paperboard (80 percent or more virgin bleached woodpulp)
3221305	Semi chemical paperboard, including corrugating medium (75 percent or more virgin woodpulp)
3221307	Recycled paperboard
3221309	Wet machine board, including binders board and shoe board

analysis. Mills using a mix of sources of pulp fiber to produce the final product were included only if the fiber sources were 50% or more from wood or wood chips. We consider the following 7-digit NAICS product types as defined in the Census of Manufacturing and shown in Table 3.2 (see Appendix C for assigning 10-digit products to the 7-digit categories).

Initially, the scope of the EPI included all integrated plants. Initial industry comments found this approach to be much too broad. The scope was then modified and defined as mills that produce primarily uncoated free sheet and/or linerboard,

relative to other products. After review of the more narrowly defined model, it was decided that it would be appropriate to expand the scope to include all integrated plants. Results for those earlier analyses are not presented here.

ENERGY STAR Energy Performance Scales and EPIs use total source energy, defined as the total Btus of purchased/transferred fuels, the total Btus consumed to produce purchased/transferred steam and hot/chilled water, plus the total amount of purchased/transferred electricity converted from kWh to Btu at roughly the average rate of conversion efficiency and T&D losses for the entire U.S. electric grid, 11,396 Btu/kWh. Source energy is used to more closely align our energy measure with the underlying goals of the EPA ENERGY STAR program: energy and emissions reductions at the source. For this reason, a kWh of electricity is treated as the equivalent energy at the production source.<sup>1</sup>

Because paper plants often use biomass to generate steam, the question of whether to aggregate across fuel types based on a lower heating value (LHV) or higher heating value (HHV) was discussed. This is important because of the large difference in the efficiency of generating steam from biomass relative to other fossil fuels (due to moisture content, etc.). The conversion of electricity to its source energy value is made on a HHV basis, so use of LHV for fuels would be inconsistent. To account for the difference in the relative efficiency of generating steam from biomass, it was proposed that all energy be converted to a natural gas (HHV) steam equivalent basis. This is discussed further in section 3.3.2.

### *3.2.2 Data Sources*

The analysis conducted to create the EPIs uses confidential plant-level data from two sources: the Census of Manufacturers (CM) and the Manufacturing Energy

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<sup>1</sup> See [http://www.energystar.gov/index.cfm?c=evaluate\\_performance.bus\\_benchmark\\_comm\\_bldgs](http://www.energystar.gov/index.cfm?c=evaluate_performance.bus_benchmark_comm_bldgs) for details.

Consumption Survey (MECS) maintained by the Center for Economic Studies (CES), U.S. Bureau of the Census (Census). The CM includes the non-public, plant-level data that are the basis of government-published statistics on manufacturing. The CM includes economic activity — for example, labor, energy, plant and equipment, materials costs, and total shipment value of output — for all plants during the years of the Economic Census. The MECS is also used. MECS is a detailed survey of energy use for a sample of plants in the CM.

Under Title 13, Sections 9 & 214, of the U.S. Code, these data are confidential; however, CES allows academic and government researchers with Special Sworn Status to access these confidential micro-data under its research associate program at one of nine designated Census Research Data Centers.<sup>2</sup> The confidentiality restrictions prevent the disclosure of any information that would allow for the identification of a specific plant's or firm's activities. Aggregate figures or statistical coefficients that do not reveal the identity of individual establishments or firms can be released publicly.

The variable specific data sources and transformations are given as following: production of different product types (using 10-digit NAICS product codes) was taken from the 2002 CM product trailer files; material input (using 7-digit NAICS material codes) was taken from the 2002 CM material trailer files; electricity use was taken from the 2002 ASM, which was available for every plant in the dataset; fuel use was taken from the 2002 MECS for those plants included in the MECS sample by converting the physical units for every fuel type into Btu content and summing; onsite water treatment was inferred from the US EPA Permit Compliance System.

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<sup>2</sup> For more information, see [http://www.census.gov/privacy/data\\_protection/title\\_13\\_protection\\_of\\_confidential\\_information.html](http://www.census.gov/privacy/data_protection/title_13_protection_of_confidential_information.html)

### 3.3 Statistical Approach

The goal of this study was to develop an estimate of the distribution of energy efficiency across the industry. Efficiency is defined as the difference between the actual energy use and predicted “best practice,” i.e., the predicted lowest energy use observable. What is actually observed is influenced by operating conditions that vary between plants, so the estimate of predicted best practice must take these conditions into account. Statistical models are well-suited for accounting for these types of observable conditions and the variability relative to those observable conditions. This section provides the background on the statistical approach, a discussion on the review process and evolution of the model’s equations, and the final model estimates.

#### *3.3.1 Measuring the Distribution of Energy Efficiency*

The concept of the stochastic frontier analysis that supports the EPI can be easily described in terms of the standard linear regression model, which is reviewed in this section. A more detailed discussion on the evolution of the statistical approaches for estimating efficiency can be found in Greene (2008). Consider at first the simple example of a production process that has a fixed energy component and a variable energy component. A simple linear equation for this can be written as

$$E_i = \alpha + \beta y_i \tag{3.1}$$

where

$E_i$  = energy use of plant  $i$  and

$y_i$  = production of plant  $i$ .

Given data on energy use and production, the parameters  $\alpha$  and  $\beta$  can be fit via a linear regression model. Since the actual data may not be perfectly measured and this simple relationship between energy and production may be only an approximation

of the “true” relationship, linear regression estimates of the parameters rely on the proposition that any departures in the plant data from Eq.(3.1) are “random.” This implies that the actual relationship, represented by Eq. (3.2), includes a random error term that follows a normal (bell-shaped) distribution with a mean of 0 and variance of  $\sigma^2$ . In other words, about half of the actual values of energy use are less than what Eq. (3.1) would predict, and half are greater.

$$E_i = \alpha + \beta y_i + \epsilon_i \tag{3.2}$$

where

$$\epsilon \sim N(0, \sigma^2)$$

The linear regression gives the average relationship between production and energy use. If the departures from the average, particularly those that are above the average, are due to energy inefficiency, we would be interested in a version of Eq.(3.1) that gives the “best” (lowest) observed energy use. For example, consider that capacity utilization can influence the energy use per unit of production due to the fixed and variable components of plant energy use (see Figure 3.1). A regression model can find the line that best explains the average response of energy use per unit of production to a change in utilization rates. The relationship between the lowest energy consumption per unit of production relative to changes in utilization can be obtained by shifting the line downward so that all the actual data points are on or above the line. This “corrected” ordinary least squares (COLS) regression is one way to represent the frontier.

While the COLS method has its appeal in terms of simplicity, a more realistic view is that not all the differences between the actual data and the frontier are due to efficiency. Since we recognize that there may still be errors in data collection/reporting, effects that are unaccounted for in the analysis, and that a linear equation is an approximation of the complex factors that determine manufacturing

energy use, we still wish to include the statistical noise, or “random error,” term  $v_i$  in the analysis but also add a second random component  $u_i$  to reflect energy inefficiency.<sup>3</sup> Unlike the statistical noise term, which may be positive or negative, this second error term will follow a one-sided distribution. If we expand the simple example of energy use and production to include a range of potential effects, we can write a version of the stochastic frontier model as energy use per unit of production as a general function of systematic economic decision variables and external factors,

$$E_i = h(Y_i, X_i, Z_i; \beta) + \epsilon_i \quad (3.3)$$

$$\epsilon_i = u_i - v_i \quad v \sim N(0, \sigma_v^2)$$

where

$E$  = TSE, total source energy (or other measure of total fuel and electricity);

$Y$  = production, measured by dollar shipments or physical production;

$X$  = systematic economic decision variables (i.e., labor-hours worked, materials processed, plant capacity, or utilization rates);

$Z$  = systematic external factors (e.g., heating and cooling loads); and

$\beta$  = all the parameters to be estimated.

We assume that energy (in)efficiency  $u$  is distributed according to one of several possible one-sided statistical distributions,<sup>4</sup> for example exponential, half normal, or truncated normal. It is then possible to estimate the parameters of Eq.(3.3), along with the distribution parameters of  $u$ .

One advantage of the approach is that the parameters used to normalize for systematic effects and describe the distribution of efficiency are jointly estimated.

The standard regression model captures the behavior of the average (see solid line in

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<sup>3</sup> By random we mean that this effect is not directly measurable by the analyst, but that it can be represented by a probability distribution.

<sup>4</sup> We also assume that the two types of errors are uncorrelated,  $\sigma_{u,v}$

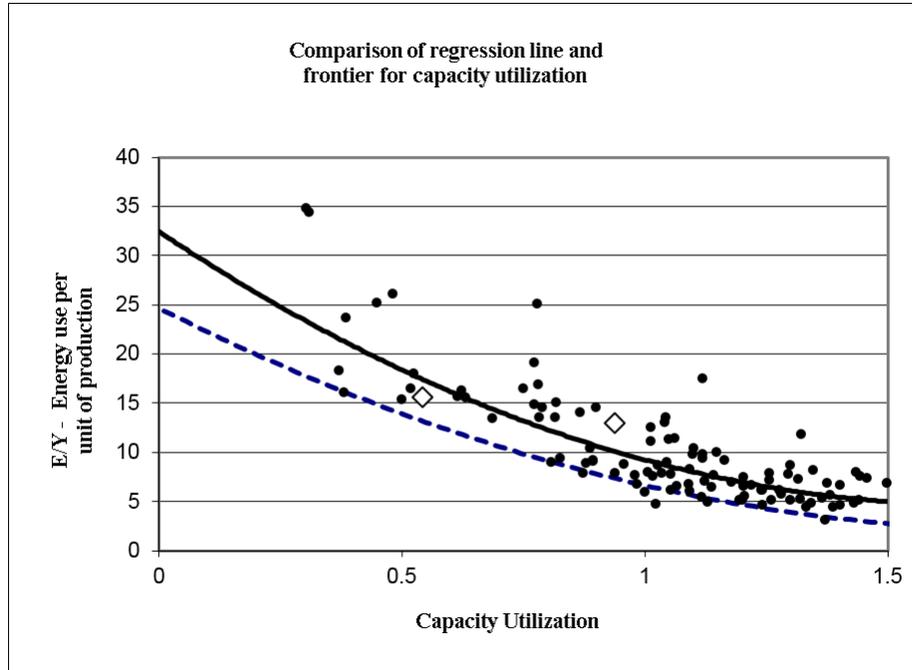


FIGURE 3.1: COLS and Frontier Regression of Energy Use per Unit of Production against Capacity Utilization

Figure 3.1), but the frontier regression (the dotted line in Figure 3.1) captures the behavior of the best performers. For example, if the best performing plants were less sensitive to capacity utilization because they use better shutdown procedures, then the estimated slope of the frontier capacity utilization curve would not be as steep as the slope for the average plants.

Another advantage of this method is that we can test if the differences in energy use, represented by the terms  $u$  and  $v$ , are statistically significant. If the estimated variance of  $u$  is small, we can conclude that the simpler statistical model in Eq.(3.2) is valid, and base our measurements on those results. Therefore, the frontier yields a more general analysis that allows for either a one-sided (skewed) distribution representing efficiency or a more “normal” (bell-shaped) distribution. If the former is the case, then we interpret that as meaning the many plants are close to one another in terms of energy use, with a smaller number being “further” from the group of

good performers. In the latter case, that of the bell-shaped, normal efficiency distribution, we have a few “good performers,” a large number of “average” plants, and a few “poor performers.” In either case, we have a statistical approach to assign a ranking for the plants.

For simplicity, we assume that the function  $h(\cdot)$  is linear in the parameters, but allow for non-linear transformations of the variables. In particular, production, materials, and labor enter the equation in log form, as does the energy variable. This means that the terms  $u$  and  $v$  can easily be interpreted as percentage deviations in energy, rather than absolute. This has implications for the model results since we now think of the distributional assumptions in terms of percent, rather than absolute level. When there is wide variation in plant scale, this seems appropriate and may avoid possible heteroscedasticity in either or both error terms.

Given data for any plant, we can rearrange Eq.(3.3) into Eq.(3.4) to compute the difference between the actual energy use and the predicted frontier energy use:

$$E_i - [h(Y_i, X_i, Z_i; \beta)] = u_i - v_i \quad (3.4)$$

In the case where the frontier model is appropriate, we have estimated the probability distribution of  $u$ . Eq.(3.5) represents the probability that the plant inefficiency is greater than this computed difference:

$$\text{Probability [energy inefficiency} \geq E_i - (h(Y_i, X_i, Z_i; \beta))] = \frac{1 - F(E_i - h(Y_i, X_i, Z_i; \beta))}{1 - F(E_i - h(Y_i, X_i, Z_i; \beta))} \quad (3.5)$$

$F(\cdot)$  is the cumulative probability density function of the appropriate one-sided density function, i.e., gamma, exponential, truncated normal, etc. The value  $1 - F(\cdot)$  in Eq.(3.5) defines the EPI score and may be interpreted as a percentile ranking of the energy efficiency of the plant. In practice, we only can measure  $E_i - h(Y_i, X_i, Z_i; \beta) = u_i - v_i$ , so this implies that the EPI score  $1 - F(\{ E_i - h(Y_i, X_i, Z_i; \beta) \}) = 1 - F(u_i - v_i)$  is affected by the random component of  $v_i$ ; that is, the

score will reflect the random influences that are not accounted for by the function  $h(*)$ .

In the case where the frontier model is not appropriate, there is no  $u$  term and corresponding estimate, only  $v$ .

$$E_i - [h(Y_i, X_i, Z_i; \beta)] = v_i \quad (3.6)$$

We can drop the minus sign for  $v$  since the normal distribution is two sided. The estimate of the variance  $v \sim N(0, \sigma_v^2)$  can be used in Eq.(3.5) where  $F(\cdot)$  is now the cumulative probability density function of a standard normal distribution.

Since this ranking is based on the distribution of inefficiency for the entire industry, but normalized to the specific systematic factors of the given plant, this statistical model allows the user to answer the hypothetical but very practical question, “How does my plant compare to everyone else’s plants in my industry, if all other plants were similar to mine?”

### *3.3.2 Evolution of the Model*

The model evolved over a period of time, based on comments from industry reviewers and subsequent analyses. The initial models were based on data from 1997 and subsequently updated to 2002, which is the current base year for the model described below.<sup>5</sup> Industry participants were given an opportunity to test and comment on each version of the model via the annual focus meetings, quarterly conference calls, and personal communications. Companies were asked to input actual data for all of their plants and then to determine whether the results were consistent with any energy efficiency assessments that may have been made for these plants. The resulting comments improved the EPI. This section summarizes this review process and the actions taken vis-à-vis the EPI analysis.

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<sup>5</sup> The Census of Manufacturers is collected every five years. Plant-level data are made available to researchers with a significant lag from the year of collection and Census publication.

### *Defining the Boundaries of the Energy System*

Unlike many industries, the PP&PB industry generates a significant portion of the energy it uses to make final products from the by-products of the manufacturing process. These by-products come from wood preparation (converting whole tree to wood chips generates bark that is used as “hog fuel”) and wood pulping (converting wood into pulp generates the fuel black liquor). Since these by-products represent a significant fuel source for the plant, it is necessary to establish the energy accounting approach that will be used for measuring energy intensity and efficiency. To do this, it was necessary to consider the energy boundaries for the EPI. Two alternatives for the boundary of the system that defines the energy input into the process were considered. The first is Net Energy Demand (see Figure 3.2). In this approach, only energy purchases into the system, net of energy sales, are considered.<sup>6</sup> The efficiency of the conversion and use of by-products is included in the measure of system energy efficiency. In other words, if a plant recovers a higher amount of by-products from production and/or uses it more efficiently (in some internal sense) then the net demand on the outside energy system will be lower, i.e., the plant will require less energy input.

The second approach is Net Energy Consumption. In this case, the system boundary accounts for the energy generated from by-product as an input (transfer in) and energy is still net of sales (transfers out). This is shown in Figure 3.3. This approach requires a higher level of information accounting for the by-product energy, with corresponding questions about unit conversion and possible double counting.

Given the issues with Net Energy Consumption, the Net Energy Demand approach was adopted because: is consistent with how co-generation (combined heat and power) is treated in other industries by the EPI; captures the availability of

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<sup>6</sup> In this context we use the term purchases and sales synonymously with any type of transfer into and out of the plant (energy system boundary)

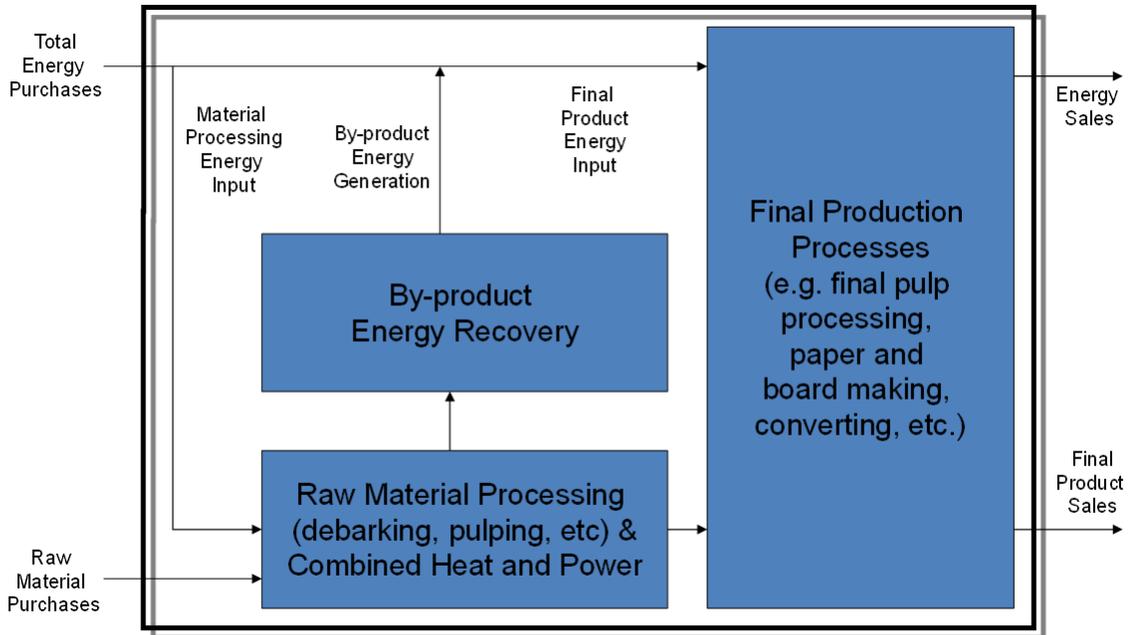


FIGURE 3.2: Net Energy Demand (purchases - sales)

biomass in some pulp and paper plants; and avoids problems associated with the measurement issues of heat value of biomass.

Both of these accounting approaches provide a useful definition of energy and energy efficiency. The choice of Net Energy Demand as the accounting definition means that “energy efficiency” is defined as both the efficient use of energy inputs as well as the efficient generation and utilization of internally generated by-product forms of energy.

*Computing BTU from Purchased Biomass*

Even though we use a Net Energy Demand accounting approach, some plants purchase biomass (typically bark or “hog fuel”). Bark has high moisture content and is not directly comparable on a Btu basis with fossil fuels when generating steam. Industry participants provided confidential operating statistics on the boiler at their plants. Table 3.3 shows the results. It is clear that the net Btu delivered as steam

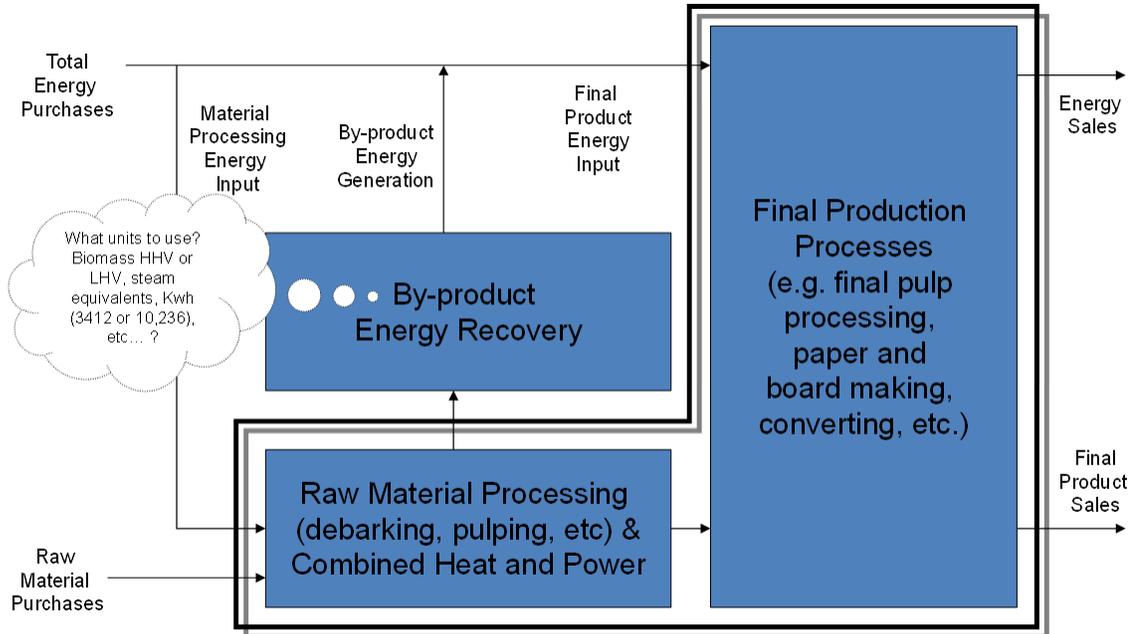


FIGURE 3.3: Net Energy Consumption (purchased + generated - sales)

per Btu on HHV basis is much lower for coal and various types of biomass. We normalize the HHV Btu for each fuel type relative to natural gas on a steam equivalent basis. This means, for example, that a Btu of purchased biomass (HHV) is treated as  $64\% / 85\% = 0.75$  Btu Natural Gas (HHV) equivalent. This approach does NOT allow companies to use plant-specific boiler efficiency in the computation. Industry averages are used for the energy accounting.

#### *Product Mix and Measurement Unit*

A wide range of products is produced in the PP&PB industry, with different characteristics for different applications. The EPI analysis examines all of the different product classes shown in Table 3.3 to determine if they differ in terms of energy requirements. However, even within a product class there can be additional difference, particularly for some types of paper and paperboard. The production of paper and paperboard is commonly reported in weight, but the surface area of the product is another way that paper and paperboard are sold and used. Paper and paperboard

Table 3.3: Steam Equivalent Conversion Rates

	AVERAGE	MEDIAN
	Net Btu/ HHV	Net Btu/ HHV
Solid Fuels		
Bituminous Coal	80%	77%
PRB Coal	68%	68%
Tire Derived Fuel(2" chips)	88%	90%
Petroleum Coke(pulverized)*	85%	85%
Mill Bark & Screenings	68%	69%
Purchased (Pur) "Biomass"	64%	64%
Pur. 50% Black Liquor (DCE)	49%	49%
Pur. 50% Black Liquor (NDC)	53%	53%
OCC Rejects (Freeman Press)	74%	74%
Purchased Steam(600 psi)	100%	100%
Liquid Fuels		
No. 6 Fuel Oil	85%	85%
No. 2 Fuel Oil	83%	83%
Gaseous Fuels		
Natural Gas	85%	85%

with identical commercial properties except for one being lighter and thinner for a given surface area may be considered a rival, or even superior product. The ratio of weight to surface area is the "basis weight" of the paper or paperboard product. Measuring paper and paperboard production in terms of weight alone will overlook this important product characteristic. Census data, like most government and trade groups, collects and reports data on a tonnage basis. Duke University attempted to get basis weight data from the American Forest & Paper Association (AF&PA) under a non-disclosure agreement from their member companies, but AF&PA was not able to share these data.

#### *Waste Water Treatment*

Reviewers' comments identified on-site waste water treatment as a major energy load that creates intra-plant differences. Mills may use a municipal or other third party to treat waste water instead of operating on-site treatment facilities. This means that

some mills energy consumption include the water treatment, while others do not. One company provided internal data that clearly demonstrated that the amount of energy was non-trivial and should be accounted for in the EPI. Plants that operate on-site water treatment must have a discharge permit from EPA. These data are public record in the EPA Permit Compliance System (PCS).<sup>7</sup>

Information on all plants with discharge permits was obtained from the PCS and merged with the Census data. Companies were invited to review the data from EPA to verify their consistency with individual company operations. While this did not provide a comprehensive review (not every company participated), the consensus was that the data were an accurate representation of whether mills used on-site treatment. Some concerns were raised that the data did not reflect the level or type of treatment that was required/used. However, more details on this were not readily available and the reviewers decided that this approach was much better than not including water treatment considerations at all.

### *Product Differences*

Census data have a wide range of product types for PP&PB. We expect that some of these products are more energy intensive than others. One broad class of PP&PB that tends to require more energy is white or “bleached” products. For pulp mills, bleached pulps are explicitly identified as separate products, as are a few specialty types of pulp. This allows the product-specific production statistics to be included in the EPI. For integrated P&PB mills this issue is more complex. Some NAICS product categories are clearly defined as “bleached,” while others may have varying levels of whiteness within a given category. To address this important product-level energy issue, data on the amount of chemicals used in the whitening process were included in the model as a proxy for the unobservable product characteristics. These chemicals

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<sup>7</sup> For more details see <http://www.epa.gov/enviro/facts/pcs-icis/index.html>

Table 3.4: Correlation between Chemical Use and Product Types

	NaOH	Total Chlorine
Clay-Coated Printing And Converting Paper	-0.12	0.11
Uncoated Freesheet Paper	0.18	0.23
Bleached Bristols	0.17	0.16
Unbleached Kraft	-0.04	-0.06
Packaging And Industrial Converting Paper	0.11	0.07
Special Industrial Paper	-0.05	-0.14
Tissue Paper And Other Machine-Creped Paper	0.05	0.08
Paperboard	-0.27	-0.35
Bleached Packaging	0.43	0.34
Semichemical Paperboard	-0.13	-0.24
Recycled Paperboard	-0.15	-0.22

include chlorine compounds (predominantly, but not limited to sodium chlorate) and caustic soda (used in chemical recovery generally, but used more intensively in the bleaching process). One reviewer conducted detailed counterfactual analysis using internal company data and felt that the estimates presented below were a reasonable proxy for the energy use related to the bleaching process.

Analysis of Census product data (see Table 3.4) shows that the correlations between plant-level product shares and the chemical use have the expected signs with respect to products that are typically “white” and “brown.” While the correlations are not particularly high, they provide support for the interpretation that the chemical use does act as a proxy for product characteristics. For example, unbleached kraft and special industrial are “brown products” and other paper types tend to be “white.” Conversely, bleached packaging is a “white” paperboard product and the other three tend to be “brown.” One anomaly is for clay-coated paper, where the correlation for the chemical has opposite signs. Overall the pattern for the correlations follow expected signs.

### *Raw Material Differences*

Type of wood (hard vs. soft) and form (chips vs. whole tree or “round wood”) can impact the energy intensity of a mill. The type and form of wood may increase the processing energy requirements, but may also increase the by-product energy generated internally by the mill. The anticipated impact of wood type is ambiguous as to which type of wood might be more or less energy intensive, but this was included in the analysis. Use of wood chips would lower the energy use for material handling, but also lower the by-products that the mill would have available for energy. Reviewers felt that round wood would be a net energy producer. It is important to account for this since a mill using chips may have to purchase more energy, but this does not mean they are less efficient, given the choice of inputs used. One company that operates off-site wood preparation to ship to its mills conducted counterfactual analysis of the results of the model estimates for integrated mills (see below). They concluded that the estimates were consistent with their internal data i.e., the estimates did capture the differences between plants using chips vs. those using round wood.

### *Moisture of Pulp*

Reviewers raised questions about pulp mills that ship product “wet” in slurry form. This would mean that those plants use much less energy than their counterparts. Census data do not allow for measurement of moisture content and no other sources were forthcoming. However, there was little evidence that this practice was widespread so further analysis of this issue was not conducted.

### *3.3.3 Model Estimates*

This section presents the current model estimates for each of the two industry segments: pulp and integrated P&PB mills. Several alternatives for specification of  $h(\cdot)$

and for the distribution of the error term  $u$  were tried. Only the “preferred” model estimates are presented.

### *Stand-alone Pulp Mills*

The final version of the pulp mills equation is

$$\begin{aligned} \ln(\text{energy}) = & A + \beta_1 \ln(\text{production}) + \beta_2 \text{Share of fiber as round wood} \\ & + \beta_3 \text{Share of production as Special Alpha} \\ & + \beta_4 \text{Share of production as Unbleached Sulfate} + \epsilon \end{aligned} \quad (3.7)$$

where

*Energy* = total source energy (MMBTU)

*Production* = production of pulp (short tons)

*Share of fiber as round wood* = Ratio of round wood (whole tree)  
as a percentage of total fiber input

*Share of production : Special Alpha* = Ratio of Special Alpha as a share  
of production

*Share of production : Sulfate, unbleached* = Ratio of unbleached Sulfate as a  
share of production

The variable  $\epsilon$  is distributed as  $N(0, \sigma^2)$  and  $\beta$  is a vector of parameters to be estimated.

The estimated parameters of the model are shown in Table 3.5. Sample size is 28 plants. All variables except those for unbleached sulfate and the constant are significant at the 95% level or higher. The variable for unbleached Sulfate is only significant at the 90% level in a one-tailed test, but has the expected sign. The variable for water treatment is not significant, but has the expected sign and magnitude. Estimates of the frontier resulted in extremely small variance estimates of  $u$ , so the simpler OLS model is used in this segment.

Table 3.5: Pulp Mill Model Estimates

Variable	Estimate	Standard Error	t-ratio
Log Production*	1.051082	0.1206943	8.71
Share of fiber as round wood*	-1.079867	0.4420925	-2.44
Share of production: Special Alpha*	1.309212	0.4093806	3.2
Share of production: Sulfate, unbleached	-0.7259908	0.5532731	-1.31
Water Treatment	0.075191	0.286776	0.26
Constant	1.56077	1.389814	1.1
Error Distribution Parameters			
$\sigma^2$	.4333		
R-square	.8153		
F(5, 22)	19.42		

*Integrated Paper and Paperboard Mills*

The final version of the integrated paper and paperboard mills energy equation is

$$\begin{aligned}
 \ln(\text{energy}) = & A + \beta_1 \ln(\text{production}) + \beta_2 \text{Share of purchased pulp} \\
 & + \beta_3 \text{Share of clay coated} + \beta_4 \text{Share of tissue} \\
 & + \beta_5 \text{Share of softwood} + \beta_6 \text{Share of chlorine} + \beta_7 \text{Share of NaOH} \\
 & + \beta_8 \text{Share of woodchips} + \beta_9 \text{Share of bleached} + \beta_{10} \text{water treatment} + \epsilon
 \end{aligned}
 \tag{3.8}$$

where

$$\text{Energy} = \text{total source energy (MMBTU)}$$

$$\text{Production} = \text{total P\&PB production (tons)}$$

$$\text{Share of Purchased pulp} = \text{Ratio of Purchased pulp to production}$$

$$\text{Share of Clay coated} = \text{Ratio of Clay - coated printing and converting to production}$$

$$\text{Share of Tissue} = \text{Ratio of Tissue and other creped plus sanitary to production}$$

$$\text{Share of soft wood} = \text{Ratio of soft wood to production}$$

$$\text{Share of Chlorine} = \text{Ratio of Total Chlorine Compounds to production}$$

*Share of NaOH = Ratio of Sodium Hydroxide to production*

*Share of woodchips = Ratio of wood chips to production*

*Share of recycled fiber = Ratio of recycled fiber to production*

*Share of Bleached = Ratio of Bleached packaging and industrial converting  
paperboard to production*

*Water treatment = Dummy variable (yes = 1, no = 0) for onsite water  
treatment plant, discharge permit*

The variable  $\epsilon$  is distributed as  $N(0, \sigma^2)$  and  $\beta$  is a vector of parameters to be estimated.

The estimated parameters of the model are shown in Table 3.6. Sample size is 99 plants with one dummy variable to control for an outlier (estimate suppressed for disclosure). All variables are jointly significant from zero. All variables listed with an asterisk are significant at 95% confidence for a two-tailed test, while the remainder are only significant at a 90% level in a one-tailed test, and have the expected sign. Estimates of the frontier resulted in extremely small variance estimates of  $u$ , so the simpler OLS model is used.

### 3.4 Scoring Pulp, Paper, and Paperboard Plant Energy Efficiency

#### 3.4.1 How the EPI Works

The pulp, paper, and paperboard plant EPIs rate the energy efficiency of two segments - pulp mills, and integrated paper and paperboard mills - based in the United States. To use the tool, the following information must be available for a plant.

1. Total energy use
  - Electricity in kWh (converted to Btus by the spreadsheet tool)
  - Fuel use for all fuel types in physical units or Btu

Table 3.6: Integrated Paper and Paperboard Energy Model Estimates

Variable	Estimate	Standard Error	t-ratio
Log Production*	0.706826	0.047991	14.7
Ratio of Purchased pulp to production*	1.119146	0.276065	4.05
Ratio of Clay coated printing and converting to production*	0.402983	0.141269	2.85
Ratio of Tissue and other creped plus sanitary to production*	0.324073	0.191126	1.70
Ratio of soft wood to production	0.206176	0.108605	1.90
Ratio of Total Chlorine Compounds to production*	0.046937	0.022145	2.12
Ratio of Sodium Hydroxide to production*	0.090371	0.033306	2.71
Ratio of wood chips to production	0.110788	0.076606	1.45
Ratio of recycled fiber to production	0.269367	0.166928	1.61
Ratio of Bleached packaging and industrial converting paperboard to production	0.171476	0.111948	1.53
Water treatment (yes/no)	0.110855	0.075578	1.47
Outlier dummy	suppressed	suppressed	suppressed
Constant*	5.782308	0.602323	9.60
Error Distribution Parameters			
$\sigma^2$	0.1013		
R-square	0.8334		
F(12, 86)	36.01		

## 2. Pulp mills

- Total production
- Share of fiber as round wood
- Share of production: Special Alpha
- Share of production: Sulfate, unbleached
- Water treatment (yes/no)

## 3. Integrated mills

- Total production

- Ratio of Purchased pulp to production
- Ratio of Clay-coated printing and converting to production
- Ratio of Tissue and other creped plus sanitary to production
- Ratio of soft wood to production
- Ratio of Total Chlorine Compounds to production
- Ratio of Sodium Hydroxide to production
- Ratio of wood chips to production
- Ratio of recycled fiber to production
- Ratio of Bleached packaging and industrial converting paperboard to production
- Water treatment (yes/no)

Based on these data inputs, these two EPIs will report an Energy Performance Score (EPS) for the plant in the current time period that reflects the relative energy efficiency of the plant compared to that of the industry. It is a percentile score on a scale of 1–100. An EPS of 75 means a particular plant is performing better than 75% of the plants in the industry, on a normalized basis. ENERGY STAR defines the *75th* percentile as efficient, so plants that score 75 or better are classified as efficient. The model also estimates what the energy use would be for an “average” plant (defined as the *50th* percentile), with the same production characteristics. While the underlying model was developed from data for U.S.-based plants, it does not contain or reveal any confidential information.





## Integrated Paper and Paperboard Manufacturing Plant

### Energy Performance Indicator Tool

Version 1.0, Release 05/05/2012

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**Plant Characteristics**

Location: **New York, NY**  
 ZIP Code: **10000**

*Please note: all product classes are further detailed in the "Notes" section at the bottom of the "Instructions" tab.*

		Current Plant	Reference Plant
		Enter Name	Enter Name
		2011	2010
<b>Production</b>	Market pulp (sold or transferred)		
	Clay coated printing and converting		
	Uncoated free sheet (<10% mechanical fiber)	550,000	550,000
	<b>Paper</b>		
	Bleached bristols		
	Unbleached kraft (>80%) packaging and industrial		
	Tissue and other creped (roll stock)		
	Sanitary tissue (toilet paper, napkins, facial tissue, etc.)		
	<b>Paperboard</b>		
	Unbleached kraft packaging and industrial converting paperboard		
Bleached packaging and industrial converting paperboard			
corrugating medium (>75% virgin)			
Recycled paperboard			
<b>Other</b>	All other paper and board		
<b>Total</b>	<b>Total production</b>	<b>550,000</b>	<b>550,000</b>
<b>Materials purchased</b>	Purchased pulp		
	Recycled fiber (purchased)		
	Wood chips		
	Softwood (share of total fiber)		
	Chlorine compounds		
	Sodium hydroxide		
	Onsite water treatment	Yes	Yes / No

---

**Energy Consumption**

Select Units: Electricity (MWh), Gas (MMBtu), Distillate Oil (Gallons), Residual Oil (MMBtu), Coal (MMBtu), Biomass (MMBtu), Other (MMBtu)

Enter Name	Annual Purchases & Transfers	Electricity	Gas	Distillate Oil	Residual Oil	Coal	Biomass	Other
2011	Annual Purchases & Transfers	30,000	1,500,000	10,000,000				1
	Annual Cost (\$)*	Enter cost	Enter cost	Enter cost				Enter cost
2010	Annual Purchases & Transfers	37,000	1,750,000	10,000,000				1
	Annual Cost (\$)*	Enter cost	Enter cost	Enter cost				Enter cost

\* Other solid fuels, e.g. pet coke or waste-derived, may also be input in this field.  
 \*\* Entering cost data is optional and does not impact the computation of the Energy Performance Score.

FIGURE 3.5: Input Section of the Integrated Paper and Paperboard Mill EPI Spreadsheet Tool

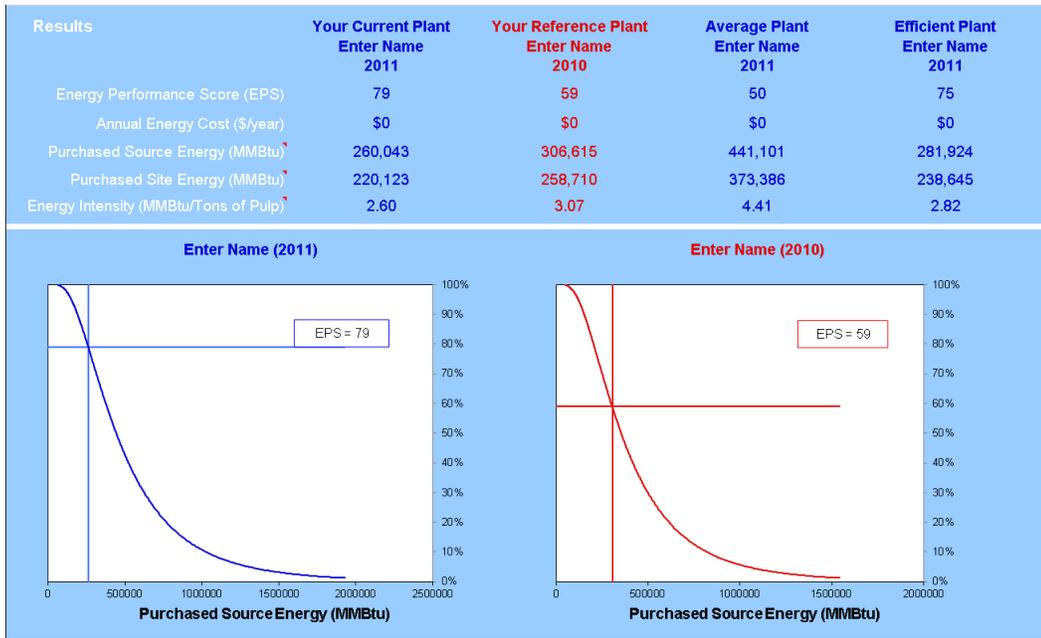


FIGURE 3.6: Output Section of the Pulp Mill EPI Spreadsheet Tool

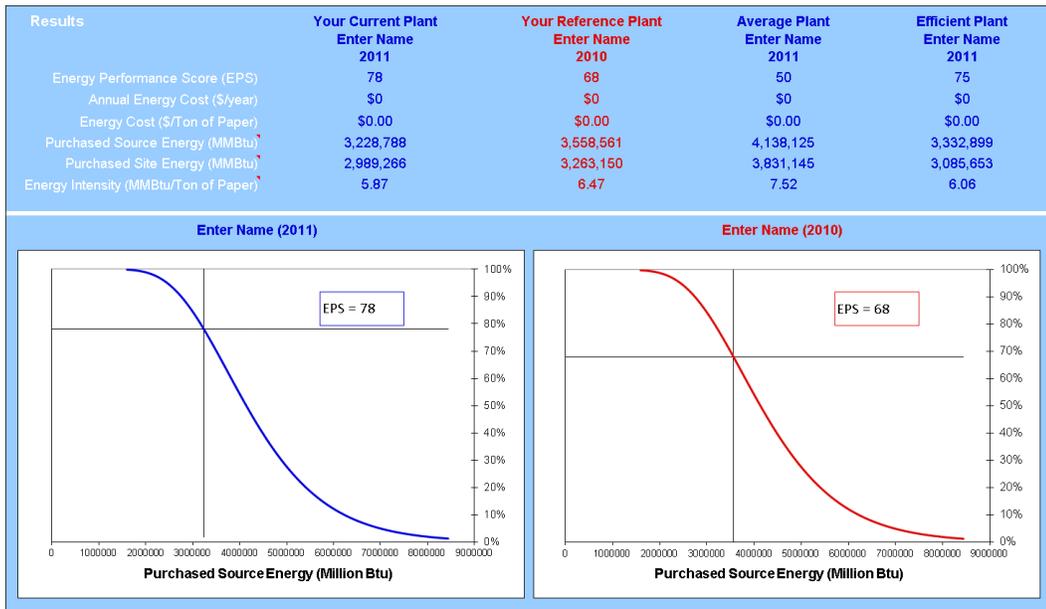


FIGURE 3.7: Output Section of the Integrated Paper and Paperboard Mill EPI Spreadsheet Tool

### *3.4.3 Use of the ENERGY STAR Pulp, Paper, and Paperboard EPI*

EPIs are developed to provide industry with a unique metric for evaluating energy performance that will lead plants to take new steps to improve their energy performance. To promote the use of EPIs, EPA works closely with the manufacturers, through an ENERGY STAR Industrial Focus on energy efficiency in manufacturing, to promote strategic energy management among the companies in this industry. The EPI is an important tool that enables companies to determine how efficiently each of the plants in the industry is using energy and whether better energy performance could be expected. The EPI and the Energy Performance Score also serve as the basis for ENERGY STAR recognition. Mills that score a 75 or higher become eligible for ENERGY STAR certification.

EPA recommends that companies use the EPIs on a regular basis. At a minimum, it is suggested that corporate energy managers benchmark each plant on an annual basis. A more proactive plan would provide for quarterly use (rolling annual basis) for every plant in a company. EPA suggests that the EPI score be used to set energy efficiency improvement goals at both the plant and corporate levels. The EPIs can also be used to inform new plant designs by establishing energy intensity targets.

The models described in this report are based on the performance of the industry for a specific period of time. One may expect that energy efficiency overall will change as technology and business practices change, so the models will need to be updated. EPA plans to update these models every few years, contingent on newer data being made available and industry use and support of the EPI tools.

### *3.4.4 Steps to Compute a Score*

All of the technical information described herein is built into spreadsheets available from EPA (<http://www.energystar.gov/epis>). Anyone can download, open the EPI spreadsheets, and enter, update, and manage data as they choose. The following

details each step involved in computing an EPS for a plant.

1. User enters plant data into the EPI spreadsheet
  - Complete energy information includes all energy purchases (or transfers) at the plant for a continuous 12-month period. The data do not need to correspond to a single calendar year.
  - The user must enter specific operational characteristic data. These characteristics are those included as independent variables in the analysis described above.
2. EPI computes the Total Source Energy Use
  - TSE is computed from the metered energy data.
  - The total site energy consumption for each energy type entered by the user is converted into source energy using the source to site conversion factors.
  - TSE is the sum of source energy across all energy types in the plant.
  - TSE per relevant unit of production is also computed.
3. EPI computes the Predicted “Best Practice” TSE
  - Predicted “Best Practice” TSE is computed using the methods above for the specific plant.
  - The terms in the regression equation are summed to yield a predicted TSE.
  - The prediction reflects the expected minimum energy use for the building, given its specific operational constraints.
4. EPI compares Actual TSE to Predicted “Best Practice” TSE

- A lookup table maps all possible values of TSE that are lower than the Predicted “Best Practice” TSE to a cumulative percent in the population.
- The table identifies how far the energy use for a plant is from best practice.
- The lookup table returns a score on a scale of 1 – to – 100.
- The Predicted TSE for a median and 75<sup>th</sup> percentile plant is computed based on the plant-specific characteristics.
- A score of 75 indicates that the building performs better than 75% of its peers.
- Plants that earn a 75 or higher may be eligible to earn the ENERGY STAR.

# Appendix A

## Technical Notes for Chapter 2

### Simulation of Consumers

The demographics of consumers include three variables: income, origin, and destination. First, I use the unconditional population distribution in DA to determine where consumers live. Second, I use the conditional income distribution based on where consumers live to determine income. Third, I use the commuting probabilities from OD survey to determine destination. The simulated market share would be

$$\hat{s}_j = \frac{\sum_i \bar{q}(o_i, d_i) P_j(r(o_i, d_i), y_i)}{\sum_i \bar{q}(o_i, d_i)}$$

Conditional on DA, the census includes data on mean, median, and standard-deviation of individual annual income. I assume the conditional income distribution follows Weibull. The parameters are derived by minimizing the difference between the reported mean, median, standard-deviation, and the corresponding predicted ones.

## Inversion Algorithm

Broyden's root-finding algorithm is proven to converge significantly faster than the standard contraction mapping algorithm proposed by Berry et al. (1995)

1. Set the starting value for the pseudo-jacobian matrix  $B^0 = I_{J_t}$ , the identity matrix of dimension  $J_t$  and  $\delta_{jt}^0$ .

2. For iteration  $k \geq 1$ :

- (a) Update the vector of mean qualities:

$$\delta_{jt}^k = \delta_{jt}^{k-1} - B^{k-1} f(\delta_t^{k-1})$$

where  $f(\delta_t^k) = \ln s_{jt}(\delta_t|\theta) - \ln \hat{s}_{jt}$ ,  $s_{jt}(\delta_t|\theta)$  is the model predicted market share at station  $j$  in period  $t$ ,  $\hat{s}_{jt}$  is the observed share.

- (b) Update the pseudo-jacobian matrix:

$$B^k = \begin{cases} B^{k-1} + (\tilde{s} - \tilde{u}) \tilde{s}' B^{k-1} (\tilde{s}' \tilde{u})^{-1} & \text{if } \|f(\delta_t^k)\| > \|f(\delta_t^{k-1})\| \\ I_{J_t} & \text{Otherwise} \end{cases}$$

where  $\tilde{s} = -B^{k-1} f(\delta_t^{k-1})$  and  $\tilde{u} = B^{k-1} [f(\delta_t^k) - f(\delta_t^{k-1})]$ .

3. Stop if  $\|f(\delta_t^k)\| \leq \textit{tolerance}$ , repeat step 2 otherwise.

# Appendix B

## An Empirical Model of Low-Price Guarantees and Consumer Search

This section relaxes the assumption of complete information on price. I build a model that allows consumers to search before making their purchase decision. It will allow me to estimate how a low-price guarantee would change consumer search behavior, to determine what is the add-on value of adopting low-price guarantee besides posting the lowest prices, and to see whether consumer search plays an important role in determining consumer surplus. By assuming that the low-price guarantee alters consumers' prior beliefs to the minimum prices within the zone, I integrate the guarantee into my demand model and solve the market equilibrium under Bertrand competition setting.

### Motivation

In reality, consumers may not be fully informed of the prices at all the gasoline stations in the market, especially back in the 90s when we did not have smartphones and the Internet was not universal. In fact, even in the high-tech year of 2015, as

**Q: How do you shop for price (asked of the 71% who said “price” was the most important factor when buying gas)?**

PERCENT OF GAS CONSUMERS	2015	TRACKED	
		2014	2013
Price sign at store	63%	57%	65%
Store tied to a loyalty card or other gas discount	18%	18%	16%
Online gas price aggregator / web site	9%	10%	7%
Company/store has reputation for low prices	9%	14%	10%
Other	1%	1%	1%

(Source: 2015 NACS Fuels Report)

**FIGURE B.1: How Consumers Shop for Price**

shown in Figure B.1, the survey data from NACS Fuels Report indicates, more than half of the consumers who take price as the most important factor for their purchase decisions still shop for price through price signs at the stores. Therefore, back in the 90s, when online gas price checkers were unavailable, we expect most consumers shopped for price through price signs at the stores.

On the other hand, when I include the low-price guarantee as a station characteristic in my previous model, the coefficient is positive and significant while other parameters do not change much. It indicates that consumers’ willingness-to-pay for the guarantee is around 1 cent per liter, if everything else is equal.

There are a few papers that have touched on consumers’ searching in retail gasoline market from different perspectives, for example, Rossi and Chintagunta (2015), Chandra and Tappata (2011). My work will also contribute to this group of literature.

## Demand

Back in the 90’s, it was almost impossible for consumers to be aware of the prices of all gas stations in the big city. Thus, I assume that consumers would form a consideration set first based on their prior beliefs of the prices of those stations. In order to find out the actual posted price of a particular station, the consumer had

to physically visit the store to find out. The cost of getting the price information is the travel time he spends to deviate from his daily commute route.

To justify the search assumption, I look into consumers' motivation to search: price dispersion and price ranking reversal. As shown in Figure B.2, the range of posted prices of stations in Quebec is about 9.4 cents on average, while the average standard error is about 1.6 cents. The price range peaked to 25.3 cents and the standard errors of prices also reached its highest level 5.9 cents in the beginning of summer in 1996 when the low-price guarantee was first introduced. The high dispersion could be partly caused by a price war initiated by some major gas stations (Caranzza et al., 2013). It could also be that Ultramar wanted to impress and convince their consumers about their low-price guarantee, while their competitors may still have not figured out how to best respond. From Figure B.2, it is not obvious the adoption of the guarantee made a difference in terms of price dispersion. However, price dispersion alone is not enough to justify the search assumption. If the ranking of price of each station is stable over time, even when stations charge different prices, consumers will stop searching once they are familiar with the ranking.

I divide the sample into two parts, one for all stations<sup>1</sup> before the low-price guarantee and the other for after the guarantee. Given that the total number of stations in the market changed every period, Figure B.3 presents the histogram of the range and the standard error of ranking percentile for each station before the guarantee, and compares with those after the guarantee. As the upper graph shows, the difference of the price ranking percentile can be larger than 10% for some stations. Notice that I have considered ties in my ranking system. The average maximum ranking for a period is 23 in my data, while the average number of stations in a period is 321. Therefore, a lot of stations post the exact same price. A station that

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<sup>1</sup> Only those stations that are in the market both before and after the guarantee. 90% of all the stations in my data satisfy this condition.

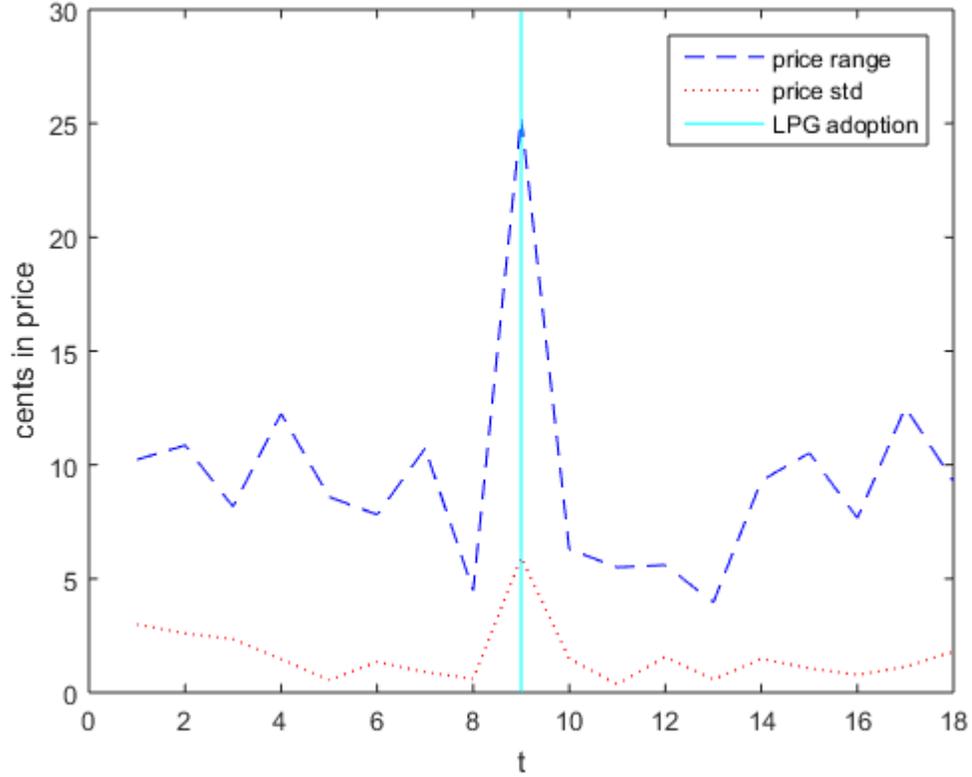


FIGURE B.2: Price Dispersion Over Time

increases 10% in the ranking percentile could mean that it has beaten about 30 other stations in price. The introduction of the low price guarantee does not change the distributions much in Figure B.3. If any, the guarantee might have decreased the ranking movement a little bit. As we have seen, even after the guarantee, consumers still had incentives to search.

Assume that the indirect utility of consumer  $i$  filling gas at station  $j$  takes the following functional form:

$$U_{ij} = \begin{cases} X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j + \varepsilon_{ij} & \text{if } j \neq 0 \\ -\kappa_0 I(o_i, d_i) + \varepsilon_{i0} & \text{otherwise} \end{cases}$$

where  $X_j$  is a vector of observed station characteristics,  $y_i$  is the log hourly wage of consumer  $i$ ,  $p_{ij}$  is the price of station  $j$  for consumer  $i$ ,  $\xi_j$  is the station

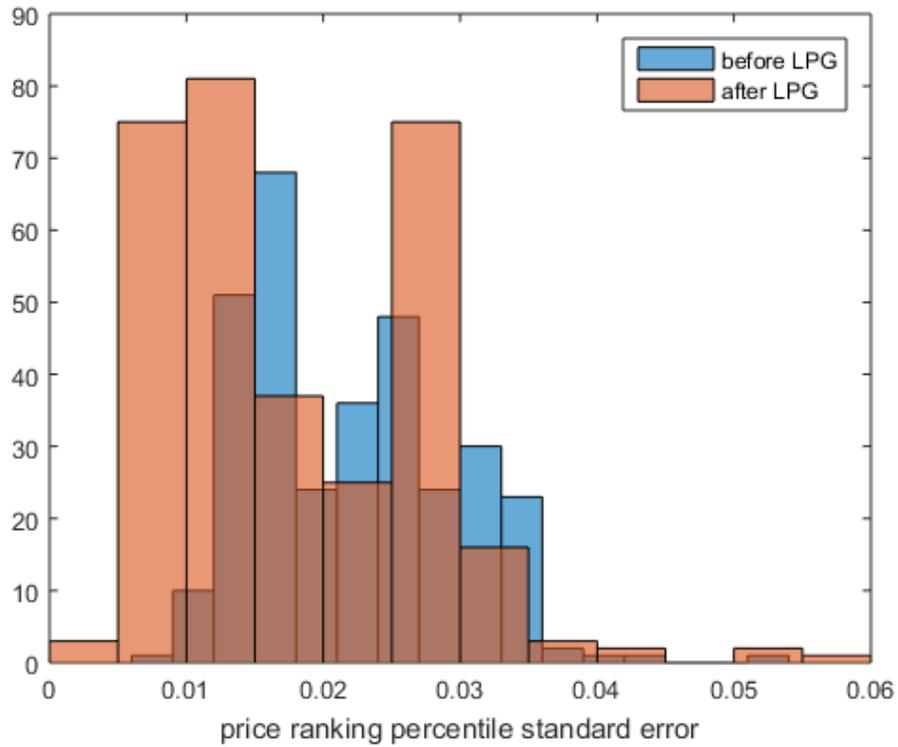
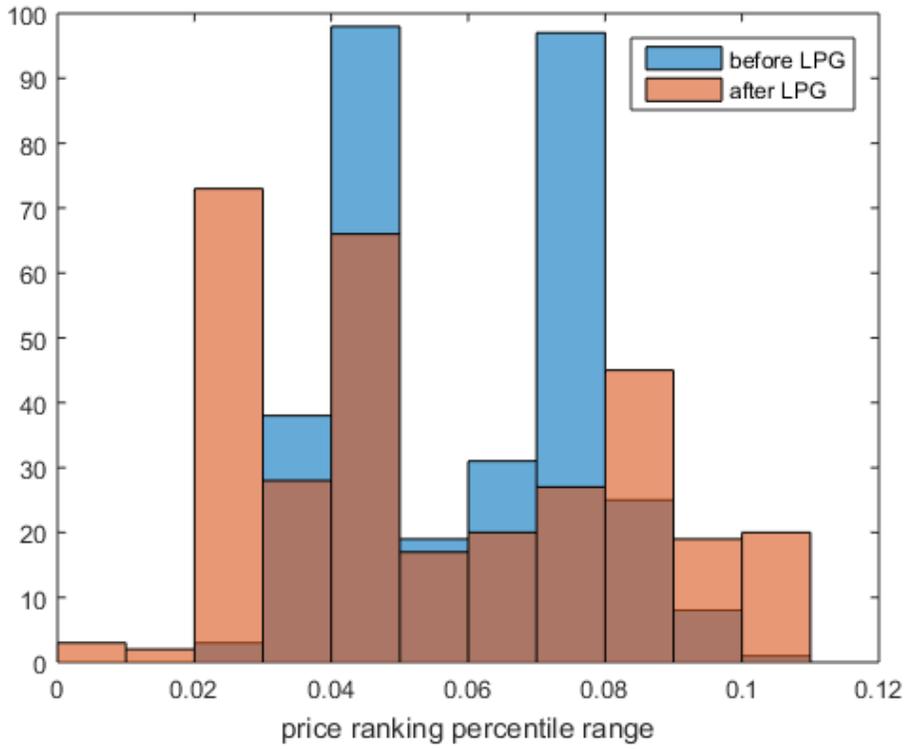


FIGURE B.3: Motivation to Search

attributes that are unobserved by econometricians but known to consumers, and  $\varepsilon_{ij}$  is an i.i.d. error term following a type-1 extreme value distribution.<sup>2</sup> Assume  $\varepsilon_{ij}$  is independent across consumers and across gas stations. Station characteristics include the number of gas pumps, the number of service islands, the type of service, the type of convenience store (if any), dummy variables indicating whether the station offers car-repair and/or car-wash services, and an indicator for major brand. A set of time-dummy variables is also added to capture time-specific unobserved variables, such as weather and temperature. Notice that, in my model, different income groups can have different price elasticity of gasoline, which is captured by  $\alpha$ .  $I(o_i, d_i)$  is an indicator variable which equals to 1 if the consumer works and lives in a different neighborhood. This set up is to capture that long-distance commuters are more likely to travel by car and consume gasoline.

We need to be careful about what  $p_{ij}$  represents in different stages. At stage one, consumers do not observe price and need to form a consideration set based on their prior beliefs of prices at all the stations. Assume consumers share a common prior belief of price, which follows a standard Weibull distribution, i.e.  $p_{ij} \sim We(\lambda_j, k)$ , with a common shape parameter.

$$F_{p_{ij}}(p_{ij}) = 1 - \exp\left[-(p_{ij}/\lambda_j)^k\right]$$

Conditional on price,  $U_{ij} | p_{ij}$  is a Gumbel distribution, so the maximum conditional utility also follows a Gumbel distribution.

$$\max \{U_{ij} | p_{ij}\}_{j \in C} \sim Gumbel\left(\ln\left[\sum_{j \in C} \exp(\tilde{\mu}_{ij})\right], 1\right)$$

where  $C$  stands for a given non-empty choice set,  $\tilde{\mu}_{ij} = X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j$ .

---

<sup>2</sup> In fact, I am assuming  $\varepsilon_{ij} - \varepsilon_{i0}$  to follow type-1 extreme value distribution. I normalize  $\varepsilon_{i0}$  to be zero.

Therefore  $E\max \{U_{ij} | p_{ij}\}_{j \in C} = \ln \left[ \sum_{j \in C} \exp(\tilde{\mu}_{ij}) \right] + \gamma$ , where  $\gamma$  is Euler's constant.

By law of iterated expectations, the unconditional expectation is

$$E\max \{U_{ij}\}_{j \in C} = E \left[ E\max \{U_{ij} | p_{ij}\}_{j \in C} \right]$$

Denote the cost of consumer  $i$  to visit station  $j$  to find out its price is  $D(r(o_i, d_i), l_j)$ , which is the time needed to travel between path  $r(o_i, d_i)$  and the location of station  $j$  (i.e.  $l_j$ ). In other words,  $D(r(o_i, d_i), l_j)$  is the extra time a consumer needs to travel to buy gasoline is defined as  $D(r(o_i, d_i), l_j) = t(o_i, l_j) + t(l_j, d_i) - t(o_i, d_i)$ , where  $t(o_i, l_j)$  and  $t(l_j, d_i)$  measure the optimal driving time to commute between  $(o_i, l_j)$  and  $(l_j, d_i)$  respectively. Consumers choose a non-empty set of stations  $C_i$  to maximize the difference of the expected value of the maximized utility of shopping at station  $j$  in the consideration set and the search cost to obtain price information of all the stations in the consideration set. Assume search cost of a choice set includes a random shock  $\eta_{iC}$  for the choice set  $C$ , and  $(-\eta_{iC}s)$  are i.i.d. type I extreme value distributed across consumers and choice sets.<sup>3</sup> Denote  $\bar{C}$  as all possible choice sets, including the empty set.

$$C_i = \operatorname{argmax}_{C \in \bar{C}} (EV_{iC} - \eta_{iC})$$

where

$$EV_{iC} = \begin{cases} E\max \{U_{ij}\}_{j \in C} - \sum_{j \in C} \kappa_1 D(r(o_i, d_i), l_j), & \text{if } C \neq \emptyset \\ -\kappa_0 I(o_i, d_i), & \text{if } C = \emptyset \end{cases}$$

Thus, the probability that consumer  $i$  finds it optimal to search gas stations in choice set  $C$  is  $P_{iC}$  where

---

<sup>3</sup> not searching means choosing the outside option

$$\begin{aligned}
P_{iC} &= \frac{\exp(EV_{iC})}{\sum_{h \in \bar{C}} \exp(EV_{ih})} \\
&= \frac{\exp \left\{ \text{Emax} \{U_{ij}\}_{j \in C} - \sum_{j \in C} \kappa_1 D(r(o_i, d_i), l_j) + \kappa_0 I(o_i, d_i) \right\}}{1 + \sum_{h \in \bar{C}/\emptyset} \exp \left\{ \text{Emax} \{U_{ij}\}_{j \in h} - \sum_{j \in h} \kappa_1 D(r(o_i, d_i), l_j) + \kappa_0 I(o_i, d_i) \right\}}
\end{aligned}$$

Suppose the value plus program from Ultramar was well advertised and consumers all learned about it. Ultramar claims that the price zone maps were available at the counter of each Ultramar gas station. Thus, I assume that consumers had good knowledge of the definitions of the price zones that Ultramar used and were aware which station was within the zone that Ultramar promised to match. Therefore, after Ultramar introduced its value plus program, consumers' prior beliefs of Ultramar's price would be adjusted to the minimum of all prices in the price zone, i.e.  $p_{ijt}^{LPG} = \min_{l \in Z(j)} p_{ilt}$  when station  $j$  is Ultramar and  $Z(j)$  stands for the set of all stations in the price zone that contains station  $j$ . Since I assumed consumers' prior beliefs of prices follow Weibull distributions, the updated prior beliefs of Ultramar's prices would still follow Weibull distributions. Remember I assumed that  $p_{ij} \sim We(\lambda_j, k)$ . Thus, for Ultramar prices after introducing the value plus program,  $p_{ij}^{LPG} = \min_{l \in Z(j)} p_{il} \sim We \left( \left( \sum_{l \in Z(j)} \lambda_l^{-k} \right)^{-1/k}, k \right)$ . Given this, I can easily derive the corresponding probability for consumers to make optimal decisions in searching.

At stage two, the utility shock  $\varepsilon_{ij}$  is realized. Consumers make choices among those stations which they have visited and learned the posted price information. Given the assumption made on the distribution of  $\varepsilon_{ij}$ , the conditional probability of buying from store  $j$  within the non-empty choice set  $C$  for a consumer commuting along route  $r(o_i, d_i)$  is as follows:

$$P_j(r(o_i, d_i), y_i | \boldsymbol{\delta}, \mathbf{p}, C) = \frac{\exp[\delta_j - \alpha y_i p_j + \kappa_0 I(o_i, d_i)]}{1 + \sum_{l \in C} \exp[\delta_l - \alpha y_i p_l + \kappa_0 I(o_i, d_i)]}$$

where  $\delta_j = X_j b - \bar{\alpha} p_j + \xi_j$  is the mean utility term, and  $[-\alpha y_i p_j + \kappa_0 I(o_i, d_i)]$  is the heterogeneous valuation term.

In order to obtain the unconditional probability that consumer  $i$  purchases from gas station  $j$ , I need to consider all the possible choice sets which include station  $j$ . Denote  $C_j$  as all possible choice sets which contain  $j$ .

$$\begin{aligned} P_j(r(o_i, d_i), y_i | \boldsymbol{\delta}, \mathbf{p}) &= \sum_{C \in C_j} P_{iC} P_j(r(o_i, d_i), y_i | \boldsymbol{\delta}, \mathbf{p}, C) \\ &= \sum_{C_j} \frac{\exp(EV_{iC})}{\sum_{h \in \bar{C}} \exp(EV_{ih})} \frac{\exp[\delta_j - \alpha y_i p_j + \kappa_0 I(o_i, d_i)]}{1 + \sum_{l \in C_j} \exp[\delta_l - \alpha y_i p_l + \kappa_0 I(o_i, d_i)]} \end{aligned}$$

The demand of consumers is heterogeneous with regard to the mileage they need to commute. The quantity of gasoline demanded by a consumer commute between  $o$  and  $d$  is denoted by  $\bar{q}(r(o, d)) = c_0 + c_1 m(o, d)$ , where  $m(o, d)$  measures the length of a round trip of path  $r(o, d)$  in kilometers.  $c_0$  represents the consumption of gasoline by shopping and leisure trips, which will be estimated.  $c_1$  is the average gasoline consumption for one kilometer traveled in the city, which is assumed to be 0.10 liters/km. Then, I can estimate the market size as  $M = \sum_o \sum_d \bar{q}(o, d) T_{o,d}$ , where  $T_{o,d}$  is the measure of commuters between  $o$  and  $d$ .

The predicted demand at the station level is obtained by aggregating individual choice probability over every origin destination pairs and income:

$$Q_j(\mathbf{p}) = \sum_o \sum_d \int \bar{q}(o, d) P_j(r(o_i, d_i), y_i | \boldsymbol{\delta}, \mathbf{p}) dF(y|o) T_{o,d}$$

### *Estimation*

In this section, I will highlight the parts which are different from the previous complete price information model, and leave out those parts that are the same. For the above demand model with consumer search, the parameters to be estimated are  $\theta = \{c_0, \kappa_0, \kappa_1, \alpha, \bar{\alpha}, b, \lambda_j, k\}$ . Among those,  $\lambda_j$  and  $k$  are the parameters of consumers' prior beliefs of the prices. I fit the effective price data to Weibull distribution and use maximum likelihood to estimate parameter  $\lambda_j$  and  $k$ . Given the estimated  $\lambda_j$  and  $k$ , I will use the demand system to estimate the rest of the parameters, where  $c_0, \kappa_0, \kappa_1, \alpha$  are the nonlinear ones, and  $\bar{\alpha}, b$  are the linear ones. I will use the same moments and same algorithm to match up observed market shares and predicted market shares. The difference is how I simulate purchase probabilities.

### *Simulation of purchase probabilities*

The purchase probability includes two parts: one is the probability for a consideration set  $C$  to be optimal, the other is the conditional probability of purchase given consideration set  $C$ . Since I do not observe which stations a consumer actually visited before purchase, I have to simulate the consideration set or search set for each consumer. The possible consideration set would be a huge set. For a market with around 300 stations, the possible number of consideration sets would be  $2^{300}$ . To tackle the difficulty of calculating the search probabilities among a large combination of possible choice sets, I use importance sampling similar to Moraga-González et al. (2015) and Goeree (2008).

First of all, I construct the importance sampling probabilities. For an arbitrary choice set  $C$ , let

$$H_{iC}(\theta) = \prod_{g \in C} \phi_{ig}(\theta) \prod_{l \notin C} (1 - \phi_{il}(\theta))$$

Define the importance sampling probabilities as the set  $\{H_{iC}\}_{C \in C_{-j}}$ , where  $C_{-j}$  denotes the set of all subsets of  $J \setminus \{j\}$ ,  $H_{iC} = H_{iC}(\theta_0)$ , and  $\theta_0$  is the initial value of the parameters used in the numerical search for the parameter estimations.

In order to estimate  $s_j$ , rewrite  $s_{ij} = \sum_{C \in C_j} P_{iC} P_{ij|C}$  as

$$s_{ij} = \sum_{C \in C_{-j}} P_{i\{j\} \cup C} P_{ij|\{j\} \cup C}$$

where  $C_j$  stands for all possible choice sets which contain  $\{j\}$ .

For  $C \in C_{-j}$ , we have

$$P_{i\{j\} \cup C} = \frac{\exp \left\{ Emax \{U_{ij}\}_{j \in \{j\} \cup C} - \sum_{j \in \{j\} \cup C} \kappa_1 D(r(o_i, d_i), l_j) \right\}}{\sum_{h \in \bar{C}} \exp \left\{ Emax \{U_{ij}\}_{j \in h} - \sum_{j \in h} \kappa_1 D(r(o_i, d_i), l_j) - \mathbf{1}(h = \emptyset) \kappa_0 I(o_i, d_i) \right\}}$$

where

$$Emax \{U_{ij} | p_{ij}\}_{j \in \{j\} \cup C} = \ln \left[ \sum_{j \in \{j\} \cup C} \exp(\tilde{\mu}_{ij}) \right] + \gamma$$

$$Emax \{U_{ij}\}_{j \in \{j\} \cup C} = E \left[ Emax \{U_{ij} | p_{ij}\}_{j \in \{j\} \cup C} \right]$$

and

$$P_{ij|\{j\} \cup C} = \frac{\exp[\delta_j - \alpha y_i p_j + \kappa_0 I(o_i, d_i)]}{1 + \sum_{l \in \{j\} \cup C} \exp[\delta_l - \alpha y_i p_l + \kappa_0 I(o_i, d_i)]}$$

Rewrite  $s_{ij}$  in the importance sampling form

$$s_{ij} = \sum_{C \in C_{-j}} H_{iC} \frac{P_{i\{j\} \cup C}}{H_{iC}} P_{ij|\{j\} \cup C}$$

where  $\sum_{C \in C_{-j}} H_{iC} = 1$  holds. A set  $C$  drawn randomly from  $C_{-j}$  can be represented as the vector of  $[0, 1]$  i.i.d. uniform random variables  $u_{i,-j} = (u_{i1}, \dots, u_{ij-1}, u_{ij+1}, \dots, u_{iJ})$  because according to the importance sampling probabilities I can draw  $C$  by drawing  $u_{i,-j}$  such that  $g \in C$  iff  $u_{ig} \leq \phi_{ig}$  for all  $g \in J \setminus \{j\}$  (I omit the argument  $\theta_0$  from  $\phi_{ig}(\theta_0)$ ). So I can use the argument  $u_{i,-j}$  in the expressions involved in  $s_{ij}$ .

$$H_{ij}(u_i) = \prod_{g \in J \setminus \{j\}} \phi_{ig}^{\mathbf{1}(u_{ig} \leq \phi_{ig})} (1 - \phi_{ig})^{\mathbf{1}(u_{ig} > \phi_{ig})}$$

$$P_{i\{j\} \cup C}(u_i) = \frac{\exp\{E_{\max}\{U_{ij}\}_{j \in \{j\} \cup C} - \kappa_1 D(r(o_i, d_i), l_j) - \sum_{g \in J \setminus \{j\}} \mathbf{1}(u_{ig} \leq \phi_{ig}) \kappa_1 D(r(o_i, d_i), l_g)\}}{\sum_{h \in \bar{C}} \exp\{E_{\max}\{U_{ij}\}_{j \in h} - \sum_{j \in h} \kappa_1 D(r(o_i, d_i), l_j) + \mathbf{1}(h = \emptyset) \kappa_0 I(o_i, d_i)\}}$$

where

$$E_{\max}\{U_{ij}\}_{j \in \{j\} \cup C} = E \left[ E_{\max}\{U_{ij} | p_{ij}\}_{j \in \{j\} \cup C} \right]$$

$$E_{\max}\{U_{ij} | p_{ij}\}_{j \in \{j\} \cup C} = \ln \left[ \exp(\tilde{\mu}_{ij}) + \sum_{g \in J \setminus \{j\}} \mathbf{1}(u_{ig} \leq \phi_{ig}) \exp(\tilde{\mu}_{ig}) \right] + \gamma$$

and

$$P_{ij\{j\} \cup C}(u_i) = \frac{\exp[\delta_j - \alpha y_i p_j + \kappa_0 I(o_i, d_i)]}{1 + \exp[\delta_j - \alpha y_i p_j + \kappa_0 I(o_i, d_i)] + \sum_{g \in J \setminus \{j\}} \mathbf{1}(u_{ig} \leq \phi_{ig}) \exp[\delta_g - \alpha y_i p_g + \kappa_0 I(o_i, d_i)]}$$

where  $\mathbf{1}(u_{ig} \leq \phi_{ig})$  is the indicator of the event  $(u_{ig} \leq \phi_{ig})$ . Note that  $H_{ij}(u_i)$  corresponds to  $H_{iC}$ . Then

$$s_{ij} = \int_{[0,1]^{J-1}} \frac{P_{i\{j\} \cup C}(u_i)}{H_{ij}(u_i)} P_{ij\{j\} \cup C}(u_i) du_{i,-j} = \int_{[0,1]^J} \frac{P_{i\{j\} \cup C}(u_i)}{H_{ij}(u_i)} P_{ij\{j\} \cup C}(u_i) du_i$$

Notice that  $s_{ij} = P_j(r(o_i, d_i), y_i | \boldsymbol{\delta}, \mathbf{p})$ . So,

$$Q_j(\mathbf{p}) = \sum_o \sum_d \int \bar{q}(o, d) s_{ij} dF(y|o) T_{o,d}$$

To estimate the above equation, I can draw a random sample of  $u_i$  ( or more precisely,  $u_{i,-f}$ ) and use Monte Carlo.

The details of the importance sampling algorithm are as follows:

1. Generate random draws of  $u_i \sim U[0, 1]^J$ , one draw for each simulated consumer;
2. For each  $j \in J$  compute  $\phi_{ij}$  and  $H_{ij}(u_i)$ ; this implicitly determines the choice set  $C_{i0} \subset J \setminus \{j\}$  of  $i$  as

$$C_{i0} = \{g \in J \setminus \{j\} : u_{ig} \leq \phi_{ig}\}$$

(note that the choice set for computing  $s_{ij}$  will be  $\{j\} \cup C_{i0}$ , which always contains  $j$ );

3. For each  $j$  compute  $P_{i\{j\} \cup C}(u_i)$ ;
4. For each  $j$  compute  $P_{ij|\{j\} \cup C}(u_i)$ ;
5. For each  $j$  compute  $s_{ij}$  and  $Q_j$ .

In order to specify  $\phi_{ij}(\theta)$ , I use the criterion that the two sets of probabilities are proportional at the singleton subsets of stations  $\{j\}$ ,  $j = 1, \dots, J$ , so that the simulation errors can be smaller, i.e.,

$$\frac{H_{i\{j\}}}{H_{i\emptyset}} = \frac{P_{i\{j\}}(u_i)}{P_{i\emptyset}(u_i)}$$

which implies that

$$\frac{\phi_{ij}}{1 - \phi_{ij}} = \exp\{\tilde{\mu}_{ij} + \gamma - \kappa_1 D(r(o_i, d_i), l_j) + \kappa_0 I(o_i, d_i)\}$$

Thus,

$$\phi_{ij} = \frac{\exp\{\tilde{\mu}_{ij} + \gamma - \kappa_1 D(r(o_i, d_i), l_j) + \kappa_0 I(o_i, d_i)\}}{1 + \exp\{\tilde{\mu}_{ij} + \gamma - \kappa_1 D(r(o_i, d_i), l_j) + \kappa_0 I(o_i, d_i)\}}$$

I still need to find an estimator for the second part of the denominator of  $P_{i\{j\}\cup C}(u_i)$ , i.e.

$$V_i = \sum_{h \in \bar{C}} \exp \left\{ Emax \{U_{ij}\}_{j \in h} - \sum_{j \in h} \kappa_1 D(r(o_i, d_i), l_j) - \mathbf{1}(h = \emptyset) \kappa_0 I(o_i, d_i) \right\}.$$

Similarly, I can use importance sampling based on the probabilities  $H_{ih}$  defined above. Thus, we have

$$\begin{aligned} V_i &= \sum_{h \in \bar{C}} H_{ih} \frac{\exp \left\{ Emax \{U_{ij}\}_{j \in h} - \sum_{j \in h} \kappa_1 D(r(o_i, d_i), l_j) - \mathbf{1}(h = \emptyset) \kappa_0 I(o_i, d_i) \right\}}{H_{ih}} \\ &= \int_{[0, 1]^J} \frac{\exp \left\{ Emax \{ \mathbf{1}(v_{ij} \leq \phi_{ij}) U_{ij} \}_{j \in J} - \sum_{j \in J} \mathbf{1}(v_{ij} \leq \phi_{ij}) \kappa_1 D(r(o_i, d_i), l_j) - \mathbf{1}(h = \emptyset) \kappa_0 I(o_i, d_i) \right\}}{H_i(v_i)} dv_i \end{aligned}$$

where

$$Emax \{U_{ij}\}_{j \in h} = E \left[ Emax \{U_{ij} | p_{ij}\}_{j \in h} \right]$$

$$Emax \{U_{ij} | p_{ij}\}_{j \in h} = \ln \left[ \sum_{j \in J} \mathbf{1}(v_{ij} \leq \phi_{ij}) \exp(\tilde{\mu}_{ij}) \right] + \gamma \mathbf{1}(h \notin \emptyset)$$

$$H_i(v_i) = \prod_{j \in J} \phi_{ij}^{\mathbf{1}(v_{ij} \leq \phi_{ij})} (1 - \phi_{ij})^{\mathbf{1}(v_{ij} > \phi_{ij})} \quad \text{with} \quad v_i = (v_{i1}, \dots, v_{iJ}) \stackrel{iid}{\sim} U[0, 1].$$

Again, use Monte Carlo simulation to estimate  $V_i$ .

*Technical Notes*

This section derives the consumers' prior belief of Ultramar's prices after the guarantee was adopted and the conditional maximum utility follows Gumbel distribution.

*Price Belief After Low-Price Guarantee*

Given  $p_{ij} \sim We(\lambda_j, k)$ , we have  $p_{ijt}^{LPG} = \min_{l \in Z(j)} p_{ilt} \sim We\left(\left(\sum_{l \in Z(j)} \lambda_l^{-k}\right)^{-1/k}, k\right)$ .

*Proof.* Assume

$$p_j \stackrel{iid}{\sim} We(\lambda_j, k)$$

then

$$F_{p_j}(x) = 1 - \exp\left(-\left(x/\lambda_j\right)^k\right)$$

If

$$Y = \min\{p_1, \dots, p_n\}$$

then

$$\begin{aligned} F_Y(y) &= 1 - [1 - F_{p_1}(y)] * \dots * [1 - F_{p_n}(y)] = 1 - \exp\left(-\sum_j (y/\lambda_j)^k\right) \\ &= 1 - \exp\left(-\left(y/\lambda_Y\right)^{k_Y}\right) \end{aligned}$$

where  $\lambda_Y = \left[\sum_j \lambda_j^{-k}\right]^{-1/k}$ ,  $k_Y = k$ .

Therefore,

$$Y \sim We(\lambda_Y, k_Y)$$

Given  $p_{ijt}^{LPG} = \min_{l \in Z(j)} p_{ilt}$ , similarly, we have

$$p_{ijt}^{LPG} \sim We \left( \left( \sum_{l \in Z(j)} \lambda_l^{-k} \right)^{-1/k}, k \right)$$

□

### *Conditional Maximum Utility*

Given  $\epsilon_{ij} \sim \text{Gumbel}(0, 1)$ , we have

$$\max \{U_{ij} | p_{ij}\}_{j \in C} \sim \text{Gumbel} \left( \ln \left[ \sum_{j \in C} \exp(\tilde{\mu}_{ij}) \right], 1 \right)$$

and

$$E \max \{U_{ij} | p_{ij}\}_{j \in C} = \ln \left[ \sum_{j \in C} \exp(\tilde{\mu}_{ij}) \right] + \gamma$$

where  $\tilde{\mu}_{ij} = X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j$ .

*Proof.* Given

$$U_{ij} | p_{ij} = X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j + \epsilon_{ij}$$

assume

$$\epsilon_{ij} \stackrel{iid}{\sim} \text{Gumbel}(0, 1)$$

then

$$F_{\epsilon_{ij}}(x) = \exp(-e^{-x})$$

$$\begin{aligned}
F_{U_{ij}|p_{ij}}(x) &= Pr(U_{ij}|p_{ij} < x) = Pr(X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j + \varepsilon_{ij} < x) \\
&= Pr(\varepsilon_{ij} < x - [X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j]) \\
&= exp\left(-e^{-x + [X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j]}\right)
\end{aligned}$$

Therefore

$$U_{ij}|p_{ij} \stackrel{iid}{\sim} \text{Gumbel}(X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j, 1)$$

For convenience, denote

$$X_{ij} = U_{ij}|p_{ij}$$

$$\Psi_i = \max\{X_{i1}, \dots, X_{in}\}$$

then

$$\begin{aligned}
F_{\Psi_i}(\varphi_i) &= F_{\Psi_1}(\varphi_i) * \dots * F_{\Psi_n}(\varphi_i) = exp\left(-\sum_{j=1}^n e^{-\varphi_i + [X_j b - (\bar{\alpha} + \alpha y_i) p_{ij} + \xi_j]}\right) \\
&= exp\left(-\sum_{j=1}^n e^{-\varphi_i + \tilde{\mu}_{ij}}\right) = exp\left(-e^{\ln(\sum_{j=1}^n e^{-\varphi_i + \tilde{\mu}_{ij}})}\right) \\
&= exp\left(-e^{\ln(e^{-\varphi_i} \sum_{j=1}^n e^{\tilde{\mu}_{ij}})}\right) \\
&= exp\left(-e^{-\varphi_i + \ln(\sum_{j=1}^n e^{\tilde{\mu}_{ij}})}\right)
\end{aligned}$$

Therefore,

$$\Psi_i \sim \text{Gumbel}\left(\ln\left[\sum_{j=1}^n exp(\tilde{\mu}_{ij})\right], 1\right)$$

Given a non-empty choice set  $C$ , similarly, we have

$$\max \{U_{ij} | p_{ij}\}_{j \in C} \sim \text{Gumbel} \left( \ln \left[ \sum_{j \in C} \exp(\tilde{\mu}_{ij}) \right], 1 \right)$$

It is easy to show the expectation of our Gumbel distribution is as follows

$$E \max \{U_{ij} | p_{ij}\}_{j \in C} = \ln \left[ \sum_{j \in C} \exp(\tilde{\mu}_{ij}) \right] + \gamma$$

□

# Appendix C

## Assigning 10-digit Products to the 7-digit Categories

### 322121 Paper

#### *3221211 Clay-Coated Printing and Converting Paper*

This category includes three product codes:

3221211111 Clay-coated groundwood printing and converting paper (containing more than 10 percent mechanical fiber), including prime-coated body stock

3221211221 Clay-coated freesheet printing and converting paper, coated one side (containing not more than 10 percent mechanical fiber), including prime-coated body stock

3221211231 Clay-coated freesheet printing and converting paper, coated two sides (containing not more than 10 percent mechanical fiber), including prime-coated body stock

#### *3221213 Uncoated Freesheet Paper (Containing not More than 10 Percent Mechanical Fiber)*

This category includes thirteen product codes:

3221213111 Bond and writing paper, including protective check, uncoated freesheet

3221213115 Form bond paper in rolls, uncoated freesheet

3221213221 Body stock for communication, copying, and related papers, uncoated freesheet

3221213225 Other uncoated freesheet technical and reproduction papers, including mimeograph and gelatin and spirit process duplicating

3221213231 Writing tablet paper, uncoated freesheet

3221213235 Other writing paper, including ledger, onion skin, papeterie and wedding, etc., uncoated freesheet

3221213341 Plain publication and printing paper, uncoated freesheet, including machine finish, English finish, antique, bulking, eggshell, and supercalendered

3221213345 Offset publication and printing paper, uncoated freesheet

3221213351 Other uncoated publication and printing freesheet paper

3221213461 Cover and text papers, uncoated freesheet

3221213471 Envelope (white wove) paper, uncoated freesheet

3221213481 Kraft envelope (bleached kraft and brown kraft) paper, uncoated freesheet

3221213491 Uncoated freesheet body stock paper for coating (base or raw stock for conversion of off-machine coating) and all other miscellaneous uncoated freesheet

*3221215 Bleached Bristols (Weight More than 150 G per SQ Meter), excluding Cotton Fiber Index and Bogus*

This category includes four product codes:

3221215111 Uncoated bleached bristol tag stock (weight more than 150g per sq meter)

3221215121 Uncoated bleached bristol file folder stock (weight more than 150 g per sq meter)

3221215131 Other uncoated bleached bristols, including tabulating card, index, printing, and postcard stock (weight more than 150g per sq meter), excluding cotton fiber index and bogus

3221215141 Coated bleached bristols (weight more than 150 g per sq meter), excluding cotton fiber index and bogus

*3221217 Cotton Fiber Paper (Containing 25 Percent or More Cotton or Similar Fibers) and Thin Paper*

This category includes two product codes:

3221217111 Cotton fiber paper (containing 25 percent or more cotton or similar fibers)

3221217121 Thin paper including carbonizing, Bible, mimeograph and duplicating stencil tissue, India, tipping, condenser, cigarette paper, etc.

*3221219 Unbleached Kraft (Not Less than 80 Percent) Packaging and Industrial Converting Paper*

This category includes four product codes:

3221219111 Unbleached kraft shipping sack paper (meets minimum Federal specifications UU-S-48) and other unbleached kraft shipping sack paper

3221219121 Unbleached kraft bag and sack paper (except shipping), including grocers and other unbleached kraft bag and sack for notion, millinery, etc.

3221219131 Unbleached kraft wrapping and specialty packaging paper (92 lb or less), including flour, sugar, dog food, fast foods, dairy products, etc.

3221219191 Other unbleached kraft converting paper, including creping (92 lb or less), asphaltting paper, coating and laminating, gumming, etc.

*322121A Packaging and Industrial Converting Paper, Except Unbleached Kraft*

This category includes five product codes:

322121A111 Shipping sack paper (except unbleached kraft), including combination kraft and rope, bleached and semibleached

322121A121 Other bag and sack paper, except unbleached kraft and shipping, including grocers, liquor, millinery, notion, variety, etc.

322121A13 Specialty packaging (92 lbs or less) and wrapping paper, except unbleached kraft (butcher, flour, sugar, fast foods, confectionery, etc.)

322121A141 Other converting stock, including asphalting and creping stocks (not more than 92 lbs), coating and laminating, gummed, twisting and spinning stock (19 lbs or more), and waxing stock (18 lbs or more)

322121A151 Glassine, greaseproof, and vegetable parchment, all grades regardless of end use (92 lb or less)

*322121C Special Industrial Paper, Except Specialty Packaging, Including Absorbent, Battery Separator, Electrical Papers, etc.*

This category includes only one product code:

322121C100 Special industrial paper, except specialty packaging, including absorbent, battery separator, electrical papers, etc.

*322121E Construction Paper*

This category includes two product codes:

322121E111 Roofing felts, saturating and dry

322121E121 Other construction paper, including sheathing paper, floor covering felts, automotive, insulating paper blankets, etc.

*322121G Tissue Paper and Other Machine-Creped Paper*

This category includes eight product codes:

322121G111 Toilet tissue stock

322121G221 Toweling paper stock, except wiper stock

322121G331 Facial tissue stock, except toweling, napkin, and toilet  
322121G341 Napkin paper stock, except sanitary napkin stock wadding  
322121G351 Wiper tissue stock, regular, facial, and wadding stock  
322121G361 Other sanitary paper stock, including sanitary napkin stock wadding,  
aseptic paper stock, reinforced paper stock, etc.

322121G371 Wrapping tissue, including florist tissue stock, hosiery paper, inter-  
leaving, antitarnish, etc.

322121G391 Other tissue paper stock, including waxing tissue stock, creped  
wadding for interior packaging (excluding sanitary and thin)

*322121K Disposable Diapers and Similar Disposable Products, Made in Paper Mills*

This category includes one product code:

322121K100 Disposable diapers and similar disposable products (including sani-  
tary napkins, tampons, training pants, and incontinent pads), made in paper mills  
1 millions

*322121N Sanitary Tissue Paper Products, Made in Paper Mills*

This category includes seven product codes:

322121N111 Facial tissues and handkerchiefs, including sputum wipes, made in  
paper mills

322121N201 Paper table napkins, industrial and retail packages, bulk and dis-  
penser types, made in paper mills

322121N331 Toilet tissue, retail packages, rolls and ovals, facial tissue type, two-  
ply or more, made in paper mills

322121N433 Toilet tissue, retail packages, rolls and ovals, regular type, single-ply,  
made in paper mills

322121N661 Paper towels, industrial packages (rolled, folded, and interfolded),

made in paper mills

322121N701 Paper towels, retail packages (rolled, folded, and interfolded), made in paper mills

322121N901 Other sanitary paper products (including industrial packaged toilet tissue (all types), paper wipers (except nonwoven), absorbent pads, etc.), made in paper mills

### 322130 Paperboard

*3221301 Unbleached Kraft Packaging and Industrial Converting Paperboard (80 Percent or More Virgin Woodpulp)*

This category includes two product codes:

3221301111 Unbleached kraft linerboard

3221301221 Other unbleached kraft packaging and industrial converting paperboard, including tube, can, and drum paperboard, corrugating medium, folding carton-type board, etc.

*3221303 Bleached Packaging and Industrial Converting Paperboard (80 Percent or More Virgin Bleached Woodpulp)*

This category includes six product codes:

3221303111 Bleached folding carton-type paperboard

3221303221 Bleached milk carton board

3221303331 Bleached linerboard

3221303341 Bleached heavyweight cup and round nested food container paperboard

3221303351 Bleached plate, dish, and tray paperboard stock

3221303361 Other solid bleached paperboard, including paperboard for moist, liquid, and oily foods

*3221305 Semichemical Paperboard, Including Corrugating Medium (75 Percent or More Virgin Woodpulp)*

This category includes only one product code:

3221305100 Semichemical paperboard, including corrugating medium (75 percent or more virgin woodpulp)

*3221307 Recycled Paperboard*

This category includes eleven product codes:

- 3221307111 Recycled corrugating medium
- 3221307221 Recycled linerboard
- 3221307231 Recycled container chip and filler board
- 3221307341 Recycled clay-coated folding carton board
- 3221307451 Recycled unlined folding carton chipboard
- 3221307461 Recycled lined folding carton board, including kraft and white
- 3221307571 Recycled setup board
- 3221307575 Recycled tube, can, and drum paperboard stock
- 3221307581 Recycled gypsum linerboard
- 3221307591 Other recycled paperboard, including panelboard and wallboard stock and other special combination packaging and industrial converting paperboard

*3221309 Wet Machine Board, Including Binders' Board and Shoe Board*

This category includes only one product code:

3221309100 Wet machine board, including binders board and shoe board

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# Biography

Yifang Guo was born on May 11th, 1988 in Ganzhou, China. She earned her B.A. degree from University of International Business of Economics (UIBE) in Beijing, China in 2009. Her undergraduate major is international trade and economics. She was also one of the 36 students in the highly selective honors program, where she received rigorous training in various divisions of economics and have found her research interests in industrial organization. In 2007, Yifang won the First Prize in Beijing Undergraduate Mathematical Competition and led a group of 3 to win the Second Prize of China Undergraduate Mathematical Contest in Modeling. In 2008, Yifang was one of the 20 Chinese students among the 135 students selected worldwide to participate Study of U.S. Institute Student Leaders hosted by U.S. Department of State. In 2009, she was honored as Beijing Outstanding Graduates. After graduating from UIBE, she was admitted to the terminal master's program in the Department of Economics at Duke University. She was awarded  $\frac{1}{2}$  tuition waiver which is merit-based and the highest possible for master students. A year later, she got enrolled in the Economics Ph.D. program at Duke. Her M.A. degree in economics from Duke University was conferred in 2015 and her Ph.D. degree in economics from Duke University is expected to confer in 2016. Her publications include Guo and Wu (2008) and Boyd and Guo (2014).