THE ECONOMICS OF THE U.S. AUTOMOTIVE INDUSTRY: STUDIES ON REGULATION AND COMPETITION

A Dissertation

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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August 2018

Major Subject: Economics

ABSTRACT

This dissertation is about the U.S. automobile industry. In the first part, I study an environmental policy that ascribes a fee or a rebate to each new vehicle in the marketplace, depending on the vehicle's fuel economy rating; thus, it is called a 'feebate'. Feebates can be designed to reach optimal outcomes given assumptions on people's preferences and welfare from buying cars. Since a feebate is a function from fuel economy ratings to cash, I study how feebate functional form affects the efficacy of the policy as well as some distributional outcomes. I conclude that a feebate policy, represented by a logistic functional form in which larger portions of consumers face high marginal incentives to increase fuel economy, brings about improved outcomes over other functional forms.

The second part of this dissertation explores the nature of local competition and tests the existence of local market power held by car dealerships. In the empirical model, I exploit variation in local competition that is caused by factors external to the dynamics of local demand and supply. I compare the pricing response of dealerships in affected local markets relative to the pricing behavior of dealerships in markets which were not affected. I find that decreased competition caused consumers to pay higher prices for their vehicles both through a sales mix, as well as a negotiations, mechanism. I find evidence that dealers target consumers strategically, as the incidence of the price increases falls disproportionately on buyers of SUVs who engaged in a secondary transaction of a trade-in. I conclude that dealers exercise local market power when afforded by consumers who signal higher willingness to pay and bargaining disutilities.

DEDICATION

To my wife, Alyssa, and to my sons, Eytan and Aryel.

ACKNOWLEDGMENTS

I would like to thank the Texas A&M Department of Economics, my dissertation committee members, my adviser, Steve Puller, the Department of Economics at the University of Haifa, the Center for Financial Research at the Federal Deposit Insurance Corporation, and seminar participants at the Federal Trade Commission for their valuable comments and suggestions. I thank Texas A&M University for the resources and opportunities for interdisciplinary communication and collaboration. I thank the Texas A&M Energy Research Society for organizing events and conferences on campus conducive to networking and professional development. I thank the participants of the 2016 and 2017 A&M Conferences on Energy, and participants of the 54th annual conference of the Missouri Valley Economics Association for their useful suggestions and comments. I thank Lisa Adams for reviewing and correcting grammar and syntax mistakes, and for ensuring a smooth read for readers of this dissertation. All errors are my own.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supported by a dissertation committee chaired by my adviser, Professor Steven L. Puller, and with Assistant Professors Yonghong An and Fernando Luco of the Department of Economics, and Professor Venkatesh Shankar of the Department of Marketing as members. Jeremy West of the Economics Department at the University of California at Santa Cruz initially prepared some of the Texas DMV and DataOne data sets while a PhD student at Texas A&M. All other work conducted for this dissertation was completed by the student independently.

Funding Sources

Graduate study was supported by a doctoral merit fellowship from Texas A&M University and departmental funding through research and teaching assistantships. I gratefully acknowledge financial assistance through research assistantships funded by the National Science Foundation—Industry/University Cooperative Research Center, "Electric Vehicle—Transportation and Electricity Convergence" (8/1/2010–11/30/2014, Award #1034995).

NOMENCLATURE

CAFE	Corporate Average Fuel Economy Standard
GM	General Motors
MPG	Miles per Gallon
NMNL	Nested Multinomial Logit Model
GPM	Gallons per Mile (or Gallons per 100 Miles)
SUV	Sport Utility Vehicle
DMV	Department of Motor Vehicles
VIN	Vehicle Identification Number
MSRP	Manufacturer Suggested Retail Price
HP	Horsepower
PC	Perfect Competition
NAFTA	North American Free Trade Agreement
BLP	Berry, Levisohn, and Pakes *Econometrica* 1995
GMM	General Method of Moments
APEEP	Air Pollution Emissions Experiment and Policy
EPA	Environmental Protection Agency
RMA	Relevant Market Area
HHI	Herfindahl-Hirschman Index
TXDMV	Texas Department of Motor Vehicles
FTC	Federal Trade Commission
MSA	Metropolitan Statistical Area
DOJ	U.S. Department of Justice

VSP	Vehicle Sales Price
FMC	Ford Motor Company
OLS	Ordinary Least Squares
IV	Instrumental Variables

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1. INTRODUCTION

Research in the U.S. auto industry has grown in significance over the last three decades. Topics ranging from international trade, environmental policy, and the study of oligopolistic competition, are all factors in this very important segment of the U.S. economy. As this industry's complexity gradually unravels, new insights and strategies are being discovered that enable the automobile market to draw closer to maximum efficiency. The nature of policy and competition dynamics define the future for the auto industry with regards to innovation as well as financial stability; the advancement of knowledge on these core fundamentals will equip our society in shaping optimal public policy and ultimately increase the welfare of our citizens. My dissertation makes a number of contributions to the advancement of knowledge in the auto industry, detailed in two distinct research chapters that cover specific aspects of environmental regulation, and retail competition and state policies that affect local competition among car dealerships. The main contributions are summarized as follows:

1.1 Optimal Feebates

The first contribution is themed around environmental policy, studying whether the adoption of feebate policies will be beneficial either in place of, or in addition to, the existing Corporate Average Fuel Efficiency (CAFE) standards, aimed at reducing emissions from passenger cars and light trucks. While the efficiency advantage of an optimal emissions tax remains a 'first-best' solution, its practical limitations motivate the study of complementary, or 'second-best' strategies. Such policies seek to subsidize higher fuel economy rather than tax fuel usage. Environmental policy is a national effort which affects the entire U.S. auto industry, and influences design and pricing decisions at the manufacturers' level. As a seemingly attractive alternative to the CAFE standards, feebate systems are theoretically capable of achieving the same outcomes at lower regulatory costs. A feebate's advantage over CAFE standards in the realm of 'second-best' solutions is manifest in the higher potential for consumers to adjust purchase decisions as a response to a fuel-efficiency subsidy or tax. The policy can raise fuel economy of the average car or light truck, and thereby help in reducing harmful emissions. I show that feebates, in general, can reduce the social cost of emissions and help increase total welfare from the purchase and utilization of new passenger cars and light trucks. I show not only that parameterization of optimal feebates yields the most benefits from a given feebate structure, but also that the choice of the feebate structure matters to welfare outcomes. Optimal feebates are calculated by optimizing a social welfare function using estimated demand and supply parameters and predicted purchasing decisions by consumers. I investigate the role of feebate functional form in achieving emission reduction from optimal feebate systems. Given each of the functional forms considered – linear, two forms of exponential, and a Log-Zigmoid (S-shaped) – I explore how consumer incentives vary over these alternative feebate systems. As a first step to this analysis, I estimate demand elasticities, supply parameters, and marginal costs using seven years of vehicle transactions data and utilizing information on vehicle characteristics, transaction prices, and geographical heterogeneity of local markets. In the second step, I predict equilibrium outcomes when a feebate system is in effect, and calculate consumer and producer surplus, as well as social costs from emissions, in order to assess the total welfare resulting from the policy. I then optimize the social welfare function and estimate the optimal feebate parameters conditional on a particular functional form. An optimal logistic (S-shaped) feebate system performs best and brings about the highest savings in terms of the social cost of emissions while still maintaining sufficient levels of consumer and producer surplus in the marketplace. This study improves on current knowledge of feebates as previous studies have primarily considered linear or step funcions only in comparing the advantages of feebates relative to other policies.

1.2 Competition Dynamics among Car Dealerships

The second contribution in this dissertation switches gears and focuses on the market structure of the new-automobile distribution system, where the competitive dynamics of local retail markets is explored. The vast majority of the literature regarding competition in the auto industry primarily approaches the national market structure and treats it as an oligopoly with imperfect competition among car manufacturers. However, the final market concerning the consumer is local, and the oligopolistic market structure varies across local market clusters, with heterogeneity in competition levels and the variety of products offered. I show that most consumers end up buying their new cars from the closest dealer who sells the particular brand. The likelihood of buying at a distant dealership increases when there are more same-brand dealerships that are close. Large metropolitan areas tend to have more available brands and higher levels of inter-brand, as well as intra-brand, competition. Conversely, smaller metropolitan areas and rural towns and counties often have only one reasonably close centralized location where car dealerships operate with lower inter-brand competition.

I study the response of new car dealerships to changes in local competition. During the second half of the 20th century, all U.S. states engaged in market intervention concerning the contractual relationships between automotive manufacturers and their franchised dealers. These specialized franchise laws were designed to provide economic and contractual protections to car dealers, and have impacted the geographic spread of dealership networks and local competition among car dealerships. Car dealerships agglomerate into local market clusters, such that only one dealer sells a particular brand in each cluster. Dealers compete on an inter-brand basis within their local markets, and on an intra-brand basis across different market clusters. Using a unique data set of vehicle transactions, I exploit quasi-random variation in a local competition index to estimate the effects of local brand competition on vehicle prices, dealer discounts, and price dispersion. During the period of time between 2008-2009, sudden shutdowns of dealerships, and the discontinuation of two GM brands, caused an external shock to the level of competition in affected local markets in a manner that is orthogonal to the local supply and demand. I use this source of exogenous variation in local competition to measure the effects of competition on dealers' pricing behavior, as otherwise it is extremely difficult to separate the effects of a competition index which depends on market shares that are co-determined with prices in the local demand and supply system. I find that the average price customers pay for their cars increases with lower levels of brand competition in markets that are relatively competitive or moderately concentrated. The source of the price increase is both from dealers offering a more expensive product mix and from dealers offering lower discounts to consumers. Some evidence points to increased price dispersion, especially in the higher end of the price distribution. It appears that dealers' pricing response was strategic and that the incidence of the effect of reduced competitive pressure was disproportional across distinct consumer groups; this suggests that dealers were deliberately choosing to exercise their market power on specific customers, effectively segmenting demand according to signals by consumers. These results inform an important public policy debate relating to state franchise laws that regulate the contractual relationship between automobile manufacturers and their franchised retail dealers. All fifty U.S. states either limit or ban direct sales by auto makers and protect dealerships' interests in their interaction with manufacturers. Local market power due to insufficient competition is harmful to consumers, and an adjustment of state franchise laws could enable higher levels of competition. Automotive dealers associations object any laws that will diminish dealers' current standing, citing that the existence of many dealerships, who sell identical products and compete with each other on price, is beneficial to consumers through intra-brand competition; however, if retail car dealerships exercise market power in their local market areas, then double marginalization may offset potential benefits from intra-brand competition, leaving little reason to ban direct distribution in the name of consumer benefits.

2. REDUCING EMISSIONS FROM PASSENGER CARS: THE ROLE OF FUNCTIONAL FORM IN DESIGNING OPTIMAL FEEBATES

The market for transportation by passenger cars and light trucks suffers from an environmental externality believed to not be fully internalized by consumers. Utilization of light duty automobiles by private households and corporations is highly dependent on emission generating fuels as inputs for energy production. While specific technological improvements could substantially reduce the dependency on such fuels, an economically efficient outcome depends on establishing mechanisms by which economic agents pay for the externality caused by their consumption of light duty travel.

A feebate policy applies either a fee or rebate to the final price of a new car or light truck, the exact amount depending on the fuel efficiency rating of the given vehicle. As such, a feebate acts as an effective subsidy to the purchases of fuel efficient vehicles at the expense of purchasers of fuel inefficient vehicles. Feebates can be designed as revenue neutral independent of other taxes or policies, which makes them more politically acceptable than fuel taxation. Different feebate systems may be applied separately to varied categories of products (e.g. cars vs. light trucks or footprint based); this in order to channel the means by which the overall fleet-wide fuel efficiency improvements are to be achieved. That is, given the known trade-off between fuel efficiency and vehicle size and weight, increasing fuel efficiency as a result of downsizing a fleet may lead to decreased road safety. In a market equilibrium that achieves a national vehicle fleet with a higher average fuel efficiency, total emissions will be reduced if driving patterns do not change significantly due to a rebound effect, in which a lower cost of travel induces increased consumption of gasoline. Recent empirical evidence shows that such a rebound effect did not take place among household who experienced an exogenous increase in fuel efficiency relative to similar households who did not (West et. al. 2017 [71]). Therefore, feebate systems have the potential to increase overall welfare by reducing the social cost from emissions, if savings in social costs more than compensate any loss of consumer and producer surplus from the levels that existed in the marketplace in the absence of the feebate.

A “first-best” solution in the presence of unmeasurable heterogeneous externalities is to impose an excise tax on consumption of the input that causes social damages. Gasoline taxes have been in effect in the United States both federally and statewide since the beginning of the 20th century, and propositions to increase fuel taxes were a point of contention for voters. Fuel taxation is regressive in its nature (Hsu, Walters, & Purgas, 2008 [35]) and it increases costs to other industries that depend heavily on transportation. Hence, raising fuel taxes is generally not politically expedient and current fuel taxes may be at a suboptimal levels. Rather than restricting real income through fuel taxation, which also increases the trade-off for transportation with consumption of other products, a ’second-best’ solution to the problem of emissions reduces the individual cost of abatement – that is, by decreasing the private cost of reducing gasoline consumption. This can be achieved if the fuel efficiency of cars and light trucks will increase. Vehicle fuel efficiency, along with the price of fuel, determine the actual price consumers have to pay for travel. Thus, by shifting the fuel-to-miles trade off curve, and depending on the rebound elasticity, concurrent higher fuel taxes could attain savings in emissions at no additional cost for consumers. Lin (2009), Gramlich (2010), Davis & Kilian (2011), and Busse, Knittel, & Zettelmeyer (2013) [47, 31, 20, 14] show that consumers are responsive to increased gasoline taxes by purchasing new vehicles that have higher fuel efficiency ratings; however, Kayser (2000) and Klier & Linn (2012) [40, 41] find that such an increase in fuel efficiency is only mild compared to the hardships imposed by the tax.

A complementary policy in the market for new vehicles, which incentivizes the innovation, production, and purchase of fuel efficient vehicles has been in effect as the Corporate Average Fuel Efficiency (CAFE) standards. First enacted in 1975 (and modified since), the policy requires auto-manufacturing firms to conform to a fuel efficiency standard. The CAFE standards set a fuel efficiency target on the weighted average of miles per gallon (MPG) ratings for vehicles sold by each manufacturer in a fiscal year. Manufacturers that do not meet the sales-weighted target must pay a fine proportional to the difference between the target and their actual sales-weighted average fuel efficiency. The CAFE regulations are intended to provide auto-makers with an incentive to invest in research and development towards improving the mechanical efficiency of their engines, which has been successful to a certain degree. However, due to the lack of specification regarding how the fuel efficiency standard is to be achieved, manufacturers often resort to other strategies that will help them reach the standard; for example, they can trade-off fuel efficiency for other vehicle characteristics that consumers value, such as weight and size, or they can change the relative prices they charge for different models in their fleets to increase sales of some fuel efficient models relative to the fuel inefficient ones. A main shortback of the CAFE regulation is manifest in the absence of immediate response to market signals by consumers. The sales mixing tactic is achieved through a manipulation of prices by the manufacturers, and no expressed input from consumers concerning their valuation of fuel efficiency is provided. In addition, once a manufacturer achieves its goals and exceeds the average fuel economy set forth by the CAFE standard, the incentive to improve fuel efficiency further disappears. Previous research suggests that the CAFE standards may not represent the most cost effective method of either reducing gasoline consumption or achieving a higher fuel efficient vehicle fleet (Austin & Dinan 2005, Jacobsen 2013 [4, 38]).

In contrast to the CAFE standards, feebate systems are market-based tools by which incentives are set for both consumers and producers to increase overall fuel economy. Historically, feebate systems have not been particularly popular in the auto market; several state and federal legislative attempts to introduce feebates have failed to pass into law (Train et al., 1997 [70]). However, the discussion regarding the potential benefits of feebate systems has become vibrant in recent years, and their availability as a viable emission abatement policy may still be very valuable. The literature that investigates feebate systems has expanded in recent years due to the implementation of feebate programs in Canada and Europe (Huse & Lucinda 2014, Adamou et al. 2014, D'Haultfaeuille et al. 2014, Klier & Linn 2015 [36, 1, 25, 42]), and due to an increased interest in establishing feebate systems in the State of California. A recent report examines the prospects of establishing a feebate system in California concludes that such a policy implementation would improve fuel efficiency at a negative social cost (Bunch et al., 2011 [12]). Since real-life experience with various feebate systems is limited, much of the existing work primarily examines hypothetical scenarios and calculates their long run effects. Most findings from these studies argue in favor of establishing large scale feebate systems, as it is predicted that the majority of the impact would be towards manufacturers' adoption of new technologies. Gillingham 2013 [29], demonstrates the mathematical equivalence between CAFE standards and feebate systems, showing that for every design of CAFE standards an equivalent feebate system exists. He emphasizes, however, that there are reasons which render feebates preferable to CAFE, including increased transparency to consumers and reduced administrative costs. One particularly important advantage of feebates over the CAFE standards is the shifting of the shadow price of fuel efficiency from behind the scenes to being directly visible to consumers. This important insight is empirically supported by the findings in Busse et al 2006 [13], who find that the pass through of auto manufacturing promotions is starkingly higher when it is advertised to consumers rather than only to dealers via sales incentives. This shows that a monetary incentive may not be fully incorporated into market outcomes if it is not salient. Therefore, since feebates shift the saliency of fuel efficiency pricing by the regulator to consumers, it is also projected to stir an appropriate response by them. Lastly, as discussed in Bunch et al 2011 [12], a feebate does not necessarily have to be in contrast to fuel efficiency standards and can serve as a supplementary program.

This chapter discusses the possibility of adopting feebate systems in the United States. It operates under the premise that out of the infinite specifications of feebate functions, there exists a subset of policies that are welfare increasing; i.e. would lead to choices of vehicle purchases and gasoline consumption that are closer to an optimal allocation. I investigate a number of feebate functional form specifications, accounting for the special incentive structures they each provide, and estimate parameters of these functional forms which control specific attributes of the feebate system - pivot point, slope(s), and scale. The procedure used to estimate optimal feebates maximizes a social welfare function composed of the expected economic surplus from the market minus the social costs of emissions. Existing literature that examines hypothetical feebate systems does so by first estimating the demand for cars in a particular market, in order to obtain the projected consumer response from counter-factual feebate policies. Virtually all of the papers published in this manner apply a Nested Multinomial Logit Model (NMNL) [70, 33, 7, 39, 50, 55, 21, 32, 10, 1, 25, 58] to retrieve demand elasticities for each of the vehicle models considered. A second optimization routine performs a numerical search over feebate parameters to maximize total welfare given the particular functional form that is used.

Up until recently, the economic literature that investigated feebates' effectiveness relative to no feebate or to other policy benchmarks, has only used a handful of ad-hoc specifications for feebate systems, as primarily linear or step-functions. Rivers & schaufele 2017 [58], demonstrate that a feebate enacted in Ontario, Canada proved to be welfare enhancing relative to a no feebate scenario, but that an optimal feebate would have yielded additional welfare while reducing fleet-wide emissions. Their main contribution was to show that rather than choosing any feebate system that would enhance welfare, an optimal policy would maximize benefits from this 'second-best' type regulation. This chapter takes that accomplishment one step further, comparing optimal feebate systems across different functional specifications.

The functional form defines the mapping between vehicle efficiency ratings and the number of dollars in fees or rebates to be charged or paid to the customer. The argument that is usually made for step functions is that their simplicity makes them more favorable to consumers (Bunch et al. 2010 [12]); however, their weakness comes in the form of introducing notches to the system. Sallee and Slemrod, 2012 [60] show that the notches in the gas guzzler tax caused vehicle manufacturers to redesign some of their model such that they just pass the threshold for the tax exemption, and when all firms game the feebate system based on its notches, then society may have an illusion of higher fuel economy while still polluting more than is optimal. Thus, these types of notches are inefficient since they create an illusion of higher fuel efficiency. Continuous feebates would be preferable in order to avoid pervasive behavior caused by a system with notches. The linear functional form is also quite simple and provides a constant and continuous incentive for increasing fuel economy; however, linear feebates provide uniform incentives regardless of the buyer's propensity to make a marginal fuel efficiency improvement. For example, a buyer of a fuel inefficient Dodge truck would face the same marginal incentive to increase efficiency as a purchaser of a Toyota Prius. It is also more useful to design a program that places higher marginal incentives on a significant portion of the population which is likely to respond to these incentives. A non-linear optimal feebate adds curvature to the linear benchmark and would take into account the heterogeneity in the propensity to make marginal improvements. Such a design would offer at the optimum the better incentives to consumers who are most likely to utilize them. I therefore consider two additional non-linear functional forms – an exponential function and a logistic one – and compare optimal feebates to their linear counterpart. I find that the logistic function offers the most effective incentive structure, brings about improved welfare, and is most effective in reducing emissions relative to the optimal linear feebate. While an optimal linear feebate brings about a reduction of 3.11% in emission costs, leading to a 4.15% increase in total welfare over a no-feebate policy, optimal exponential and logistic feebates produce 4.76% and 7.19% emission costs reduction and 6.27% and 9.34% increase in total welfare. Optimal feebates are sensitive to certain program parameters; all optimal feebates are estimated with a constraint on the maximum allowable payment of the program, and I explore the implications of shifting that constraint. Logistic feebates are identified with an additional constraint which places a cap on the maximum allowable marginal incentive, a parameter which implicitly defines the trade-off between program efficacy and distributional effects. I explore the implications of shifting that constraint in the logistic setting. Ultimately, this paper reveals the potential of continuous, smooth, and curved feebates to provide additional welfare gains over traditional feebates, and also emphasizes the additional trade-offs that must be faced between program efficacy and political acceptability.

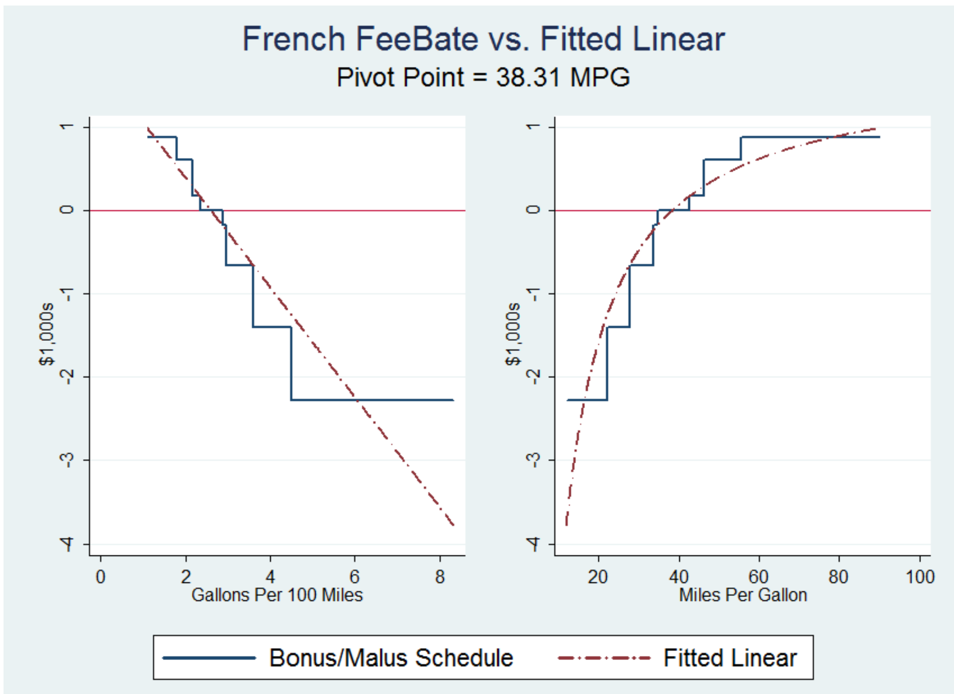
In the next section, I provide an overview to the reader about the central topics of discussion relating to feebates, touching on the existing literature and its focuses as well as some of the main issues that arise with fuel efficiency regulation. I then describe in section 2.2 the source of the proprietary data which is used in the estimation of the demand and supply model that can predict market equilibrium under policy interventions. In section 2.3, I describe the theoretical model for supply and demand, and I introduce the feebate functions evaluated in this paper and discuss their properties. Section 2.4 outlines the two-step estimation process and explains the numerical optimization for both stages of the process. Section 2.5 discusses the results of both stages of the estimation illustrating the main properties of optimal feebates, and section 4.1 of the last chapter concludes.

2.1 Fee-Bate Systems: Past, Present, and Future

This section covers certain issues that come up frequently in the policy discussions of feebates, and provides the reader with a background that enables him or her to understand the relative strengths and weaknesses of particular feebate designs. Some popular issues consist of the ability of a policy to induce technology adoption in order to obtain long run positive effects, the application of separate feebate policies to segments of household vehicles (i.e. pickups vs. cars) or applying size-specific feebates, and the magnitude of the scale for the policy. Ultimately, alternative feebate approaches represent trade-offs between policy effectiveness and other undesirable outcomes. Often the task of quantifying the entirety of these trade-offs in a single study is burdensome, and I will conclude this section by detailing the aspects that this paper will consider and explaining the reasoning behind the limitations of this study.

A central advocacy point for introducing feebates is their potential efficacy in reducing emissions through technology adoption. Contrary to a CAFE policy which does not allow for trading credits, feebates offer continuous market incentives for auto manufacturers to adopt existing fuel efficiency technologies, as well as to compete in the research and development of new technologies. Train et al., 1997 and Greene et al., 2005 [70, 33] find that technology adoption by firms would be responsible for 90% of the achieved emissions reduction in the long run, while the remaining 10% would be due to sales shifts by consumers. Incentives for firms to increase their fleet fuel efficiency exist so long as consumers respond to changes in the relative prices; they do not depend on a specific standard and exist whether or not a certain level of compliance is achieved. In addition, contrary to cap-and-trade schemes in which one firm's pollution abatement enables another firm to increase its pollution, under a feebate system, fuel efficiency improvements that are attained by one firm place further competitive pressure on other firms to improve their energy ratings as well (Johnson, 2006 [39]). Thus, feebate systems may be considerably more effective at increasing corporate average fuel efficiency than raising CAFE standards or implementing cap-and-trade. Placing the crux of the competition for fuel efficiency in the realm of technological innovation relaxes the concerns that higher fuel efficiency gains will come at the expense of negative outcomes from sales mixing or downsizing.

Figure 2.1: Example of an Actual Feebate Policy



Despite many findings in favor of adopting feebate systems, either as a substitution or complement to the CAFE policy, there is still little real-life experience with various feebate schedules that would enable researchers to empirically examine their impacts. Historically, efforts to pass feebate schemes both federally and by individual states have not been particularly successful (Train et al., 1997 [70]). The closest form of feebate schedule that has been prevalent in the U.S. since the 1990's is the gas guzzler tax, which does not contain a rebate criterion and has limited applicability due to the low market shares of the set of vehicles that are subject to the tax (Sallee, 2011 [59]). Experience from feebate schedules that have been implemented in other countries is also limited and mostly consists of either linear or step functional forms. Figure 2.1 shows the most recent feebate policy enacted in France, which has been the focus of studies such as Adamou et al 2014 and Klier & Lynn 2015 [1, 42]. The figure on the left-hand-side depicts the feebate program as it maps fuel efficiency measured in the number of gallons required to drive 100 miles, which is a measure linear with fuel and externality cost.[1] The right-hand-side graph depicts the exact same program when the fuel efficiency support is defined by the traditional measure of miles per gallon (MPG). The obvious observation is made that the linear feebate fitted to the French step-function feebate is not linear in MPG but appears to have decreasing marginal incentives with MPG, though the marginal incentives are constant with GPM and fuel costs. The second observation is that applying the French feebate to the U.S. market, many Americans will end up paying the fee rather than receiving a rebate, as the pivot point is set at around 40 MPG. Simply imposing any feebate on the U.S. market will not necessarily improve total welfare; the illustration from the French feebate shows that optimal smooth feebates may be superior to ad-hoc step functions, but they must be estimated prior to enactment.

Successful propositions for establishing feebate systems in the U.S. ought to emphasize several concerns in order to pass basic requirements for political acceptability. Outcomes which the public is typically concerned about are: (a) How effective will a feebate system be at reducing emissions from transportation? (b) How will the distribution of fees and rebates affect distinct groups in the population, for example will the system be progressive or regressive? (c) Will a separate feebate policy be implemented for defined vehicle groups or as a footprint based policy? Generally, a uniform policy across vehicle types and sizes is more likely to create substitution towards light weight vehicles and may induce higher emissions savings at the cost of lower safety. Footprint based policies reduce the incentive to downsize the fleet but can instead create incentives to buy a heavier and less efficient vehicle. (d) How will a feebate system impact the automobile industry in terms of changes to manufacturers' market shares? If sales-shifts by consumers towards more fuel efficient vehicles favor foreign manufacturers, this may have an adverse effect on employment and economic growth, at least until domestic firms can recapture profits as they compete with better

[1]The actual French feebate publicizes the fees/rebates paid in €'s as they depend on CO_2 emissions per kilometer. The above-mentioned figure utilized a conversion to U.S. $'s and to the imperial system.

fuel efficiency technology. (e) Can a feebate schedule be revenue neutral or will it depend on external sources for financing? feebate systems are more likely to be accepted by the public if it can be self-sustaining and will not be dependent on raising other taxes.

Addressing the concerns with regards to controlling for vehicle size and type in feebate systems, two solution concepts are generally available. The first, regarding the proper unit of measurement that ought to be used for ranking energy performance, the usage of a traditional absolute measure for fuel economy in which a dollar value is assigned to the actual unit of externality regardless of the type of vehicle. Performance is measured by fuel consumption alone and compared across all vehicles with varying characteristics such as weight, volume, or footprint. Gallons per Mile driven (GPM), or its inverse, Miles per Gallon (MPG), are the common absolute indicators for fuel economy in the U.S. (In Europe, the measure is by grams of Co2 per Kilometer). Using GPM as an absolute unit of performance for a single-benchmark policy creates a single standard that equates marginal costs of reducing fuel consumption across all consumers, vehicle manufacturers, and vehicle classes. The second approach considers applying different feebate schedules for specific sub-groups of vehicles. Under a unified feebate policy, due to the high correlation between fuel efficiency ratings and vehicle mass, feebate systems may create incentives for consumers and producers to extract gains by sacrificing weight and size in favor of higher fuel efficiency. This effect is known as 'downsizing' and it may impact manufacturers differently resulting in some firms receiving better treatment from the feebate system than others due to the inherent differences in their fleets. While the calculation of fees and rebates based off the absolute measure would extract the most gains in terms of emissions reduction, some negative impacts of this method on the industry may not be desirable.

Four possible ways to deal with this trade-off are as follows: (a) maintaining that the negative outcomes from possible downsizing effects are dwarfed compared to efficiency improvements that occur beyond downsizing through technology adoption, (b) creating different feebate schedules for separate classes of vehicles, allowing incentives for downsizing to exist only within a particular vehicle class but not across different classes (i.e. reducing the incentives to substitute a car for an SUV or a pickup), (c) applying a single schedule for all classes and redefining energy efficiency ranking to depend on other vehicle characteristics; for example emissions-per-vehicle-ton (Johnson, 2006 [39]), or (d) having a single feebate function applicable to all vehicles, while using gallons per mile as the efficiency measure and requiring that the pivot point be a continuous function of vehicle footprint (Greene, 2009 [32]). Following (b) may lead to perverse outcomes as firms will attempt to make small changes to existing vehicles in order to re-classify models so that they qualify under a more favorable schedule. In addition, such a system may oddly encourage consumers to switch their purchase decisions across classes, as there may well be high monetary incentives in buying less fuel efficient vehicles - e.g. deciding to buy a SUV or a Pickup nd receive a rebate rather than pay a fee for a sedan. Even when applying a constant dollar rate per GPM across all classes in a feebate system linear in GPM with pivot points that differ across vehicle classes (firms still equate marginal cost of saving a gallon of fuel across all vehicles (Greene, et al. 2005 [33])), the mere difference in pivot points could lead to this counter-productive result.

Defining energy performance in terms of emissions-per-vehicle-ton, as in (c), and applying a single feebate schedule across classes may still not yield the best solution. Similar incentives as in (b) exist for consumers to buy larger and heavier cars, and though as a measure of energy efficiency it may seem appealing, its efficacy in reducing emissions is questionable. A large source of concern with the downsizing incentive has been that lighter weight cars are less safe, and hence, an efficiency measure based on vehicle weight would mitigate that concerns. However, vehicle safety (considering, for instance, the probability of death in a two vehicle collision), will not be affected if the masses of all vehicles in the market are reduced simultaneously. This is because fatality risk depends in a two vehicle collision depends on the ratio of masses between the colliding vehicles and not on the absolute mass (Greene 2009 [32]). The trade-off between following (c) as opposed to (a) or (b) is summarized by the efficacy of the feebate system in increasing average fuel efficiency versus incentives to buy smaller or larger cars.

It is apparent that any attempt to segment a proposed feebate system, in order to accommodate concerns regarding certain distributional effects, encounters additional perversions of market outcomes. Perverse responses typically occur when large marginal gains can be attained by agents making small changes in behavior relative to an original decision. Introducing kinks, notches, or segmentation to a feebate schedule does exactly that, and in order to avoid perverse responses, program designers must specify the criteria that are important for the program and define incentives in a way that depends on these criteria in a continuous manner. An example can be illustrated by applying (d), as presented by Greene 2009 [32]. This approach 'solves' the problem of notches in the definition of vehicle class by requiring that at least the pivot point of the feebate system be dependent upon vehicle footprint. In effect, this approach minimizes the problem of notches, but it does not solve it completely, as even though the feebate function is continuous, differences in footprint of actual vehicles that are offered for sale are discrete. I focus this paper on feebates that do not have separate pivot points or feebate structures based on characteristics other than fuel efficiency. It is clear that there are trade-off between attribute based and non-attributes based feebates. For the purposes of assessing the role of functional form, having smooth and differentiable feebate functions are necessary to reach numerical convergence and I fix all feebates at these properties.

Other considerations that are relevant to designing feebate systems are the market coverage and the interactions with other large scale environmental policies. Since there is a high reliance on technology adoption by firms for efficiency gains under feebate systems, high economies of scale are available for markets sharing such a program. Bunch et al., 2011 [12] show that emission reduction gains of a potential feebate system in California are greater by a factor of 3 if the feebate system is applied to the entire United States as opposed to California alone, and twice as great than if the program is applied in 13 "Opt-In" states. Though specific feebate schedules need not be identical across separate markets, the establishment of incentives for a greater number of consumers to prefer higher fuel efficiency will drive auto manufacturers to respond more promptly and with larger scale across these markets. This may have an added advantage if the new models marketed in the U.S. are also offered elsewhere in the world, suggesting a global positive spillover. As for interaction of feebates with existing regulatory policies, depending on the level of current mandated standards, feebate schedules can benefit automakers by allowing them to more easily comply with regulation and to avoid penalties. Introducing feebates to markets that face high fuel efficiency standards may detract from the marginal value of the feebate system, but most likely, a well-designed system would provide additional incentives to improve efficiency, especially in firms for which the standards are not binding. Fee-bate systems should not be seen as a substitute to carbon taxation in the form of an excise tax on gasoline; they affect a completely different decision issue for consumers. While gasoline taxes may affect the market for automobiles, and while increased fuel efficiency from feebates may encounter a rebound effect of increased gasoline consumption, these two policies do not compete with one another and should be seen as complements for the general purpose of achieving efficiency in the allocation of travel and emissions.

2.2 Data

The data set utilized in this paper consists of all DMV registration records in Texas between 2004 and 2010. Each DMV record contains both a time stamp and information regarding the vehicle being registered. Vehicles are uniquely identified by their 17-digit Vehicle-Identification-Number (VIN), a truncation of which (1st-8th and 10th-11th digits) is linked to a unique profile of characteristics including its make and model, model year, size, weight, horsepower, number of doors, fuel efficiency rating, MSRP, and more. Information on vehicle attributes based on the 10-digit VIN is provided by output from the "DataOne" software. The registrations data include the actual transaction price, as well as the manufacturer suggested retail price (MSRP) and the amount paid net of a trade-in transaction. I distinguish among markets based on geography and time-periods proxied by the vehicle model year. A transaction belongs to the geographical market where the seller is located. I extract information about buyers' income level based on the distribution of income in the census tract associated with their registration address, which is obtained from the Census2000. I estimate the distribution for income to be log-normal, deriving the parametric distribution for each census tract by applying a method-of-moments estimation using 11 sample moments, including the median and percentage of population in ten income brackets. Each household's address, as listed in the DMV records, is linked to a unique census tract.

The estimation sample is composed of new vehicle transactions that occurred in the state of

Table 2.1: Average Prices and Characteristics of Select Models

Product Name (Market Share)	Average Price	Gallons per 100 Miles	Weight (1,000s lbs)	Footprint (Sq Inches)	Height (Inches)	Maximum Horsepower
Pickups (28.44%)						
Ford F-150	$27,235	6.93	5.18	84.26	74.27	265.00
(6.22%)	(6,682)	(0.76)	(0.28)	(11.01)	(1.21)	(38.66)
Silverado 1500	$25,416	6.86	4.95	78.63	73.00	287.63
(4.54%)	(5,658)	(1.07)	(0.31)	(4.77)	(1.26)	(42.54)
Toyota Tundra	$29,210	6.50	5.05	78.67	74.86	316.15
(1.49%)	(5,788)	(0.55)	(0.39)	(4.70)	(1.65)	(60.82)
SUVs (25.95%)						
Honda CRV	$23,276	4.38	3.39	50.93	66.13	165.84
(1.22%)	(2,879)	(0.14)	(0.07)	(0.48)	(0.05)	(6.90)
Toyota 4Runner	$30,644	5.70	4.14	57.04	70.38	243.68
(0.68%)	(3,782)	(0.33)	(0.16)	(0.55)	(1.33)	(10.78)
Chevrolet Tahoe	$36,199	7.50	5.19	63.59	76.45	308.65
(2.06%)	(5,814)	(1.05)	(0.23)	(0.07)	(0.78)	(14.68)
Ford Escape	$21,813	4.86	3.30	52.52	68.53	183.76
(1.03%)	(2,942)	(0.56)	(0.08)	(3.49)	(0.86)	(29.30)
Lexus RX-350	$40,813	4.92	4.00	54.56	66.70	271.88
(0.38%)	(3,568)	(0.13)	(0.15)	(0.81)	(0.77)	(2.42)
BMW X5	$54,248	5.88	4.93	61.03	68.59	267.33
(0.11%)	(6,884)	(0.47)	(0.22)	(4.79)	(1.04)	(41.77)
Sedans (29.25%)						
Mercedes C-Class	$35,817	4.98	3.47	53.46	56.01	220.53
(0.39%)	(5,261)	(0.75)	(0.12)	(3.92)	(0.75)	(37.08)
Cadillac CTS	$34,750	5.22	3.65	56.08	57.23	257.35
(0.5%)	(5,510)	(0.21)	(0.18)	(0.83)	(0.65)	(28.16)
Volkswagen Jetta	$22,758	3.88	3.20	49.03	57.40	146.19
(0.66%)	(3,139)	(0.64)	(0.10)	(0.99)	(0.53)	(28.35)
Nissan Altima	$22,460	4.07	3.13	53.51	57.68	185.80
(1.69%)	(3,321)	(0.30)	(0.09)	(0.59)	(0.73)	(28.99)
Honda Accord	$23,612	4.22	3.31	54.26	57.33	193.44
(2.69%)	(3,437)	(0.26)	(0.14)	(1.11)	(0.70)	(38.11)
Chevrolet Malibu	$20,076	4.27	3.37	53.27	57.28	178.42
(0.68%)	(3,404)	(0.36)	(0.12)	(1.68)	(0.20)	(30.82)

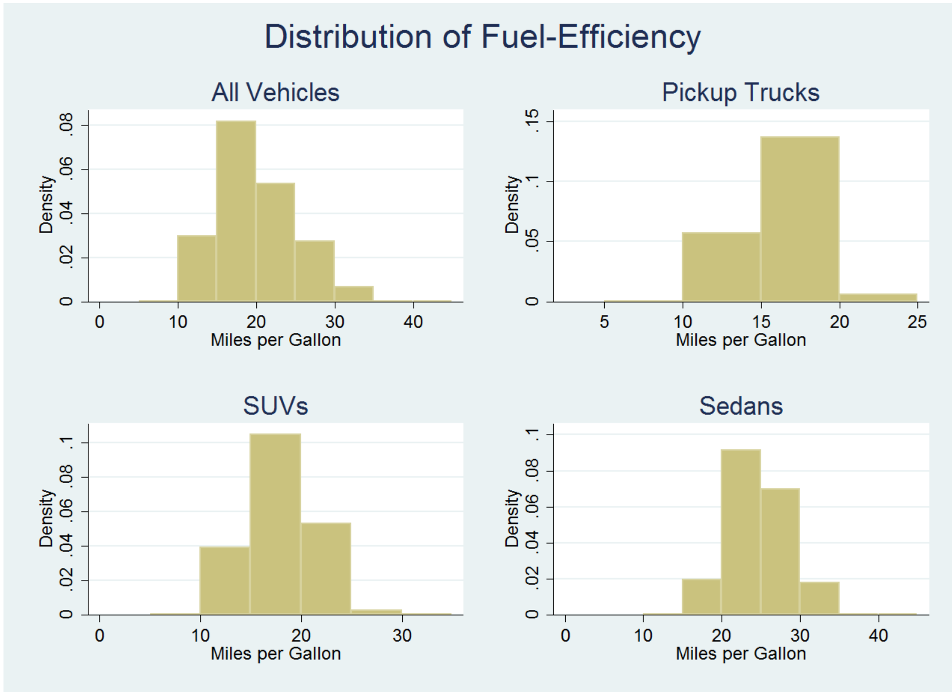
Texas from January 1st, 2004 through December 31st, 2010. A registration record is determined to represent a new vehicle transaction if it meets all of the following criteria: (a) the model year is not earlier than the year of purchase, (b) the vehicle's odometer reading does not exceed 1,000 miles, and (c) the previous owner is a car dealership that owns a franchise agreement with the manufacturer of the same brand.[2], and (d) The price paid is at least $5,000.00. The sample is narrowed down to 50 out of the 312 local markets in Texas, each containing markets for seven model years between 2004-2010. Vehicles in the choice set are differentiated by their make and model, as well as some key characteristics such as fuel consumption[3]; choices include, for example, several options for a Ford F-150, Toyota Camry, BMW X5, each having a different fuel efficiency rating. Since variation in vehicle characteristics is present within each model, other characteristics are averaged across all vehicle sales of the model profile. Thus, some vehicle characteristics may be different across markets and years due to varying consumer preferences over these attributes. Because every vehicle transaction has its own price, I average the transaction prices for each model profile, in each market, in a similar way.

Each market consists of anywhere between 30-150 different options in its choice set. Geographic areas that are less populated will have fewer options available to the local consumers. Table 2.1 lists a set of 15 of the popular models in the categories of pickup trucks, SUVs, and sedans, also distinguishing among some luxury options. The table summarizes the main areas of variation among these options, the standard deviation of each measure is reported in parentheses below the mean. It is clear that luxury models (e.g. BMW, Lexus, Cadillac, and Mercedes) are more expensive and less fuel efficient on average than their non-luxury counterparts in each vehicle category. Table 2.1 also depicts the correlation between size, weight, and horsepower, and fuel efficiency. Fuel efficiency is measured in gallons per 100 miles, which is a measure linear with fuel costs. The three vehicle body types comprise 83.64% of all car purchases in Texas, and so I exclude other body types such as mini-vans, hatchbacks, and convertibles which have a disproportionate

[2] If, for instance, a registration record shows a Ford being sold by a Toyota dealership, then it is not considered to be a new vehicle transaction.

[3] There is significant variation in characteristics for trim lines of the same make and model.

Figure 2.2: Distribution of MPG among Vehicles in the Sample



concentration in large urban areas. The relatively high market share observed for the models under the pickup category is due to the fact that only five manufacturers produce over 98% of all pick-ups that are sold,[4] whereas all manufacturers produce product lines for sedans and SUVs. Luxury items have a lower market share than volume goods in the same category, and a good is considered to be popular when its market share is relatively high compared to other brands with a comparable set of attributes. Apart from price and fuel consumption, which represent costs of purchase and utilization, all other attributes represent goods such that a higher value of them should increase utility. The next section details the utility specification and the complete theoretical model.

2.3 Model

I specify an empirical model in order to assess the welfare benefits of a number of optimal feebate systems. Since feebates alter market prices, counter-factual simulations will depend on the specification of demand and supply system in market equilibrium. The first step is thus to obtain

[4]Ford, GM (Silverados and GMCs), Dodge (Ram), Toyota, and Nissan

parameters of market equilibrium which will enable the prediction of outcomes given alternative feebate policies. This is done by specifying a demand system in which consumers make a discrete choice to buy one vehicle, which they will later utilize. The supply side is responsive to consumer demand, and is specified as an oligopoly of manufacturer-dealer teams who compete with one another in local markets. Once demand and supply parameters are estimated, market outcomes can be predicted by applying counter-factual feebate policies which changing prices. The optimal feebate is the policy which brings about the best total welfare outcomes compared to all other counter-factual feebates that are specified by the same functional form.

DEMAND

I specify consumer demand in accordance with discrete choice models developed since the 1970's, recovering consumer tastes with respect to select characteristics of the products that they are buying. After estimating the distribution of these taste parameters in the population, the model generates demand elasticities and substitution patterns which determine the market response to a planned intervention. The theoretical model specifies a discrete choice problem for demand of a durable good and an oligopolistic market structure in which firms maximize expected profits conditional on demand elasticities. The discrete choice model assumes that rational consumers maximize utility of the form:[5]

$$U_{ijt} = \alpha_i P_{jt} + X^1_{jt}\bar{\beta} + X^2_{jt}\sigma^{\beta}_i + \xi_{jt} + \epsilon_{ijt} \tag{2.1}$$

where i indexes individual households, t indexes a specific market, and $j \in \{0, 1, \ldots, J_t\}$ indexes each discrete choice available in market t ($j = 0$ indicates an outside option - either non participation in the market or buying a vehicle not included in $\{1, \ldots, J_t\}$). The $J_t \times K^1$ and $J_t \times K^2$ matrices, X^1_t and X^2_t, represent characteristics of the vehicles available at the choice set of market t. These are segmented into two matrices in order to allow flexibility in terms of random utility

[5] The color coding is facilitated to distinguish among observables (black), unobservables (red), and parameters that require estimation (pine green).

tastes. The portion of equation 2.1 which depends on individual characteristics is decomposed as:

$$X_{jt}^2 \sigma_i^\beta = \sum_k x_{jtk}^2 \nu_{itk}^\beta \sigma_k^\beta \quad \text{and} \quad \alpha_i = \bar{\alpha} + \sigma^\alpha \nu_{it}^\alpha + \frac{\Pi^\alpha}{y_{it}}$$

where k refers to a particular vehicle characteristic. Individuals' unobserved random variation in tastes (the ν_{it}^β's), and in price sensitivity (the ν_{it}^α's), as well as the unobserved term for individual income (y_{it}), are taken as random simulation draws from a multivariate standard normal distribution. The income term is assumed to be log-normal with mean and standard deviation parameters estimated from the census data. The unobserved error term ξ_{jt} is a measure of the utility obtained from product attributes which are not included in X_{jt}^1 or X_{jt}^2. All unmeasured aspects of vehicle quality, such as safety features and reputation, aesthetics, or unobserved options that are purchased at the dealership (these may include technology packages, towing equipment, supplemental warranty coverage, etc.), are summed into one error term in ξ_{jt}. Since the value of ξ_{jt} is highly correlated with transaction prices, the identification of the parameters for price sensitivity is accomplished with instrumental variables to counter the omitted variable bias. Unobserved idiosyncratic shocks to consumer preferences for vehicle attributes, which affect the valuation of each vehicle in the choice set, are represented by the error term ϵ_{ij}, assumed to be distributed i.i.d. extreme value, which yields the standard Logit model with analytic equations for the purchase probabilities.

The parameters that require estimation are $\bar{\alpha}$ and $\bar{\beta}$ - representing the mean price sensitivity and taste parameters, σ^α and σ^β - representing the standard deviations of the price sensitivity and the taste parameters for attributes included in X^2, and Π^α which provides additional variation of price sensitivity with respect to household income. Since the anticipated sign of $\bar{\alpha}$ is negative, the expected sign for Π^α is also negative, which means that individuals with a lower income will be more averse to higher prices. The total number of linear parameters is $K_1 + 1$, one for each vehicle characteristic included in X^1 plus the mean aversion to price. The total number of random coefficients (non-linear parameters) to estimate is K_2+2, one for each characteristic included in X_2, and two for the random terms of individual price aversion and income. A model that assumes the following equalities: $\sigma^{\alpha} = 0$, $\Pi^{\alpha} = 0$, and $\sigma^{\beta} = 0$ is the traditional simple Logit specification which can be estimated with a linear Ordinary Least Squares equation, or by a 2 Stage Least Squares approach that accounts for endogenous prices. It is useful to decompose the random utility term into two parts in the following manner:

$$U_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{ijt} \tag{2.2}$$

where

$$\delta_{jt} = \bar{\alpha} P_{jt} + X^{1}_{jt}\bar{\beta} + \xi_{jt} \quad \text{and} \quad \mu_{ijt} = (\sigma^{\alpha}\nu^{\alpha}_{it} + \frac{\Pi^{\alpha}}{y_{it}})P_{jt} + \sum_{k} x^{2}_{jtk}\nu^{\beta}_{itk}\sigma^{\beta}_{k}$$

such that the first term is determined by the linear parameters and the unobserved common utility factor, while the second term allows individual level variation in tastes. This decomposition is instrumental in the estimation procedure which I describe in section 2.4. Due to the distributional assumption of the idiosyncratic term ϵ_{ijt}, it is possible to write the "individual market share" for each vehicle in the individual's choice set, as the probability of individual i in market t to purchase vehicle j conditional on the characteristics of all alternatives in market t - $X_t = (P_t, X^1_t, X^2_t)$, individual tastes and income $\Gamma_{it} = (\nu^{\alpha}_{it}, \nu^{\beta}_{it}, y_{it})$, and parameters $\theta = (\alpha, \beta, \sigma, \Pi)$:

$$\text{Prob}(j \in \{0, 1, \ldots, J_t\} | X_{jt}, \Gamma_{it}; \theta) = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{q=1}^{J_t} \exp(\delta_{qt} + \mu_{iqt})} \tag{2.3}$$

With these choice probabilities, the model produces shares for each available product j at a given market t as the average of individual shares across all simulated individuals:

$$S_{jt} = \frac{1}{ns}\sum_{i=1}^{ns} \text{Prob}(j \in \{0, 1, \ldots, J_t\} | X_{jt}, \Gamma_{it}; \theta) \tag{2.4}$$

SUPPLY

I define the supply side model as marginal costs being determined by product characteristics and location of production, where the production inputs depend on one-another. This is modeled in a log-linear regression, following the literature:

$$log(MC_{jt}) = \gamma W_{jt} + \zeta_{jt} \tag{2.5}$$

with W_{jt} being a vector of observable vehicle attributes, γ is a vector of linear parameters, and ζ_{jt} is an i.i.d error term. Equation 2.5 can be estimated with ordinary least squares, once measures of marginal costs are obtained. When assuming a benchmark model of perfect competition, the marginal costs are taken to be the actual vehicle prices; however, the automobile industry is far from perfectly competitive, especially when considering local dealership retail markets. In an oligopolistic setting, firms and dealerships maximize expected profits given their beliefs on the demand elasticities for their products. Following BLP 1995, I obtain marginal costs which satisfy the first order conditions for profit maximization:

$$\sum_{q_j}^{Q_j} \left(P_{q_j t} - MC_{q_j t}\right) \frac{\partial S_{q_j t}}{\partial P_{jt}} + S_{jt} = 0$$

where q_j and Q_j reference the set of vehicles produced and sold by the same firm. The terms for the shares and their derivatives are computed by and dependent on the demand model. Marginal costs are computed for each vehicle in each market with the following matrix equation:

$$MC_t = P_t - \Delta^{-1} S_t$$

thus the markups depend on the inverse of the matrix Δ, defined as $-\frac{\partial S_{qt}}{\partial P_{jt}}$ if j and q are sold by the same firm and zero elsewhere, and on the vector of shares determined by equation 2.4. Firm profits are the sum of markups over all vehicles sold.

FEEBATES

Fixing demand side estimates, alternative feebate systems are examined. Optimal feebate systems are not arbitrarily chosen but must be estimated in order to find the most welfare increasing program conditional on a specific functional specification. From section 2.1 we learned that if a feebate maps fuel efficiency to a price change by using steps or kinks in its function, then we would anticipate inefficiencies resulting from bunching at those kinks. In addition, kinks and steps render a function to be not continuously differentiable, which hinders the ability to optimize its parameters. I therefore introduce a variety of smooth functions to be considered for defining the mapping of fuel efficiency rating into fees and rebates, affecting the final price that consumers pay for new cars. I convert the traditional "Miles per Gallon" measure of fuel efficiency to gallons per 100 miles, which is simple the inverse of MPG multiplied by 100 (I will refer to this measure henceforth as GPM). This measure is linear with respect to fuel costs and emissions of pollutants per mile, and is a natural measure to consider for the purpose of second-best pollution taxation.

Fee-bate functions are considered for their varying incentive structures, and optimal results are compared across functional specifications. As discussed in section 2.1, previous literature has not explored the consequences of allowing curvature in a smooth feebate function. The benchmark linear (in gallons per mile) feebate is formulated by set of two parameters - a pivot point GPM_0 and a slope τ. In particular, for a given vehicle j, with energy rating GPM_j, the feebate formula is simply:

$$FB_j^{linear} = \tau \cdot (GPM_0 - GPM_j)$$

The marginal incentive to improve on fuel efficiency is constant and there is no limit or cap regarding the maximal payment that is "built-in" to the feebate function. If a vehicle is less fuel efficient, its GPM_j will be higher, which means the feebate will be negative and buyers of this vehicle will pay the fee. Otherwise, if a vehicle is more efficient relative to the pivot point, then $GPM_j < GPM_0$ and the buyers will receive a rebate. The marginal incentive to increase fuel efficiency by one unit of GPM is given by the parameter τ, and the sign of the derivative will be zero as increasing GPM will cause the rebate to decrease and the tax to increase. An important reminder is that the linear feebate is not linear in miles per gallon, because MPG is non-linear in fuel costs and emission rates. Therefore, it appears that a linear feebate entails marginal incentives which are decreasing in MPG - which means that buyers of fuel inefficient vehicles face a higher incentive to upgrade by one MPG. In appendix A, I provide the mathematical proofs for the marginal incentives formula of each functional form under consideration, for fuel efficiency increases of one MPG or a reduction in one GPM unit.

A second functional approach is the exponential function in which the marginal incentive to increase fuel efficiency is non-linear and monotonic with respect to GPM. It can be specifies in two alternative ways, one in which the marginal incentives are increasing and the other decreasing, with a higher GPM. Because of the inverse relationship between GPM and MPG, the exponential function which has marginal incentives increase with GPM will appear to be more linear in MPG. Each formulation of the exponential function affects the curvature of the feebate in opposite directions - the middle ground between the two exponential specifications is the linear feebate. In comparison to the linear benchmark, the exponential feebate has three parameters defining it: The pivot point GPM_0 is similar in its determination of which vehicles are taxed and which are subsidized; the "slope" parameter τ controls the curvature but it is no longer the representative marginal incentive; an additional parameter S is introduced to control the scale of the program - that is, increasing S will allow fee and rebate payments to increase up to an upper bound. S is thus the adjustment of the exponential function's asymptotic limit. The two versions of the exponential function are as follows:

$$FB_j^{exp1} = S \cdot [1 - exp^{-\tau \cdot (GPM_0 - GPM_j)}] \quad \text{and} \quad FB_j^{exp2} = S \cdot [exp^{\tau \cdot (GPM_0 - GPM_j)} - 1]$$

The exponential function is smooth and easily differentiable, so an optimal program can be searched for numerically. When $GPM_j > GPM_0$, the exponential term will become positive in the first formulation and negative in the second, and in both cases the feebate will be negative - rendering a tax to be paid. The opposite is true when $GPM_j < GPM_0$. Since the term in parentheses cannot be higher or lower than 1 in formulation 1 and 2 respectively, the effective limit on the bound of payments and fees is determined by the scale parameter S. This is a major difference in relation to the linear case which has no built-in cap on payments.

The last formulation for a continuous feebate function is the Log-zigmoid S-shaped function, which introduces non-linear marginal incentives that are not monotonic. It is also smooth and continuously differentiable. With the logistic formulation, marginal incentives to improve fuel efficiency are maximized at the pivot point and are close to zero at the extreme values (also to be shown in the appendix). There are three parameters defining the function in a similar fashion as the exponential cases - GPM_0 is the pivot point, τ controls sloping and curvature, and S controls the scale of the feebate and determines the bounds for maximum payments, which in the logistic case is bounded both at the fees and rebates. The formulation is as follows:

$$FB_j^{logistic} = S \cdot \left[\frac{1}{1 + exp^{-\tau(GPM_0 - GPM_j)}} - 1 \right]$$

Interestingly, the logistic structure in GPM preserves the shape with respect to MPG - both appear to be S-shaped. Since The majority of vehicles are concentrated around the pivot point, the logistic feebate has the highest potential to influence the incentives of many buyers and sellers in transitioning to higher fuel economy, rendering the program much more effective. Lastly, the logistic feebate is very sensitive to changes in the τ, and has a narrow parameter space for which small changes in τ produce different curvature structures. For the feebate to maintain fees on fuel inefficient vehicles and rebates on fuel-efficient ones, τ must be greater than zero (otherwise, the incentives switch signs). When $\tau \to 0^+$, the logistic function approaches a flat line; and when $\tau \to +\infty$, the feebate function will be a one-step function with an infinite slope at the pivot and flat everywhere else, with the limits determined by S. At high values of τ the feebate will reward everyone buying a car above the pivot with the highest rebate possible, and will punish those who buy below the pivot with the highest fee possible, creating one massive notch. Therefore, if higher

τ's produce more transition to higher fuel economy, the apparent trade-off is between effective emission reduction and negative distributional effects.

2.4 Estimation

I proceed by executing a two-step estimation procedure. The first stage employs the transactions data derived from Texas DMV registration records in estimating the theoretical model of demand and supply and retrieving the parameters of consumers' price sensitivity and tastes of characteristics, and of producers' markups over marginal costs in the case of imperfect competition. I run the estimation routine for several specifications of random utility term with respect to the choices of characteristics for which consumers have a random taste. I then choose the 'best' specification and perform counter-factual policy simulations to estimate optimal feebates. The quality of the first step results must be at a level that enables reasonable predictions for the counter-factual simulations, and so, I elect the model which provides the most reasonable distribution of price sensitivity, as well as plausible substitution patterns and markups. The process of the second stage depends on these model attributes as it calculates a new market equilibrium when prices are artificially changed by the feebate system.

2.4.1 Demand and Marginal Costs

I use the data structure as described in section 2.2, identifying random taste from variation across 50 Texas local retail clusters over seven model years. The majority of geographic units are located either in urban areas or in relative proximity to metropolitan statistical areas, and as such, each geographic market has a large set of vehicle alternatives offered by local dealerships. The choice set size is correlated with the market size, and specific brands (typically luxury) may only be offered at very urbanized locations. A transaction in the data is incorporated into a geographic unit based on the location of the seller, not the buyer; yet, information about the buyers' address is incorporated into the distribution of income from which I extract the random term y_{it} (the income level of individual i at market t).[6] A choice of a vehicle j in a market t is defined as a make and

[6]Specifically, after estimating the mean and standard deviation parameters for each census tract from the information obtained in the Census2000, I assign each individual to the income distribution of his/her census tract. When I

model with a specific fuel efficiency rating. As manufacturers offer varying trim lines for many car models at each given model year, several characteristics vary within the same make-model and across those trim lines. Allowing too much variation in characteristics within the same make and model turns out to be detrimental to the estimation as too many similarities in a single choice set hinders the identification of random tastes. Thus, I average the remaining characteristics for which there is variation within each make-model-fuel efficiency combination. To avoid incorporating too many choices with a market share that is close to zero, I include only the most popular models for each manufacturer, maintaining consideration of at least half of the entire product lines for each firm and each model year. All purchased vehicles that are not included in the model are considered to be a part of the market share for the outside option.

I maintain a consistent set of linear regressors, represented by the matrix X^1, for the demand equation. These include the endogenous vehicle transaction price measured in \$1,000's, characteristics such as fuel efficiency (measured in gallons per 100 miles), curb weight (1,000's lbs), footprint (square inches), height (100's inches), and horsepower (measured in units of HP), as well as controls for brand loyalty (dummies for brand parent company), model year common shocks, and preferences for pickup trucks, SUVs, and luxury cars (all dummy variables). I choose a similar set of characteristics to estimate the marginal costs parameters of attributes represented by the matrix W, except that I remove the preference for luxury goods, and I add a regressor for engine displacement as well as dummies for engine type and drive type. I also include dummies for the location of the plant where the car is manufactured relative to U.S. plants.[7] The purpose of estimating the marginal cost parameters is to compare the performance of the model in comparison with the perfect competition benchmark. I regress the log of marginal cost on the regressors (in PC, this is the price) and check whether the regressors have the appropriate sign. I explore the differences in the results across several specifications of the X^2 matrix of characteristics for which consumers

collapse the information for individual markets, I average the distribution of income of all individuals who participated in the market to obtain the market-specific income distribution from which I obtain the random income draws for the estimation.

[7]For example, if a plant is located within the NAFTA region but not in the U.S. the marginal cost of production should be lower; and if a car is manufactured in Europe, Australia, or South Africa, then scale economies and labor costs do not offset shipping costs in comparison with vehicles manufactured in Japan.

are allowed to have random tastes. I include fuel efficiency in each specification and explore the implications of adding vehicle weight, footprint, or engine displacement. I run each specification with and without the inclusion of a random term for price sensitivity which depends on income (that is - with and without Π^{α} in addition to the σ^{α}). The random term for price sensitivity is included in each specification.

Table 2.2: First Stage of Instruments' Effect on Prices

Transaction Price	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Demand Signals									
Non-Private	\$699.49		\$533.09	\$876.79		\$655.9	\$882.52		\$662.06
	(176.84)		(173.03)	(175.76)		(172.37)	(175.61)		(172.21)
Lien	-\$2,151.92		-\$2,046.74	-\$2,086.16		-\$1,964.27	-\$2,073.43		-\$1,949.75
	(132.15)		(129.19)	(131.24)		(128.58)	(131.15)		(128.48)
Trade-in	\$767.98		\$886.3	\$784.5		\$892.68	\$749.68		\$858.25
	(106.42)		(104.07)	(105.86)		(103.74)	(105.89)		(103.76)
Plant Location									
NAFTA		-\$351.71	-\$350.47		-\$287.62	-\$285.47		-\$287.17	-\$285.31
		(72.36)	(72.02)		(71.83)	(71.50)		(71.75)	(71.43)
Europe		\$5,104.93	\$5,045.17		\$4,925.47	\$4,842.72		\$4,933.63	\$4,849.54
		(137.46)	(136.93)		(138.44)	(137.98)		(138.29)	(137.86)
Asia		\$1,479.36	\$1491.78		\$1488.02	\$1496.64		\$1492.93	\$1500.65
		(79.78)	(79.46)		(79.58)	(79.27)		(79.50)	(79.19)
Exits due to Bailouts									
One Exit							\$480.54	\$470.74	\$434.55
							(156.04)	(153.51)	(152.81)
Two Exits							\$912.83	\$1,212.36	\$1,094.47
							(419.37)	(412.57)	(410.71)
Pontiac Dropped							\$1,263.06	\$1,509.62	\$1,427.67
							(374.69)	(368.59)	(366.95)
R^2	0.846	0.852	0.853	0.85	0.855	0.856	0.85	0.855	0.856
F-Statistic	126.83	588.99	358.37	86.56	170.63	163.54	58.03	111.39	112.98
(Critical value[a])	(22.3)	(22.3)	(29.18)	(50.39)	(50.39)	(57.53)	(71.85)	(71.85)	(79.01)
BLP IV's	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

[a] According to Stock & Yogo, 2005 [68]: size of nominal 5% Wald test with rejection ratio of no more than 10%. All but the seventh specification reject the null hypothesis that the instruments are weak.

To instrument for the endogeneity of prices and to identify the random coefficients, I utilize four sets of instrumental variables which help in providing variation in pricing behavior which is unrelated to vehicle characteristics. The first set is defined by the region of the world in which the particular model was produced, as there is some significant variation in area of production across different brands, within the same brand over time, and even within the same brand and model year. Areas of production are determined by whether the location of the manufacturing plant is in the United States, in Mexico or Canada (NAFTA), in Europe, or in Asia. Thus, there are three instruments as dummy variables, one for each region other than the United States, indicating the vehicles' manufacturing plant location. The anticipated differentiation in costs across these regions is due to the differences in labor costs, economies of scale, and shipping costs. The second set of instruments uses exit shocks to local markets, that occurred during the 2008-2009 financial crisis. During that time, many GM, Chrysler, Suzuki, and other dealerships were shut down in a single wave, and two entire GM brand divisions were discontinued. These exit shocks differ from the normal entry and exit events that happen in local markets over time, since they were caused by a national crisis, stirring a macro event which differentially affected micro units in a manner unrelated to the *local* supply and demand. For these instruments to be effective, I include in the sample only transactions which occurred at dealerships that never entered or exited their local market during the sample period, such that transactions are affected by the dealers' response to an exiting rival and decreased competition. The third set of instruments is composed of average characteristics of the purchasing status of consumers who participated in the local market at time t. These include the portion of consumers in the market who financed their purchase with a loan, the portion who traded-in their old vehicle, and the ratio of business-to-private purchasers. The intuition behind this set of instruments is that they represent a demand signal to sellers, which indicates willingness to pay. Given the nature of new-vehicle transactions as involving a high degree of price negotiations, and given the literature that demonstrates the importance of demand signals in the final negotiated price, these instruments should be correlated with prices and not with unobserved vehicle characteristics. The last set of instruments is composed of functions of characteristics of other products sold in a particular market; these are the classic BLP instruments, calculated as the sum of all characteristics of vehicles sold in the same market by the same seller, as well as the sum of all characteristics of vehicles sold in the same market by all other sellers.

In table 2.2, I report the first stage of the proposed instruments and test whether these instruments are weak. I check the sign and significance of all but the BLP instruments, and find that all are relevant, statistically significant, and have the expected sign. The top panel reports the first stage of the demand signals; it shows that (a) business customers pay on average around $600 more than private households for similar vehicles, (b) people who finance their purchase with a loan offset the final negotiated price by around $2,000, and (c) customers who utilize a trade-in towards the payment of the final price pay on average between $700-$800 more than customers who do not include a secondary trade-in transaction. The latter is consistent with Rao et al 2009, Busse & Silva-Risso 2010, and Kwon et al 2015 [56, 15, 44], who find that the informational role of trade-in is associated with higher willingness to pay by consumers.

The middle panel reports the first stage of the effect of plant location on prices, through costs associated with shipping, economies of scale, and labor costs. Manufacturing in plants located in Mexico or Canada – within the NAFTA region, but not in the United States – is less costly than manufacturing in the United States, and there is no significant additional cost for shipping. In contrast, we see that cars manufactured in Asia are priced higher since trans-pacific shipping from Asia adds at least around $1,500 to costs. Manufacturing in Europe is associated with around $5,000 higher prices - possibly due to a combination of high labor and shipping costs, low-to-average economies of scale, and usage of expensive components and materials.

The bottom panel shows the average effect of an exit shock on transaction prices in the immediate following period; the average response of a single exit was a price increase of around $470, and two exits about double this effect. The discontinuation of the Pontiac brand involved a significant price increase for the following period. In a separate paper, I showed that these local average treatment effects lasted around two periods before returning to having parallel trends with non-affected local markets. Lastly, I report the R-squared and the Wald F-statistic and test the null hypothesis that the proposed instruments are weak. I find that using the most rigorous critical value in the secondary test proposed by Stock and Yogo, 2005 [68], in all but one of the reported specification I reject the null hypothesis that the instruments are weak. I proceed by including all of the proposed instruments in estimating the structural demand model (Specification 9).

I estimate the demand and supply equations separately, following a similar configuration as in Reynaert 2015 [57]. The estimation algorithm for demand closely follows the construction in BLP 1995 [8], using a nested fixed point algorithm and minimizing the GMM objective function. I specify the tolerance level to be $1e^{-12}$, and I take 200 pseudo-random multivariate draws for the random individual shocks. For each specification that estimates the model on a different set of X^2, I use the appropriate set of instruments related to the characteristics in X^2. I calculate the own-and-cross elasticities by averaging the individual elasticities for each simulated consumer. The Nelder-Mead simplex method algorithm converges well from different starting points fairly quickly, with computation time increasing proportionally to the number of simulated individuals. Parallel computing speeds up run-time by at least double, and proper scaling of the characteristic space prevents the fixed-point iteration from drifting to undefined areas.

2.4.2 Optimal FeeBates

To measure welfare changes resulting from policy interventions relative to the baseline in which there is no feebate policy, I evaluate the social welfare function occurring at an equilibrium with and without policy interventions. The demand and supply models followed assumptions of utility and profit maximization without accounting for social costs of emissions; thus, the expected consumer utility obtained from automobiles characteristics plus the sum of all markups over all purchases yield the total surplus for the entire sample. It is an expected utility term because the Logit-based demand model provides predictions in probabilistic terms. The expected producer surplus is simply the sum of the product of markups with shares and market size:

$$E(CS) = \sum_{t=1}^{T} \sum_{i \in N_t} \frac{1}{\alpha_i} log\left(\sum_{j=1}^{J_t} e^{U_{ijt}} \right) \quad \text{and} \quad E(PS) = \sum_{t=1}^{T} N_t \cdot \sum_{j=1}^{J_t} S_{jt} \left(P_{jt} - MC_{jt} \right)$$

Without incorporating externalities, the total surplus is the sum of these two terms above, which is maximized by the model.

Table 2.3: Emission Rates and Externality Costs of Gasoline Usage

Pollutant	Grams Emitted per Gallon	Social Cost per Ton	Externality Cost per Gallon
Carbon Dioxide (CO_2)	8,878.44	\$18-\$220	¢36.21[a]
Particulates - $PM_{2.5}$	0.099	\$3,300	¢0.04
Particulates - PM_{10}	0.106	\$500	¢0.01
Volatile Organic Compounds (VOC)	24.92	\$500	¢1.37
Nitrogen Oxides (NO_x)	16.7	\$300	¢0.55
Total			**¢38.18**

[a] Using the official EPA estimate of \$37 per ton as of 2015

Social costs from emissions are calculated as the sum of all pollutants emitted as a result of utilizing all vehicles which were purchased as the model predicts, multiplied by the marginal cost assigned to each pollutant. These include carbon dioxide (CO_2), particulate matters ($PM_{2.5}$ and PM_{10}), volatile organic compounds (VOC), and nitrogen oxides (NO_x). Table 2.3 lists the emission rates per gallon of gasoline usage as well as the estimated marginal social cost per ton of emissions for each pollutant. The emission rates at the first column are published by the Environmental Protection Agency and are made available at [26] and [27]. The numbers for the marginal social costs of the local area pollutants (all but carbon dioxide) are obtained from the Air Pollution Emissions Experiments and Policy analysis model (APEEP - Mueller & Mendelsohn 2007 [53]). The official EPA estimate in 2015 was a cost of \$37 per ton of CO_2 emissions, though other estimates range from conservative estimates at \$18 per ton to higher estimates of \$220 per ton

(Moore & Diaz 2015 [51, 69]). The final column in table 2.3 calculates the externality cost from the utilization of one gallon of gasoline which totals ¢38.18 using the official estimate for carbon costs. Given the federal gasoline tax of ¢18.4, plus the Texas gasoline tax of ¢20 per gallon, it appears that the current total gasoline tax about equals the estimated externality costs. However, if the true cost of carbon dioxide emissions is actually $220 per ton, then the marginal externality cost is estimated to be over five times larger at $2.17 per gallon of gasoline. Raising the gasoline tax by over 400% is not likely to be publicly accepted; hence, second-best feebate policies are appropriate. The emission costs factored into the total welfare are then calculated as:

$$E(EmissionCost) = \sum_{p=1}^{P} \Big(\sum_{t=1}^{T} N_t \cdot \sum_{j=1}^{J_t} S_{jt} \frac{\Upsilon_{jt}}{MPG_{jt}} \Big) \cdot \rho_p \cdot \pi_p$$

where $p \in \{1, \ldots, P\}$ indexes the different pollutants as described in table 2.3, S_{jt}, Υ_{jt}, and MPG_{jt} are the predicted market share, average utilization observed for vehicle j at market t, and the official fuel efficiency rating. The terms ρ_p and π_p represent the emission rates in tons and the cost per ton, respectively for pollutant p, and the entire term in parentheses represents the total annual consumption of gasoline from all vehicles purchased in all markets in the sample. The total welfare function to be utilized in the estimation of optimal feebates, and accounting for all externalities, is then:

$$E(TW) = E(CS) + E(PS) - E(EmissionCost) \tag{2.6}$$

Table 2.4 summarizes the annual individual externality as it depends on vehicle utilization and fuel efficiency. The externality is non-linear in MPG but linear in utilization. An optimal feebate will cause a transition of most consumers to higher fuel efficiency, hence to lower externality costs. Gillingham et al 2013, and West et al 2017 [29, 71] demonstrate that a rebound effect does not cause a "backfire" where increased fuel efficiency leads to increased gasoline usage, the latter showing that vehicle utilization depends on a variety of factors other than fuel efficiency, leading to an overall zero rebound effect. Thus, table 2.4 shows that even if utilization increases with an

Table 2.4: Annual Non-Internalized Individual Environmental Externality

Vehicle Fuel Efficiency	Annual Miles Driven 10000	12000	15000	17500	20000
10 (MPG)	$381.79	$458.15	$572.68	$668.13	$763.58
15	$254.53	$305.43	$381.79	$445.42	$509.05
20	$190.89	$229.07	$286.34	$334.06	$381.79
25	$152.72	$183.26	$229.07	$267.25	$305.43
30	$127.26	$152.72	$190.89	$222.71	$254.53
35	$109.08	$130.9	$163.62	$190.89	$218.16 [a]

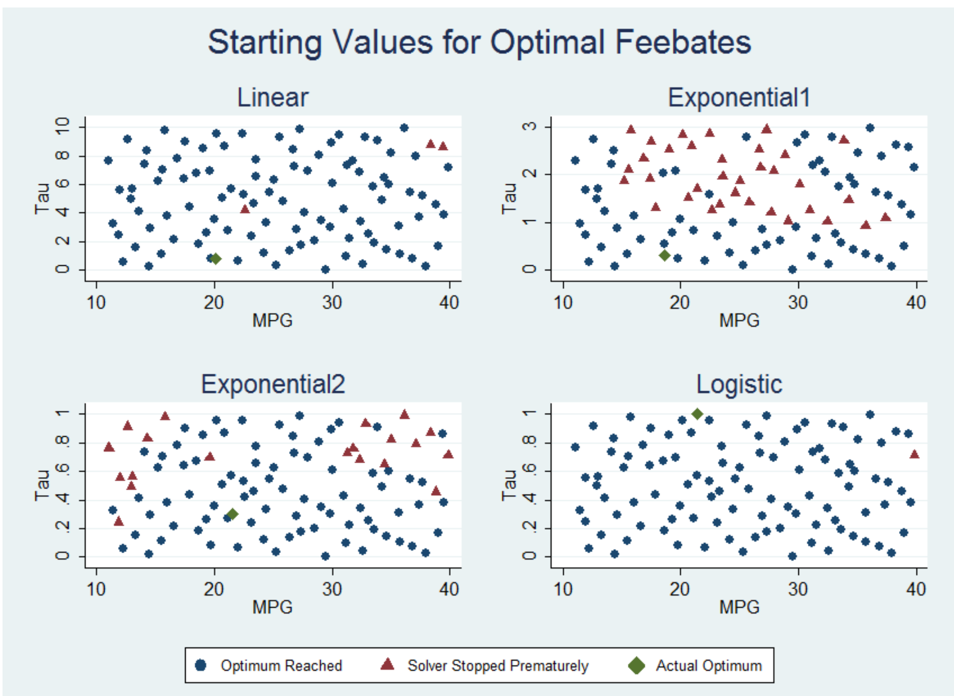
[a]Using the official estimate of $37 per ton of CO_2 emissions

exogenous increase of fuel efficiency, then as long as vehicle utilization increases by a lower rate than miles per gallon, annual externality costs will be reduced.

The estimation of optimal feebates is performed by a numerical search of the parameters that maximize equation 2.6. I use the constrained optimization routine in order to ensure that the optimal feebates satisfy two key requirements: (1) maintaining budget balance such that all rebates are financed by all fees, and (2) placement of a cap on the maximum fee or maximum rebate that may be dispersed. Without imposing these two constraints, the numerical optimization routine will attempt to reach non-feasible solutions that are certainly not politically acceptable. For instance, not accounting for budget balance will cause the algorithm to distribute infinite rebates in order to increase consumer surplus, and without imposing a maximum cap on feebate payments, the algorithm will try to tax very few individuals an extremely high amount in order to distribute rebates to many other people. Thus, a constrained optimization that counters these issues delivers the optimal feebate parameters under the specified terms. I explore the sensitivity of each of the four feebate structures to the cap on maximum payments. Budget balance remains a consistent constraint across all specifications. For the logistic function specification, the imposition of a cap on payments translates to limiting the parameter space of the scale parameter S. Once the scale is limited, the other two parameters τ and GPM_0 are found endogenously for all specifications.

Each iteration of the objective function calculates the new set of prices under the proposed feebate. The new prices for all vehilces in the choice set for each market influences individuals' utility and determine a new set of purchase probabilities, which translate to a new set of market shares. The new shares and prices provide a new equilibrium, where sellers are allowed to respond once to the change in market shares - producing yet another set of prices after the pass-through effect. Then, the new prices and shares produce new levels of total surplus as calculated in equation 2.6. The algorithm converges consistently to the same fixed point and finds the optimal feebates for each specification in about five minutes, totaling fewer than 200 iterations for each specification.

Figure 2.3: Convergence to Optimum from Different Starting Values



The linear feebate is the fastest to reach the optimum. Figure 2.3 shows the range of starting values for the slope and pivot point parameters, used to reach the optimal feebates numerically. All three non-linear feebates include an additional scale parameter, which is pre-calibrated as it determines the maximum allowable payment. I specify the range for fuel economy according to the levels of MPG observed in the data, such that I allow the starting pivot point to be anywhere between 11-40 miles per gallon. The normal range for the slope parameter τ is typically between zero and one, but when the algorithm allows to explore further, I increase this range by a factor of 10 for the linear feebate, and three for the exponential feebate with decreasing marginal incentives. Figure 2.3 shows that the slope parameter converges to the upper bound, set at one. The rate of successful convergence is high for both the linear and logistic functional forms, and for the exponential functions convergence to the optimum is inhibited by starting values with either a higher τ, or extreme pivot points. The typical reason for when the solver fails to reach the optimum is exceeding the maximum iterations. In these instances, the solver does not yield a better outcome, and the constraints are not satisfied. I conclude that when the constraints are satisfied, the solver does find a global optimum.

2.5 Results

The theoretical model delivers consistent results that converge from various starting points to a unique solution of the random demand coefficients. The properties of the demand and supply system seem reasonable with respect to expected outcomes in equilibrium. Stage two delivers consistent and unique solutions for the numerical optimization routine, which raises the confidence that the entire model is properly identified.

2.5.1 Price Sensitivity, Taste Parameters, and Marginal Costs

I report the estimation results for the benchmark basic Logit model (assuming the random parameters equal zero) in table 2.5, alongside select specifications for random coefficients Logit models that differ in the inclusion of random terms on vehicle weight, footprint, and engine displacement. I am reassured that all of the mean parameter estimates have their expected sign, and that the mean parameters estimated in the random coefficients models maintain their signs and relative size. For example, the coefficient which represent sensitivity to price and valuation of fuel economy are both negative - indicating that individuals dislike higher prices and that they value fuel efficiency even when controlling for vehicle size, weight, and body-type. Individuals value the reduction of one gallon of gasoline for each 100 miles driven at around \$2,000, and an increase of 1,000 lbs in weight at around \$4,100, as implied by these coefficients. It is also implied that consumers value the average characteristics that accompany luxury vehicles at over \$13,000. Other vehicle attributes, such as horsepower, size, and height, are also valued positively. Overall, these factors indicate that the demand model is well specified at least in the mean valuations.

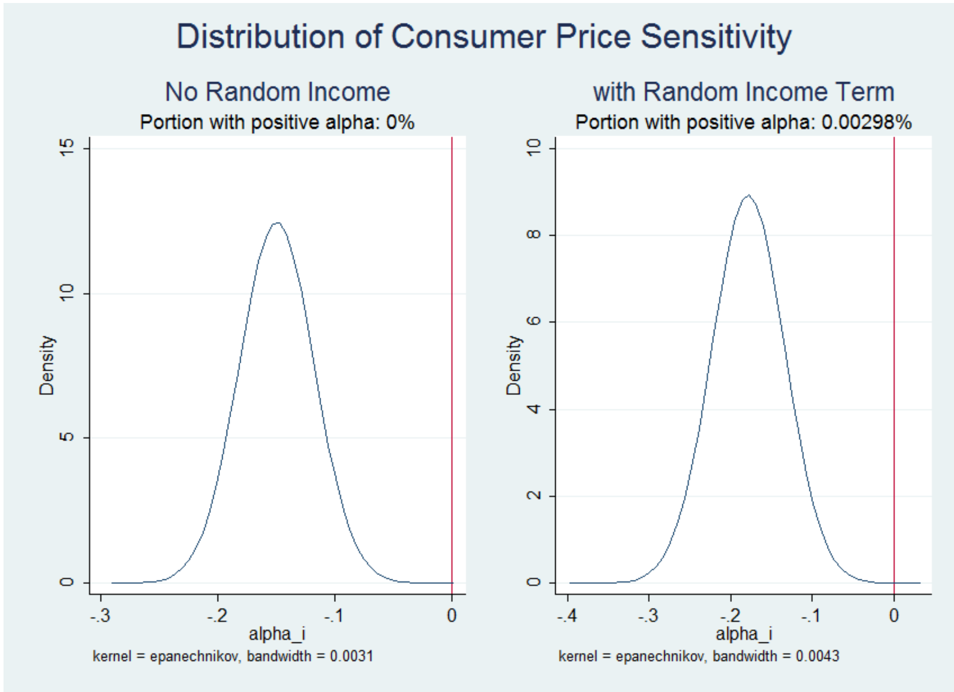
At the bottom panel of table 2.5 the random coefficients are reported in their respective specifications. Throughout all specifications, the σ^{α} random coefficient on price sensitivity is accurately estimated. The next best accuracy is attached to the term on income - Π^{α}, while the remaining random coefficients are not accurately estimated and cannot be determined to be statistically different from zero. I favor the specifications that deliver the higher point estimates for these random parameters, and I favor specifications that identify $\Pi^{\alpha} < 0$ which indicates that lower income consumers are more sensitive to higher prices. It appears that the instrumental variables do a good job at identifying random coefficients on price sensitivity, but not on variation in tastes. It may also be that the model identifies the taste parameters to be accurate around their means. I proceed by analyzing the distribution of the price sensitivity parameter for the two favored specifications, one which incorporates the random term on individuals' income level, and one which does not. These distributions are seen in figure 2.4 and show a spread of consumer price sensitivity around the mean with only a few instances of individuals who actually "like" higher prices. The addition of the random term on individual income helps in identifying a wider spread of price sensitivity.

The supply side estimates are reported in table 2.6, comparing the OLS regression results across the perfect competition and basic-Logit with oligopoly benchmarks. The left-hand-side variable is the log of marginal costs as computed by subtracting the estimated markups derived from the demand model and first order conditions for firms' profit maximization from the price of each vehicle at each market. Due to the high collinearity of horsepower with engine displacement, and of weight with vehicle size, and since the log-linear specification is sensitive to interactions of collinear attributes, I estimate the terms of these attributes on costs separately and report them in table 2.6. The results show that, as expected, costs increase with the addition of weight, size,

Table 2.5: Demand Estimation Results

	Basic Logit	Random Coefficients Logit							
		(1)	(2)	**(3)**	(4)	(5)	**(6)**	(7)	(8)
$\bar{\alpha}$	-0.148	-0.176	-0.169	**-0.150**	-0.119	-0.177	**-0.172**	-0.149	-0.120
	(0.007)	(0.010)	(0.009)	(0.009)	(0.011)	(0.012)	(0.014)	(0.012)	(0.013)
β_{FE}	-0.323	-0.355	-0.349	**-0.332**	-0.297	-0.357	**-0.356**	-0.330	-0.295
	(0.013)	(0.043)	(0.042)	(0.043)	(0.044)	(0.019)	(0.032)	(0.016)	(0.019)
β_{weight}	0.707	0.741	0.684	**0.585**	0.432	0.749	**0.713**	0.576	0.423
	(0.066)	(0.072)	(0.072)	(0.067)	(0.080)	(0.077)	(0.113)	(0.114)	(0.104)
$\beta_{footprint}$	4.790	5.114	5.267	**5.332**	5.447	5.116	**5.318**	5.306	5.423
	(0.243)	(0.482)	(0.271)	(0.403)	(0.424)	(0.478)	(0.263)	(0.471)	(0.452)
β_{HP}	0.638	0.706	0.656	**0.565**	0.427	0.713	**0.683**	0.557	0.421
	(0.050)	(0.058)	(0.060)	(0.053)	(0.074)	(0.063)	(0.066)	(0.052)	(0.072)
β_{height}	0.049	0.047	0.049	**0.054**	0.061	0.046	**0.048**	0.054	0.062
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)
β_{Luxury}	2.329	2.384	2.293	**2.136**	1.922	2.394	**2.334**	2.126	1.916
	(0.089)	(0.098)	(0.099)	(0.091)	(0.090)	(0.107)	(0.113)	(0.089)	(0.093)
σ^{α}		0.039	0.039	**0.032**	0.016	0.040	**0.044**	0.029	0.011
		(0.005)	(0.004)	(0.005)	(0.009)	(0.007)	(0.008)	(0.007)	(0.015)
Π^{α}						-0.055	**-0.227**	0.121	0.142
						(0.197)	(0.241)	(0.213)	(0.227)
σ_{FE}		0.004	0.004	**0.004**	0.003	0.000	**0.001**	0.000	-0.001
		(1.577)	(1.629)	(1.566)	(1.705)	(2.973)	(2.881)	(3.356)	(5.220)
σ_{weight}			0.001	**-0.001**	-0.001		**0.014**	0.013	0.009
			(3.718)	(3.908)	(4.432)		(1.401)	(1.723)	(1.888)
$\sigma_{footprint}$		0.065		**0.188**	0.092	0.199		0.107	0.014
		(9.491)		(2.693)	(5.332)	(3.261)		(6.180)	(32.651)
$\sigma_{displacement}$					0.004				-0.007
					(2.551)				(2.008)

Figure 2.4: Distribution of MPG among Vehicles in the Sample



engine power, and fuel-efficiency (which is controlled for each time). Model specifications which produce larger markups show a higher point estimate for the attributes. Overall, the cost side estimates appear to be stable across the different model specifications.

2.5.2 Elasticities and Markups

In order to best perform the policy counter-factual simulations that estimate optimal feebates, I choose the most demand and supply system which yields the most reasonable equilibrium predictions. The two candidates are specifications (3) and (6) listed in bold at table 2.5. These seem to deliver the most reliable insights given the demand specifications, algorithm, and data used in the estimation of stage one.

I observe the estimated demand own-and-cross elasticities evaluated at the equilibrium prices and shares, and which are reported in by the two tables in appendix B, corresponding to specifications (3) and (6) respectively. The estimated markups are reported in the first column of each table, showing that the more expensive models, considered to be luxury vehicles, receive higher

Table 2.6: Estimates of the Marginal Costs Parameters (Log-Linear Regression)

	Perfect Competition	Oligopoly Basic Logit	Random Coefficients Logit							
γ_{FE}	-0.032	-0.042	-0.038	-0.038	-0.04	-0.044	-0.038	-0.038	-0.04	-0.044
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
γ_{weight}	0.2	0.275	0.245	0.247	0.257	0.286	0.243	0.242	0.26	0.29
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
$\gamma_{footprint}$	0.439	0.707	0.6	0.609	0.649	0.765	0.595	0.596	0.659	0.785
	(0.024)	(0.034)	(0.030)	(0.031)	(0.032)	(0.036)	(0.030)	(0.030)	(0.032)	(0.037)
γ_{HP}	0.236	0.33	0.297	0.3	0.314	0.353	0.295	0.294	0.318	0.36
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
γ_{height}	0.02	0.027	0.024	0.024	0.025	0.027	0.024	0.024	0.025	0.028
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\gamma_{dsplmnt}$	0.231	0.307	0.283	0.285	0.297	0.326	0.281	0.28	0.3	0.332
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)

markups. The difference between the markups of a BMW X-5 and a Chevrolet Malibu exceeds \$2,000. In addition, we observe that the markups for American pickup trucks are higher than the Japanese alternative manufactured by Toyota, and that the markup for the large SUV Tahoe is higher than that of any pickup truck. German automobiles tend to have higher markups, even for the non-luxury VW Jetta. Small SUVs like the Ford Escape and the Honda CR-V seem to be priced in a similar fashion to popular sedans. The model which accounts for heterogeneity in consumer income predicts lower markups for each model by around \$500-\$900, which seems to be more reasonable.

Regarding elasticities, it is clear that the own price elasticities measured along the diagonal are in line with the conventional conjecture that luxury products, and products that are priced with higher markups, meet the demand curve at a higher price - where the demand is relatively elastic. In those instances, lowering the price may result in higher revenues, but not in higher profits. The largest own-price elasticities appear among the luxury goods - with brands such as BMW, Mercedes-Benz, Cadillac, and Lexus, followed by the large SUVs - Toyota 4Runner and Chevrolet

Tahoe. The magnitudes of these elasticities seem to be consistent across the two specifications under consideration. Regarding substitution patterns, these appear to depend more on the relative similarities across vehicles, in terms of vehicle size, body type, brand loyalty, and luxury status. There is higher substitutability from luxuries to other luxuries, and from heavy vehicles to other heavy vehicles. There appears to be a lower substitutability from pickup truck to luxuries relative to regular SUVs and sedans. After comparison of the relative elasticities and predicted markups, I choose to proceed with specification (6) to perform the feebate policy simulations.

2.5.3 Welfare Simulations

I explore the attributes of each of the four feebate specifications detailed in section 2.3. Unique solutions to the numerical optimizations are obtained for each feebate functional form given two constraints: one requires that the feebate finances itself such that all fees are paid for by the rebates, and the second places a cap on the maximum payment allowed. Relaxing one of these conditions results in no unique solution; however, within the realm of politically acceptable feebate programs that satisfy budget balance and scale restrictions, the unique optimal feebates are welfare increasing with certainty over a situation with no feebate. It remains to explore the extent of welfare enhancement that is possible to obtain with each feebate specification, to determine the better feebate specification, and to ascertain the trade-off that exists between welfare enhancement and the consequences of relaxing or extending the limits of the scale constraints. An additional trade-off is observed with the logistic specification.

Table 2.7 provides a clear description of some of the attributes optimal feebates introduce. For each functional form I estimate the optimal feebate under five scale caps with the lowest cap set at \$1,000 and the highest at \$5,000. Conceptually, it is possible to assess the optimal feebates across higher or lower caps. The consistent pattern shows that higher scale feebates are more effective in reducing costs from emissions and in increasing overall total welfare. With a couple of exceptions, the welfare increases come at the expense of consumer surplus, with firm profits being very mildly affected. This finding should help in mitigating firms' objections to feebates, as all firms may have the ability to adjust production to demand that favors fuel efficiency. The decrease in consumer

Table 2.7: Attributes and Effects of Optimal Feebates

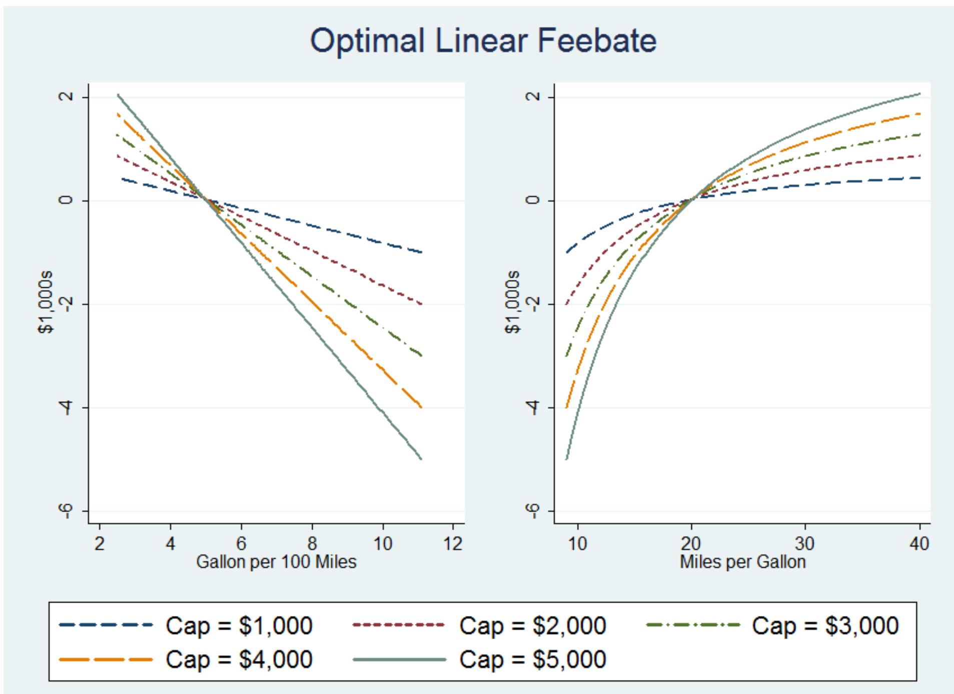
Functional Form	Max Fee	Avg. Fee	Max Rebate	Avg. Rebate	Pivot Point[a]	Marginal Incentive[b]	Δ% CS	Δ% PS	Δ% ER[c]	Δ% TW[d]
linear	$1,000	$110.98	$458.21	$64.89	19.52	$43.86	+0.13%	-0.01%	0.62%	0.84%
	$2,000	$225.84	$902.37	$124.48	19.63	$86.31	-0.86%	-0.04%	1.24%	1.68%
	$3,000	$344.38	$1,333.3	$179.06	19.74	$127.44	-2.88%	-0.09%	1.86%	2.51%
	$4,000	$466.39	$1,751.6	$228.91	19.84	$167.33	-5.88%	-0.16%	2.49%	3.33%
	$5,000	$591.68	$2158.1	$227.28	19.95	$206.05	-9.78%	-0.25%	3.11%	4.15%
Exp[e]	$1,000	$88.46	$325.94	$53.07	19.19	$35.26	+0.1%	-0.01%	0.51%	0.69%
	$2,000	$152.9	$508.95	$89.13	19.05	$59.72	-0.41%	-0.02%	0.88%	1.19%
	$3,000	$205.13	$630.46	$116.69	18.95	$78.64	-1.17%	-0.04%	1.18%	1.59%
	$4,000	$249.95	$718.67	$139.14	18.87	$94.14	-2.06%	-0.06%	1.43%	1.93%
	$5,000	$289.52	$786.41	$157.91	18.81	$107.3	-3.01%	-0.08%	1.65%	2.23%
Exp[f]	$821.48	$167.64	$1,000	$90.93	20.47	$66.06	+0.23%	-0.02%	0.87%	1.18%
	$1,657.2	$349.3	$2,000	$173.85	20.64	$132.07	-2.01%	-0.09%	1.78%	2.39%
	$2,506.8	$545.22	$3,000	$248.55	20.82	$198.06	-6.76%	-0.21%	2.73%	3.65%
	$3,370	$755.6	$4,000	$314.78	21	$264.06	-14.07%	-0.38%	3.73%	4.95%
	$4,246.5	$985.59	$5,000	$377.27	21.18	$296.17	-24%	-0.61%	4.76%	6.27%
Logistic[g]	$1,000	$271.16	$864.3	$147.49	20	$125.06	-0.88%	-0.05%	1.37%	1.85%
	$2,000	$568.54	$1,712	$273.08	20.25	$243.77	-7.21%	-0.21%	2.78%	3.71%
	$3,000	$889.73	$2,542.9	$377.73	20.51	$356.67	-18.6%	-0.46%	4.22%	5.59%
	$4,000	$1,232.3	$3,356.8	$462.32	20.76	$464.24	-34.71%	-0.82%	5.69%	7.49%
	$5,000	$1,594	$4,153.8	$527.85	21	$566.94	-55.16%	-1.25%	7.19%	9.34%

[a]In terms of Miles per Gallon
[b]Slope at the pivot point
[c]Emission Costs Reduction
[d]Total Welfare Increase
[e]Marginal incentives increase with fuel costs
[f]Marginal incentives decrease with fuel costs
[g]Slope parameter is fixed at $\tau = 1$

surplus relative to the benchmark of having no feebates may be a result of the optimal feebates imposing high fees on average on a significant portion of consumers, while rewarding many other consumers with lower rebates. Budget balance implies that the majority of consumers receive rebates rather than pay fees. With one exception, we observe that feebates tend to reach the cap at the maximum fee rather than the maximum rebate. It appears that the pivot point changes only by a little as the scale of the feebate cap increases. By increasing the maximum allowable payment, the parameter affecting the slopes, or marginal incentives, increases. This is evident in the column which reports the marginal incentive to increase fuel efficiency by one unit of MPG (rather than GPM), seeing that the slope at the pivot point increases with the scale of the program.

In addition to the comparisons within each functional form specification, it is clear from table 2.7 that significant differences exist across functional forms. First, we see that the linear feebate is superior to the exponential specification which places increasing marginal incentives with GPM - i.e. incentives to improve fuel economy are highest for the most polluting vehicles. The relative effectiveness of the feebate program seems to be correlated with higher marginal incentives at the pivot point, which seems to be the weakness of the increasing-incentives exponential specification. The decreasing-marginal-incentives exponential specification provides an additional improvement over the performance of the linear specification, with an increase of over 2% in welfare benefits at the \$5,000 cap level. The most welfare enhancing functional form turns out to be the logistic function. This is not a surprising result given that the structure of the logistic function is designed to set the highest incentives around the center of the fuel efficiency distribution, affecting the largest portion of consumers with incentives to improve fuel economy. Nevertheless, this large welfare increase of 9.34% at the \$5,000 cap level comes with a reduction of 55.16% in consumer surplus. This happens because of two reasons. First, the scale of total consumer surplus is lower by a large factor than the scale of emission costs, so a million dollar reduction in consumer surplus is a large percentage reduction, but it may justify higher savings in emission costs. Second, the difference between the average fee and the average rebate is over \$1,000, such that consumers who are penalized with a fee experience a higher percentage reduction in their consumer surplus than the percentage increase in the surplus of consumers who are rewarded with a rebate. Though the large percentage reduction in overall consumer surplus may be alarming, it is useful to remember the actual trade-offs between enhancing welfare vs. distributional differences between payers of a fee and receivers of a rebate.

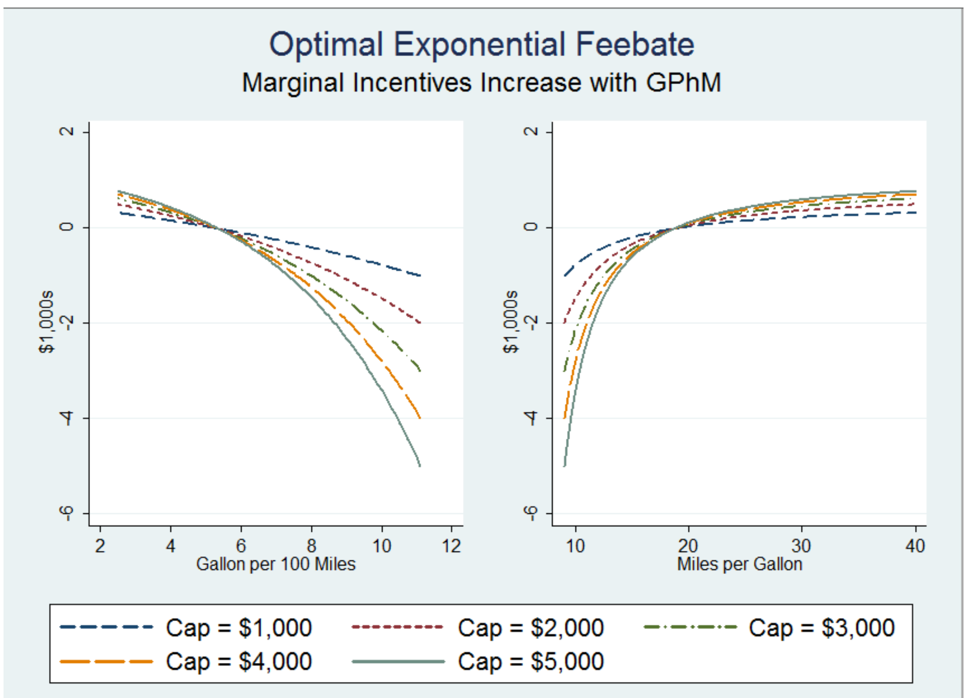
Figure 2.5: Sensitivity of Linear Feebate w.r.t Cap on Maximum Payment



In figures 2.5 through 2.8, I show the shapes of the optimal feebates for each functional form, as they differ across the allowable maximum cap, as well as show the same optimal rebates with the supports of GPM - linear in fuel and emission costs, and MPG - the traditional measure observed on the Monroney sticker. Figure 2.5 depicts the linear in GPM feebate, illustrating how a constant marginal incentive to increase fuel efficiency in the measure linear with fuel costs appears to depict increasing incentives to improve fuel efficiency as measured by MPG. The additional monetary reward of increasing MPG by one unit is greater when transitioning from for a fuel inefficient car with a rating of 15 MPG to a 16 MPG, then it is making the transition from 25 MPG to 26 MPG.

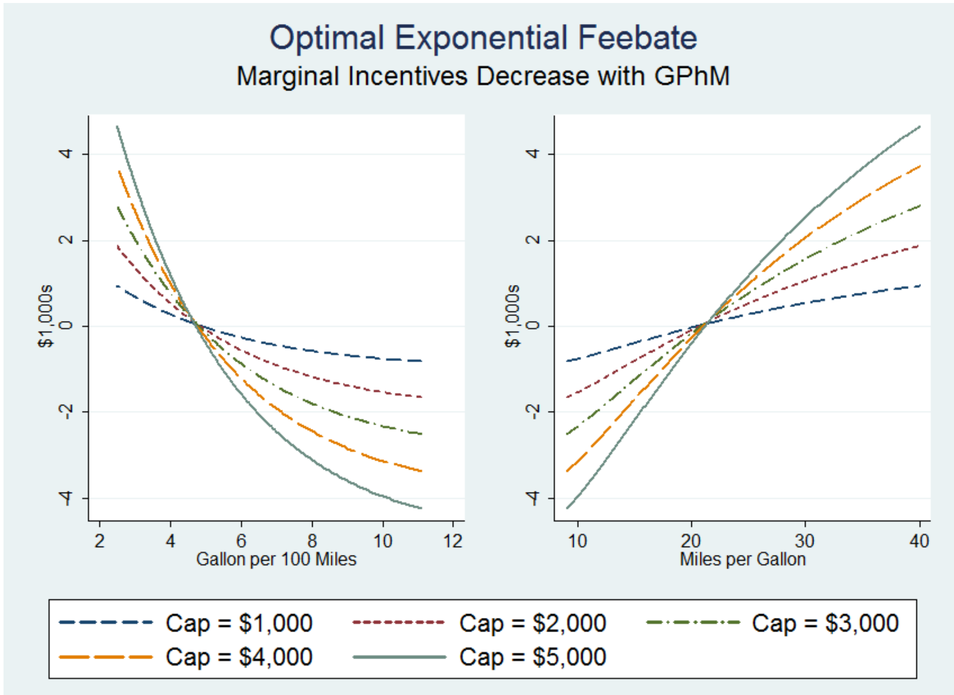
The question then becomes how will adding curvature to the feebate that is linear in GPM affect the curvature in the same feebate with MPG as its support. The answer is shown in figures 2.6 and 2.7. Imposing curvature that places increasing marginal incentives with GPM exacerbates the same tendency when showing the feebate relative to MPG, and placing decreasing marginal incentives with GPM makes the same curve with respect to MPG seem more linearized. Thus, the two forms of exponential feebates impose curvatures in opposite directions relative to the linear benchmark, showing that having marginal incentives that decrease with higher GPM levels - i.e. with fuel efficiency decreases - is welfare enhancing and more effective in reducing emission costs.

Figure 2.6: Sensitivity of Exponential Feebate w.r.t Cap on Maximum Payment



As the cap on the maximum payment is increased, the optimal feebate increases in scale, which increases the slopes and marginal incentives in the support region of fuel efficiency. As shown in the linear and exponential cases, the constraints on maximum payments do not manifest as constraints on the parameters - the estimated slope (τ) and pivot points are obtained endogenously.

Figure 2.7: Sensitivity of Exponential Feebate w.r.t Cap on Maximum Payment



However, the scale parameter S in the exponential cases must be restricted to an upper bound equal to the cap, and the optimal feebate is reached at a corner solution for this parameter.

I also explore the sensitivity of optimal feebates to different estimates for the cost of carbon dioxide emissions. This analysis is proposed in order to test the consequences of getting a wrong estimate for the cost of carbon, which has estimates ranging between \$18 and \$220. Surprisingly, different levels of social costs of carbon emissions do not affect the unique solution for optimal feebates. Empirically, every algorithm converged to the same solution when I specified different ranges for the cost of carbon. The same solution yields similar percentage changes on consumer and producer surplus as well as emission cost reduction. Since the costs of emissions exceed the economic surplus from the market for a wide range of estimates for the carbon emissions costs per gram, if there are any non-internalized externalities caused by consumption of gasoline, then a feebate system will bring about a reduction in the consumption of gasoline which translates to increased total welfare. In table 2.8, I list the impact of assessing the total welfare increase as the

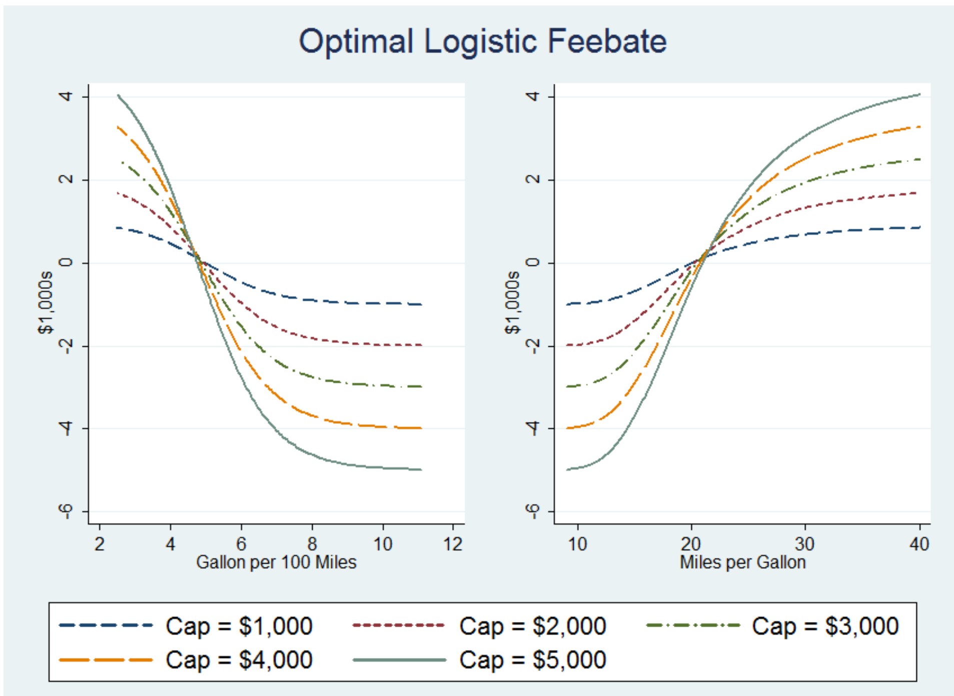
Table 2.8: Sensitivity of Increase in Total Welfare w.r.t Carbon Costs

Functional Form	Maximum Fee/ Rebate Cap	Total Welfare Increase CC=$18	CC=$25	CC=$37	CC=$50	CC=$100	CC=$220
Linear	$1,000	1.28%	1%	0.84%	0.77%	0.69%	0.65%
	$2,000	2.55%	1.99%	1.68%	1.54%	1.38%	1.3%
	$3,000	3.79%	2.98%	2.51%	2.31%	2.06%	1.95%
	$4,000	5.01%	3.95%	3.33%	3.07%	2.75%	2.6%
	$5,000	6.22%	4.91%	4.15%	3.83%	3.44%	3.25%
Exponential[a]	$1,000	1.05%	0.82%	0.69%	0.63%	0.56%	0.53%
	$2,000	1.81%	1.42%	1.19%	1.09%	0.98%	0.92%
	$3,000	2.42%	1.89%	1.59%	1.46%	1.31%	1.23%
	$4,000	2.93%	2.3%	1.93%	1.78%	1.59%	1.5%
	$5,000	3.37%	2.64%	2.23%	2.05%	1.83%	1.73%
Exponential[b]	$1,000	1.8%	1.4%	1.18%	1.08%	0.97%	0.91%
	$2,000	3.62%	2.84%	2.39%	2.21%	1.97%	1.87%
	$3,000	5.48%	4.32%	3.65%	3.37%	3.02%	2.86%
	$4,000	7.36%	5.83%	4.95%	4.57%	4.11%	3.89%
	$5,000	9.27%	7.37%	6.27%	5.8%	5.23%	4.97%
Logistic[c]	$1,000	2.8%	2.19%	1.85%	1.7%	1.52%	1.43%
	$2,000	5.57%	4.39%	3.71%	3.42%	3.07%	2.9%
	$3,000	8.3%	6.58%	5.59%	5.16%	4.65%	4.41%
	$4,000	10.98%	8.75%	7.49%	6.91%	6.25%	5.94%
	$5,000	13.6%	10.9%	9.34%	8.67%	7.86%	7.48%

[a]Marginal incentives increase with fuel costs
[b]Marginal incentives decrease with fuel costs
[c]The parameter slope is fixed at $\tau = 1$

social price of carbon emissions changes. It is still evident that the logistic function brings about the highest total welfare increase relative to the other feebate alternatives. When carbon costs are estimated lower, the percentage effect on total welfare is higher.

Figure 2.8: Sensitivity of Logistic Feebate w.r.t Cap on Maximum Payment



Lastly, I explore the properties of the logistic functional form, which delivers the highest efficacy in emission reduction and seems to be superior to the other feebate specifications. Figures 2.8 and 2.9 illustrate how the logistic function preserves its shape across both fuel efficiency measurements. The logistic function is unique in that its scale parameter S also defines the maximum payment, as it determines the upper and lower asymptotic limits. Thus, placing the constraint of the maximum payment is achieved by specifying an upper bound for S (The implied lower bound is zero, but it is not binding since if S goes below zero then the incentives flip over to prefer fuel inefficiency). Figure 2.8 illustrates both the symmetry in maintaining the S-shape across the GPM and MPG supports as well as the consequences of increasing the program's scale. It also illustrates how the marginal incentive is maximized for purchasers who would otherwise buy a vehicle with fuel efficiency around the pivot point. As the scale grows, so do the slope and marginal incentive at the pivot.

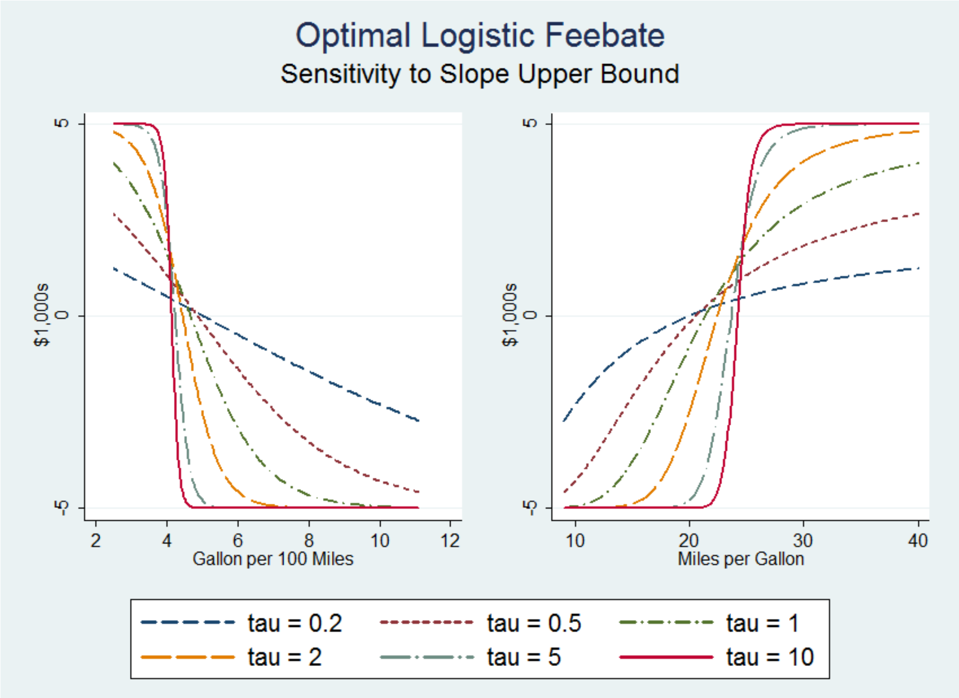
Table 2.9: Sensitivity of Optimal Logistic Feebate to its Slope Parameter

Functional Form	τ Upper Bound	Avg. Fee	Max Rebate	Avg. Rebate	Pivot Point[a]	Marginal Incentive[b]	Δ\$ CS	Δ\$ PS	Δ\$ ER[c]	Δ\$ TW[d]
Logistic[e]	0.2	\$348.23	\$1,296.5	\$171.58	19.86	\$126.73	-0.76%	-0.11%	2.36%	2.92%
	0.5	\$900.12	\$2,767.4	\$336.96	20.51	\$297.01	-10.42%	-0.67%	5.52%	6.73%
	1	\$1,692.1	\$4,084.8	\$467.31	21.39	\$546.65	-32.31%	-1.85%	9.19%	10.99%
	2	\$2,661.9	\$4,843.5	\$553.47	22.46	\$990.87	-64.24%	-3.58%	12.45%	14.6%
	5	\$3,642	\$4,999	\$621.4	23.65	\$2,235.8	-103.88%	-5.69%	14.8%	16.97%
	10	\$4,005.3	\$5,000	\$648.16	24.18	\$4277.3	-125.39%	-6.76%	15.76%	17.88%

[a]In terms of Miles per Gallon
[b]Slope at the pivot point
[c]Emission Costs Reduction
[d]Total Welfare Increase
[e]Cap = \$5,000

The logistic functional specification is also unique in that a new trade-off is introduced between program efficacy and political acceptability. By placing an upper bound only on the scale parameter S, the optimization algorithm cannot reach an optimum because it tries to increase the slope parameter τ to infinity. Placing an additional upper bound on τ generates a unique corner solution at the upper bound, while the pivot point is not constrained. Table 2.9 explores the consequences of changing the upper bound for τ, reporting optimal feebate attributes at $\tau \in \{0.2, 0.5, 1, 2, 5, 10\}$, holding the upper bound for S by fixing the cap at \$5,000. Additional welfare gains are achieved at higher values of τ; however, we notice that consumer surplus decreases substantially by more than 100% (i.e. becoming negative) as the logistic function approaches a one-step shape. As τ increases, the average fees increase at a faster rate than the rebates and the pivot point shifts to a higher fuel efficiency. Therefore, the reason for the dramatic reduction in consumer surplus is the transition of a much higher portion of consumers to paying much higher fees with a massive shift

Figure 2.9: Sensitivity of Logistic Feebate w.r.t Slope Upper Bound



from fees to rebates just at the pivot point. This kind of feebate system will likely cause a huge notch and bunching at the positive side of the pivot. It may also lead to gaming the fuel efficiency rating system. Thus, a high value of τ produces negative consequences which are not factored explicitly in the model and which are difficult to measure. Therefore, I present this trade-off in terms of additional welfare increases at the expense of distributional inequity between payers of a fee and receivers of a rebate. This trade-off can clearly be seen in figure 2.9, which shows the logistic function specification with $\tau = 0.2$ as resembling a linear feebate, while the other extreme case of $\tau = 10$ produces a single-step function. It is likely that a specification in the range of $\tau \in [0.5, 2]$ delivers more desirable outcomes. Even maintaining a reasonable guess of $\tau = 1$ already is shown to be welfare enhancing compared to all other feebate alternatives explored in this paper. Additional exploration may be necessary to ascertain the exact welfare optimizing level of τ for the logistic feebate function.

3. COMPETITION DYNAMICS IN RETAIL AUTO SALES: QUASI-EXPERIMENTAL EVIDENCE FROM LOCAL DEALERSHIPS

Retail competition among new car dealerships is distinguished between inter-brand and intra-brand rivalry. Car dealerships are independent franchisees who both sell new vehicles to the consuming public and provide post-sale warranty services for the brands they represent. Geographic agglomeration combined with strategic placement of physical retail outlets by auto manufacturers have generated, over time, dealership networks divided among distinct local market areas. The operation of more than one dealership owning a franchise of a particular brand is extremely rare (Sewell, 2011 in [65] addresses the formation of local dealership clusters in the context of competition). Thus, retail car dealerships compete on a brand basis within their immediate Relevant Market Areas (RMAs), and on an intra-brand basis across the RMA clusters around them.[1]

New car dealerships extract profits from the sales of new vehicles by marking up prices over the cost of purchasing the vehicle from manufacturers, plus the costs associated with brand promotion, holding inventory, and sales services. As the second highest expense among end use products and services purchased by households, new vehicles are distinct from many other expenses by the existence of bargaining for the final transaction price. By engaging in bargaining-based price discrimination, car dealerships can increase their profits from individual sales when consumers signal their willingness to pay as well as their likelihood of buying a car elsewhere. Knowing a buyer's reservation price enables the seller to extract the highest possible price, and since consumers' price elasticity depends on the availability of a varied choice set, dealers can be less flexible on prices with lower levels of local competition. Information plays a vital role in new-car transactions. Many previous studies have explored the conditions that enable bargaining-based price discrimination and have tested bargaining theories in the setting of new car transactions. Ayers & Siegelman 1995 and Goldberg 1996 in [5, 30] show that dealers sometimes use information content about

[1] The inception of online search and referral service websites has increased the availability of information to consumers and facilitated intra-brand competition on prices. This issue is further elaborated on in section 3.3.

their customers' willingness-to-pay based on race and gender. The existence of asymmetric information about dealers' opportunity costs, combined with search costs associated with obtaining information about other alternatives, dictates an equilibrium in which heterogeneous consumers pay different prices for similar products. Scott-Morton et al 2004 and 2011 [64, 62], and Zeng et al 2012 [73] show that consumers who have better information about dealers' invoice prices and who obtained more knowledge about their outside options can get a significantly lower price; while buyers who have a bargaining disutility, are not patient, or who do not engage in searches pay higher prices on average. Madarász 2015 [48] indicates that sellers increase profits when consumers name their price or provide the seller with a price range. Rao et al 2009, Busse & Silva-Risso 2010, and Kwon et al 2015 [56, 15, 44], demonstrate that it is profitable for dealers to engage in trade-in transactions; moreover, they infer a higher willingness-to-pay and charge higher prices to consumers who trade-in a used vehicle.[2] Even in the presence of competition, but especially in instances where sellers can utilize market power, maintaining a haggling environment is profitable for sellers when they can utilize information asymmetries, and even influence buyers' perceptions using promotions (Busse et al 2006 and 2010, and Demirag et al 2011 [13, 16, 22]); this applies as long as consumers are heterogeneous and a significant portion of buyers are averse to bargaining and to search (Desai & Purohit 2004, Allen et al 2014, D'Haultfoeuille et al 2014, and Gill & Thanassoulis 2016 [23, 2, 24, 28]).

Concerning a market structure in which big-ticket items are transacted via bargaining, and in which many local marketplaces consist of varying levels of competitive pressure, policy that affects the geographic spread of sellers and the levels of local competition should be sensitive to potential inefficiencies and to its influence on local market power. When new-car dealerships enjoy market power in their local RMAs, the portion of the consumer population with higher search costs and higher bargaining disutility will be worse off because other options are not readily available and information about dealers' costs is not offered for free. When consumers incur high search costs, price dispersion increases, price elasticities are lower, and markups are higher (Chandra & Tappata

[2]This is shown to be plausible as results in section 3.5 are consistent with this claim.

2011, and Moraga-Gonzales et al, 2015 [17, 52]). This is exacerbated when a significant portion of the population does not engage in search.

In this paper, I estimate the effect of local brand competition on the transaction prices, MSRP, and dealership discounts of new vehicles. I measure the response by new car dealers to changes in local competition at their immediate RMAs. I differentiate between two possible sources for the change in overall average prices – a sales mixing response is explained by higher average MSRPs, while increased aggressiveness in sales is explained by a decrease in dealer discounts or an increase of add-on sales at the dealership. Lastly, I examine whether or not changes in local brand competition affect the quantity of vehicles sold per quarter as well as the price dispersion at individual dealerships. Findings illustrate that new car dealerships do exercise market power, partly when it is afforded to them by less-price-sensitive consumers (decreasing discounts or increasing add-on sales), and partly when dealers perceive that their customers may have a higher willingness-to-pay (ordering a more expensive inventory with higher MSRP).

Using data from seven years of Texas vehicle registrations, I assemble a data set that includes over five million new car transactions between dealerships and private households. For each transaction, I know the household's zip code, the location of the dealership from which the household purchased, *and all other dealerships from whom the households could have purchased*. I use these transactions in conjunction with several events that led to exogenous variation in brand competition in certain local markets. I employ two identification strategies that measure the response by dealers, who never entered or exited their market during the sample period, to the sudden exit by one of their rivals. The primary model estimates the effects of the Herfindahl-Hirschman Index (HHI) on transaction prices, MSRP, and discounts, while utilizing instrumental variables which indicate whether the local market area experienced a quasi-random shock to correct for the endogeneity of HHI. A quasi-random shock is an exit by a brand or an entire dealership that occurred as a result of the 2008-2009 bailouts.[3] By utilizing exogenous dealership exits as instrumental variables

[3] A natural concern in this context will be whether selection bias hinders the validity of these results. While the exit by entire brands is not subject to any selection bias by the parent company (such as Pontiac and Saturn, which were discontinued altogether; and Suzuki and Isuzu, which ceased operations in North America), some discretion was possible in the closure of other dealerships by GM or Chrysler. I explain in section 3.4 why this is not a major concern.

in an instrumental variables regression, I am able to measure the general distributional effects of competition on dealerships' pricing behavior both at the mean as well as at different areas of the price distribution, thereby gauging the differential pricing responses based on willingness-to-pay. This identification strategy is similar to that in Hastings 2004 [34], as she exploits the geographical proximity of gas stations to rivals that experienced a contract change, in measuring the pricing effects of vertical relationships.

The main sources of identification in this paper are the nationwide events which took place from the end of 2008 through the end of 2009, when mass dealership exits and brand discontinuations followed the financial crisis and the effects it had on two of the big three American car manufacturers – GM and Chrysler. Certain dealership closures posed a uniform change in local brand competition unrelated to local demand and supply shocks, and affecting both relatively competitive and relatively concentrated dealership clusters. Thus, I am afforded a unique opportunity to isolate variation in competition that is unrelated to the local interaction of demand and supply, and therefore, uncorrelated with local pricing dynamics. This is a significant contribution, as this paper is the first to measure the *causal effects* of local brand competition on new vehicle prices, an important economic question which would normally be impossible to answer with regular observational data and without imposing strict modeling assumptions.

In order to address specific concerns from the primary model with regards to the mechanism of the pricing effect, I employ a secondary model which utilizes the immediate closure of the Saturn and Pontiac brands, as these events differ from other dealership closures in a sense that eliminates any concerns for selection bias. In addition, having some control on the inclusion of transactions based on their proximity to exiting Pontiac or Saturn dealerships, I demonstrate how the measured price increase in response to the exit by a rival is most likely a supply type response explained by a change in pricing behavior, rather than a demand side response or another effect that has to do with market characteristics which are correlated with a previous placement of a Saturn or a Pontiac dealership. By separating local markets into "treatment" and "control" groups, I exploit a difference-in-differences research design on individual transactions in which "treated" sales are transactions that occurred at a competing dealership located within a certain distance from a place where the Pontiac or Saturn brand was previously sold.

The main result shows that the marginal effect of an increase in HHI on prices is non-linear and tends to be significant in local markets which are relatively competitive or moderately concentrated. Local markets which are already concentrated do not experience an additional increase in prices with even lower competition. For each of the 312 local markets and in each quarter between 2004-Q1 and 2010-Q4, I calculate the HHI based on brand shares of the parent company. I find that an increase in 100 and 200 points in HHI at a market with relatively high competition (HHI=1500) increases average prices by $105 and $207 respectively. Similarly, an increase in 100 and 200 points in HHI at a moderately competitive market (HHI=2500) increases average prices by $73 and $144 respectively. Whether the price increase is due to consumers buying more expensive vehicles due to a sales mix with higher MSRPs, or from dealerships offering lower discounts, depends on the relative price sensitivity and willingness-to-pay. Sales in the higher end of the price distribution experience higher prices due to a decrease in the difference between the MSRP and the transaction price, which could be explained by receiving lower discounts or increasing add-on sales (both driven by lower price-sensitivity), while sales in the lower end of the price distribution experience higher average prices due to a more expensive sales mix (likely due to dealers perceiving consumers with higher willingness-to-pay). The two sets of results from the difference-in-differences design (one for Pontiac and one for Saturn) show that prices at dealerships located within one mile to a Saturn or a Pontiac dealership were higher than their counterfactuals starting exactly one period after the sudden exit. As the radius around the exiting dealership is gradually increased in the treatment group, the intensity of the price response declines, indicating that the supply response is more pronounced in dealerships that are more physically close to their exiting rival. This means that the price increase is not likely to be caused by shifts in demand. Additionally, the different types of price increases at different ends of the price distribution propose an explanation which is consistent with dealers exercising market power when afforded by consumers who are less price sensitive and when dealers perceive their residual demand increasing in a way that includes more customers with higher willingness to pay.

This chapter shows that local brand competition is relevant to pricing decisions made by retail dealerships selling new cars under franchised licenses. Results are consistent with local dealerships exercising a degree of market power, and differentiating their consumers according to willingness-to-pay. As market concentration increases locally, dealers extract higher profit margins by raising prices on vehicles at the higher end of the price distribution, as such customers are less likely to be price sensitive. The marginal effect of decreased competition on the distribution of prices varies across markets with different levels of concentration. Dealers cause consumers to pay higher prices both by ordering more expensive vehicles from manufacturers, and by offering lower discounts.

The implications of these results are significant in two primary ways. First, double marginalization induced by market power of franchisees leads to allocative inefficiencies in any market. An increase in prices with the existence of market power slows down the efficient replacement of old cars. Second, the results of this study speak to an important public policy debate concerning the regulation of the automotive franchise system and state laws governing the relationship between car manufacturers and their dealership networks. A recent effort to remove decades-old state bans on manufacturer-to-consumer direct sales has been stirred by Tesla and supported by the Federal Trade Commission.[4] Removing these bans has the potential of increasing market efficiency as it will allow all car manufacturers to freely select the distribution mode which best suits their production technology. Moreover, it is expected that if bans on direct distribution are removed, car manufacturers will have more freedom to consolidate their dealership networks, which would lead to fewer, but more competitive, local market areas. However, fierce opposition by automotive dealers' associations, raising doubts about the potential benefits to consumers from removing bans on direct distribution, has significantly slowed down this process. The strongest argument made by the dealers' associations is that a distribution system consisting of independent dealership networks only, as opposed to one in which manufacturers have more centralized control, benefits consumers through enhanced intra-brand competition. Whereas not only intra-brand but also inter-brand com-

[4]See for example: FTC blog article by Lao, Feinstein and Lafontaine, 2015 in [46]

petition increases competitive pressure on dealers, it is uncertain that the dealers' argument is valid in light of evidence that inter-brand competition has a significant effect in local RMAs.

The following sections of this chapter are structured as follows: Section 3.1 provides the background on the history and issues concerning state franchise laws and direct distribution bans, and illustrates the contribution of this paper in informing this important public policy debate. Section 3.2 details the data and the construction of key variables used in estimation. It outlines the structure of the sample and details the method used to identify dealerships and local market clusters. Section 3.3 covers intra-brand competition, reviews the relevant literature relating to online sales and referral services, and provides descriptive evidence in the DMV data. Section 3.4 details the identification strategies and illustrates the validity of the instruments. Section 3.5 outlines and discusses the results. A summary and conclusions are exposited in section 4.2 of this dissertation.

3.1 Debate over Direct Distribution

All fifty U.S. states regulate the contractual relationship between automobile manufacturers and their franchised dealers through industry-specific franchise laws. Since its inception, the industry's three main U.S. manufacturers have organized their distribution system through independent small businesses which they entrusted with selling their goods to the public (Pashigian, 1960 [54]). This paper informs an important public policy debate concerning the direct distribution and sales of automobiles by car manufacturers. Under the status quo, only independent car dealers may obtain a license to distribute new cars to consumers. While these statutes vary across states on specific details, they all carry a common theme of protecting dealers' interests against opportunistic behavior by car manufacturers. Independent dealers' associations were able to gain these protections in legislative processes, across all states and throughout the decades, seeking assistance in order to counter unequal bargaining power by auto manufacturers in dealings with individual contracts (Smith 1982 [67]). As state legislatures were keen on assisting local small businesses, political support was garnered in favor of independent dealers.

State regulatory statutes achieve protection for the common dealer through two key mechanisms: by restricting manufacturers on the termination and non-renewal of contracts with their dealers, and by establishing the right of an incumbent dealer who operates in a given 'Relevant Market Area' (RMA) to protest an action by a manufacturer who seeks to add or ccate another dealer of the same brand to the incumbent's territory. The restrictions on termination of contracts place the burden of proof on manufacturers to demonstrate that the dealer is being terminated with good cause and in good faith. A material breach of the contract by the dealer is generally not sufficient cause for termination. The provisions establishing rights for dealers to protest market actions that affect their relevant market areas are generally viewed as granting them "exclusive territories". By assigning only one dealer of a particular brand to a given market area, manufacturers and dealers limit the degree of intra-brand competition. Excessive intra-brand competition in a specific area is harmful to both dealers' and manufacturers' revenues, and creates an incentive problem of under-investment in sales services due to free-riding. If, for instance, two dealers offer identical products and compete for the same population of consumers, while one dealer may invest in sales services that increase the knowledge of the product among consumers, the other dealer, who did not bear the marketing costs, can benefit from its competitor's investment and offer a lower price for the same product, thereby free-riding on the other dealers' investment. Manufacturers initially prefer to distribute their dealership networks in a way that minimizes intra-brand competition among dealers; but, as some market areas grow and others decline, certain dynamic adjustments to the dealership networks may be necessary (Lafontaine & Scott-Morton 2010 [45]). Without dealers' ability to protest such actions, relocations and add-points could be used by manufacturers as a way to bypass the restrictions on contract termination in order to replace less desirable dealers.

Prohibitions on direct distribution by car manufacturers serve as the lifeblood to the two aforementioned protection mechanisms. If all auto manufacturers were allowed to own dealerships and sell their products to consumers directly, they would have additional power to determine which independent dealerships will stay in business and which will have to close shop. Faster consolidation and geographic redistribution of dealership networks could take place if manufacturers were able to undercut certain market areas via company-operated stores or build-to-order sales. Possible outcomes of allowing direct distribution by manufacturers, as it pertains to independent dealers, can take one of three forms: (1) All existing dealerships remain in business independent of manufacturers. (2) Some dealerships remain independent while others become manufacturer-operated. (3) All dealerships become manufacturer operated. In addition to (1)-(3), manufacturers may or may not engage in online build-to-order sales, and in addition to (2)-(3), manufacturers may or may not consolidate dealership networks. Bans on direct distribution ensure that (1) is the de-facto scenario, prohibit build-to-order sales, and limit dealer network consolidation.

Existing economic literature which evaluates these state franchise laws largely concludes that their ultimate effect is to transfer wealth from manufacturers and consumers to independent franchised dealers (Smith 1982, Mathewson & Winter 1989, Brickly et al 1991, Bodisch 2009 Lafontaine & Scott-Morton 2010 [67, 49, 11, 9, 45]). Findings are consistent with a-priori predictions; namely, that state regulations serve to protect dealers from entry by competitors and from termination by manufacturers, which results in fewer cars being sold at higher prices. However, no price and quantity effects were revisited since the 1980's studies. Despite the economic evidence, the past few decades have seen little to no effort to seriously challenge the existing system of state franchise regulation. Meanwhile, independent dealers and dealers' associations extract significant economic profits, with many dealership groups being consistently listed among the fortune 500, and are politically active in making political donations to state and local legislatures, maintaining an active car dealership lobby (Crane, 2014 and 2015 [18, 19]).

In 2012, a new challenge to dealer protection status has emerged as Tesla, Inc. – an automobile manufacturer selling electric vehicles – has decided to employ a business model that does not rely on independent dealers for retail distribution. Operating sales points and showrooms located in shopping malls within large cities, and combining an online build-to-order sales service, Tesla simply cannot advance its brand by using the traditional dealer network. Admittedly, Tesla did express that the reason why dealers could not make a profit from selling their brand is that consumers can order vehicles online at a lower price than the dealer could offer.[5] Despite its efforts to penetrate

[5] At an FTC workshop titled "Auto Distribution: Current Issues and Future Trends", a Tesla representative provided a detailed explanation listing several reasons why Tesla would rather battle for direct distribution rather than engage in distribution through independent dealers. A full transcript of the workshop hosted by the Federal Trade Commission on January 19, 2016 is available at: https://www.ftc.gov/news-events/events-calendar/2016/01/auto-distribution-current-

state laws and market their products across the U.S., Tesla has been experiencing a large degree of resistance from dealers' associations and incumbent manufacturers, combating their efforts to change state laws. So far, Tesla has only seen limited success in operating its business model under the shadow of state franchise regulations, with some states posing a more pronounced opposition than others. This difficulty to pass legislation has led some critics to allege that state regulators have been captured by the industry's strong dealer lobbyists (Schwartz 2014, Crane 2015 [61, 19]). The opposition to Tesla's innovative approach of automobile distribution has stirred the national debate regarding the economic legitimacy of state bans on direct distribution.

Among those who support the deregulation of franchise laws, at least in eliminating the bans on direct sales, are academic economists, FTC staff, and bipartisan consumer protection groups. The arguments they make are derived from sound economic theory; however, these largely cannot be tested empirically as no counterfactual market exists with pure direct distribution. The main argument that they use makes the case that if independent dealers offer real economic value to the industry, then the dealers should continue to prosper even in the absence of the bans. If manufacturers try to distribute directly and experience higher costs and lower volumes as a result, then they will quickly return to the franchised dealers for their specialty in distributing their vehicles. If, however, manufacturers are able to reduce distribution costs and offer lower prices to consumers by distributing directly, then the dealers' opposition is not grounded on concerns for the consuming public but rather to protect their own interests. The bottom line is that the removal of direct distribution bans is good for the market – buyers and sellers should choose to structure the industry in the best way that benefits them, and a mandate to rely on a third party middleman does not make any economic sense. Moreover, if dealerships can exercise market power in their respective RMAs, then it is well known that double marginalization would lead to an inefficient allocation.

Faced with a perceived threat to their profitability let alone to their existence, representatives of dealerships and dealers' associations tend to quote statistics that they believe should strengthen the public's view of their importance to the industry. Citing their revenues, local business special-

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issues-future-trends

ization, amount of local taxes transmitted to municipalities and states, and the amount of services provided to local consumers, most of their arguments do not offer a real economic reason as to why there must be bans on direct distribution. Yet the most interesting and potentially compelling argument that they make in their favor is the fact that *independent dealers compete on an intra-brand basis*. Dealers argue that in their absence, average prices will be higher for consumers, because if all sales spots were operated by the manufacturers, there would be no intra-brand competition to drive prices down. Though there are issues that cast doubt on the validity of this argument,[6] given the odds that are at stake for dealers, one must afford this argument the benefit of the doubt and put it to an empirical test. All of anticipated outcomes of removing bans on direct distribution (increased entry by innovative manufacturers, build-to-order by manufacturers, and dealership consolidation), will result in more inter-brand and less intra-brand competition, since fewer independent sellers from each brand will have an increased consumer population and more consumers will have access to additional brands. *Therefore, a true comparison of the trade-offs between less intra-brand competition and more inter-brand competition is necessary in order to determine if consumers will be better off in the absence of direct distribution bans. This is one of the first papers that explores the causal effects of inter-brand competition in local market clusters.*

Lastly, it is important to listen to the testimony of automotive dealership associations, indicating that profits from new car sales are not their primary source of economic profits. A significant portion of recent state franchise legislations addresses warranty reimbursements by manufacturers to dealers, and dealers themselves state that their main source of revenue and profits are service departments and warranty repairs. This fact further proves why local inter-brand competition matters to dealerships more than intra-brand competition. Suppose a customer walks in to a dealership and identifies as a local resident in search of a new car. If the customer engaged in sequential search, then he or she has already committed to purchasing a particular brand; so while the seller would like to earn the customer's business, they will likely be less concerned if the buyer purchases their

[6]For example, one could point out that intra-brand competition among dealers simply drives the price back to the original competitive level and that if manufacturers would choose to mark up vehicles higher in the absence of independent dealers, then they are not acting in their own self interest currently.

brand at a different same-brand dealership. However, if the buyer holds a small choice set consisting of several different brands, then the opportunity cost of not selling to this buyer is much higher if the buyer indicates a possible substitution to a different brand – because not only will the dealer lose the revenues from the sale, but also from subsequent warranty service and repairs.

This study contributes to this national policy debate regarding direct distribution by informing a major component about the nature of local retail competition among new car dealerships. Most importantly, this paper reveals the importance of local inter-brand competition and points to the degree to which dealerships can exercise local market power afforded to them by consumers who may not engage in sufficient search. If dealerships exercise local market power, then the industry may be subject to inefficiencies in the form of double marginalization. If double marginalization offsets any potential benefits from intra-brand competition, there is little reason to ban direct distribution in the name of consumer benefits.

3.2 Data

The data used in this study is obtained from seven years of vehicle registration records at the Texas Department of Motor Vehicles (TXDMV), supplemented with detailed information on vehicle characteristics available through the "DataOne" software. A registration record contains information that includes the unique Vehicle Identification Number (VIN), the vehicle's sales price, the name and physical address of the buyer, and the name and city of the previous owner. Ten out of the seventeen digits of the VIN define a vehicle's unique profile of characteristics at the manufacturing level – which includes the physical dimensions, weight, fuel efficiency rating, engine size, and MSRP.[7] By comparing each vehicle's sales price to the amount of sales tax paid, I can determine whether a transaction consisted of a trade-in (without a trade-in, these prices are equal), and what the trade-in value was. The DMV registration data indicates whether or not a registered vehicle has a lien, but the loan amounts or creditors are not mentioned. The data reveals that 49.11% of transactions involved both a trade-in and a loan, 37.44% involved a loan but not a trade-in, 6.77%

[7] Additional add-ons can usually be purchased at the local dealership but these options are not observed in the data; however, they do affect the transaction price. Additionally, terms of payment and financing incentives are not observed in the data.

involved a trade-in but not a loan, and 6.68% involved neither a trade-in nor a loan.

I identify new car transactions using the first registration record of each vehicle (identified by its VIN) found in the data set. If the record meets all of the following criteria, it is considered to be a transaction of a new car: (a) the model year is not earlier than the year of purchase, (b) the vehicle's odometer reading does not exceed 1,000 miles, and (c) the previous owner is a car dealership that owns a franchise agreement with the manufacturer of the same brand.[8]

A publicly available list of licensed auto dealerships was obtained through the TXDMV.[9] The external list includes all presently active dealerships, and it matches only a subset of the dealerships observed in the DMV registration data. The remaining dealerships were matched manually according to available online resources.[10] The data consists of 2,094 dealerships operating in 1,440 locations between 2004-Q1 and 2010-Q4. A dealer's period of operation is determined according to recorded dates of the purchases made at that dealership; that is, entry or exit of a particular dealer is observed when its sales begin or cease to occur. Dealerships are grouped according to their commercial name (i.e. DBA – 'Doing Business As'), the type of brand franchise they own, and their physical location. For example, a Ford-Lincoln-Mercury combination is commonly grouped into one dealership if all brands are sold at the same location. Many GM dealerships may have many combinations of the brands Buick, Cadillac, Chevrolet, GMC, Pontiac, and others, being sold at one location under one dealership. Most often, Buick, GMC and Pontiac will be sold together, while Chevrolet and Cadillac may be sold at the same location or at independent facilities. The Scion brand would often be sold alongside the Toyota, though Lexus is most likely to be sold separately. Independent dealerships are allowed to sell more than one brand of cars, and engage in franchise agreements with many manufacturers. During the inception of the automotive dealership sector, the vast majority of dealerships were characterized as small family businesses or "mom-and-pop shops"; however, nowadays, many dealerships are a part of a much

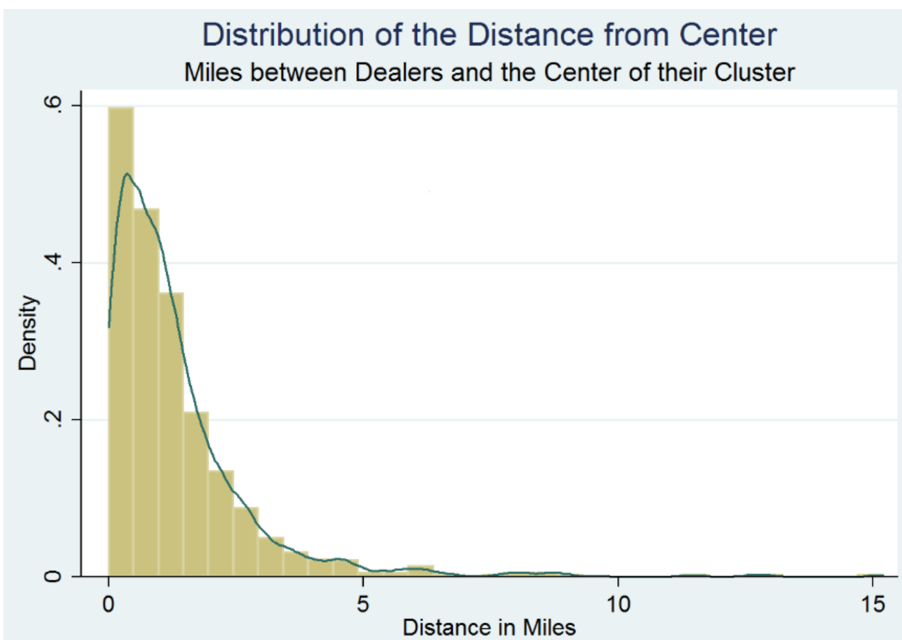
[8] If, for instance, a registration record shows a Ford being sold by a Toyota dealership, then it is not considered to be a new vehicle transaction.

[9] http://txdmv.force.com/dealers/motorvehicledealerliststaging (last accessed on 5/19/2018).

[10] Many dealership locations were verified using the street view feature of Google Maps, which includes a number of images dating back to around 2006-2007. Other dealers were verified using online sources such as manta.com or the Better Business Bureau.

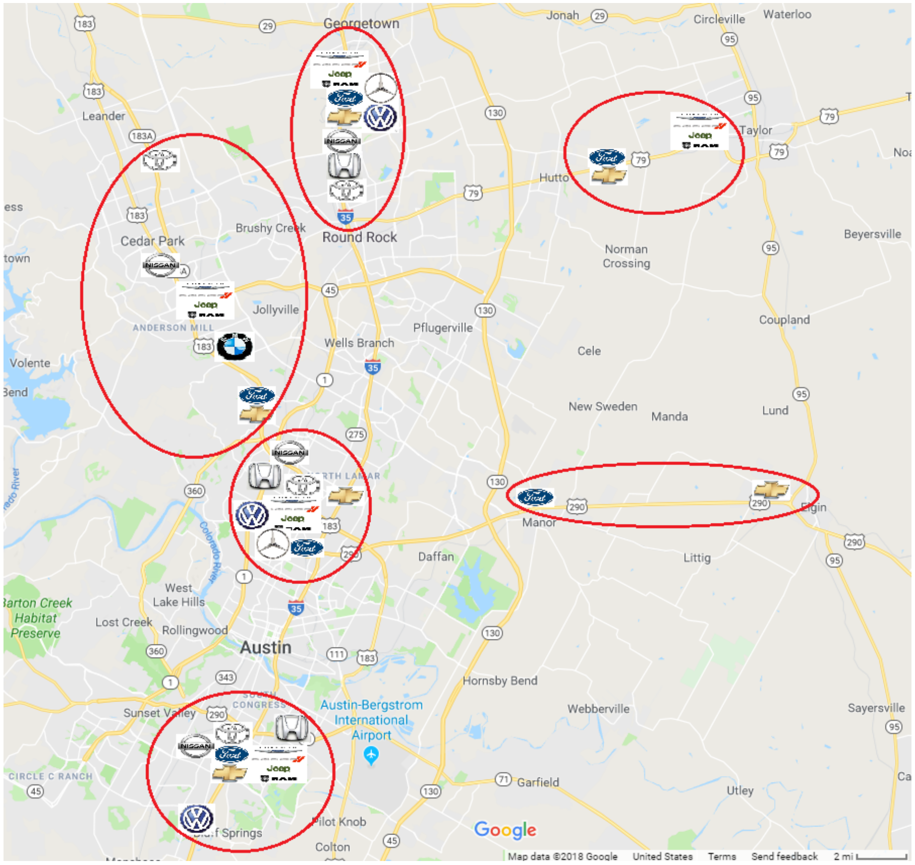
larger corporate network, and large dealership groups such as AutoNation Inc., Lithia Motors Inc., Sonic Automotive, etc., engage in several franchise contracts in many different local market areas. Dealership groups can own many franchised dealers – both in a given location selling different brands, and selling a particular brand across separate market areas. In contrast, dealerships owned by smaller businesses typically have only one franchise license agreement with a single manufacturer, in which case the dealer's interests to promote the brand will likely be more aligned with that of the manufacturer. Despite the ability for one dealership to own many franchise contracts in a single RMA, this occurrence is typically the exception rather than the rule, and in most local RMAs the dealership network market share is the same as the brand manufacturers' share.

Figure 3.1: Dealers' Distance from the Center of their Cluster



The geographic distribution of dealerships is a result of dealers' strategic choices placing the physical location of their retail outlets as they seek to extract a long term steady flow of sales from the surrounding population. Agglomeration of dealerships into clusters (or "rows" on a major highway) is typically observed in areas where there is a significant resident population. Dealerships within clusters are located in close proximity to one another; as figure 3.1 shows, it is rare for a dealership to be located more than five miles away from the center of a cluster. Figure 3.2 depicts the city of Austin, TX, and illustrates how local market areas are formed, where they are located in relation to one-another in an urban area, as well as how condensed dealerships are within the same cluster (one inch is translated to two miles). As explained in Lafontaine & Scott-Morton 2010 [45], local markets are formed around the dealerships which were the first entrants to introduce their brands to the local population. These first entrants were the big three American manufacturers, and their presence is prevalent in all Texas local markets. These dealerships are also the only ones operating in the two RMAs east of Austin, TX, between Manor, TX, and Elgin, TX, and between Hutto, TX and Taylor, TX. Due to franchise laws that restrict dynamic adjustments of dealership relocations, most observed clusters have originated prior to the market penetration of foreign brands. Later entrants enjoyed more freedom than the incumbents in selecting the location of their dealers, and they were able to choose the locations to where the population had moved. When the Japanese manufacturers entered Austin and placed their dealerships, the population had already become more centralized, and the new market of Austin-Northwest emerged farther from the city center. This is why we see the Ford and Chevrolet dealerships in this cluster located so close to the central cluster. The European brands, which arrived later, have strategically chosen the more condensed and central markets, with BMW operating only one dealership. It seems that if dealership terminations and relocations were not subject to strict legal limitations in the framework of state franchise laws, then the American and Japanese brands will likely be more consolidated into the central locations where they can still serve the surrounding population.

Figure 3.2: Illustration of Clustering by Car Dealerships



Geographic clustering of new-car dealerships in Austin, TX, and its neighboring towns. Most clusters, such as Austin-South, Round Rock / Georgetown, and the markets to the east are clearly separated, while the segmentation of Austin-Center and Austin-Northwest is somewhat fuzzy.

I define local market clusters in the data by tracking their formation over time, starting with either a Ford or Chevrolet dealership (or a Ford-Chevrolet pair), gradually adding new entrants and assigning them to the market defined by the closest Ford or Chevrolet dealer. There are a total of 1,440 distinct dealership locations spread throughout 312 clusters, the majority of which are in rural area that are isolated from other market clusters. Over 97% of all dealership locations are within five miles from the center of the cluster in which they are located. Around 61.53% of all transactions in the sample occur in one of 114 local markets found within Texas' largest MSAs. The remaining 198 clusters are disbursed in rural areas and non-metropolitan municipalities, and consist of the remaining 38.47% of transactions, as summarized in table 3.1. This construction allows for the existence of multiple local markets within one city, as well as having one local market that includes several municipalities. The distinction between clusters in urban areas can sometimes be somewhat fuzzy, as seen in figure 3.2, but as I will discuss in section 3.4, this is not a major concern as potential spillover effects from markets affected by an exit will not contribute to an overestimation of my results.

Table 3.1: Dealership Clusters by MSA Status

	Number of Sales	Percent in Sample	Number of Clusters
MSA	3,530,525	61.53%	114
Non-MSA	2,207,078	38.47%	198

During the sample period, certain changes to dealerships' regular operation take place. For example, many dealerships experienced entry into and/or exit out of local markets, and some dealerships added or dropped a secondary brand belonging to the primary manufacturer (e.g. Toyota dealerships adding the Scion, or GM dealerships dropping the Pontiac brand, etc.) On occasion, a new dealer enters a market area, taking over sales of a brand and immediately replacing an existing dealer selling that brand – shutting down the previous location and operating in a new one. This type of relocation usually entails a replacement of the dealer itself – one dealer is terminated and the manufacturer enters a new contract with another dealer in that market area. Lastly, acquisitions are observed when a new dealerships takes over sales of a particular brand in the existing location of the replaced dealership, with a smooth and immediate transition to new ownership and management. During the sample period, 761 of the 2,094 dealerships experienced no changes in operation status (i.e. no entry/exit, add/drop brand, acquisition or relocation) throughout the sample period between 2004-Q1 and 2010-Q4. There were 268 acquisitions, 119 relocations, 208 new entries, and 383 exits. Lastly, 64 dealerships added a secondary brand of the same parent company, while 169 dropped a brand they were previously selling.

Of particular interest are the events that caused nationwide dealership closures and brand discontinuation during the financial crisis of 2008-2009. From the end of 2008 through the end of 2009 – a period consisting of a high volume of dealership exits as well as 142 of the 169 instances of brand discontinuation – radical changes to local brand competition were received differentially at each of the 312 local dealership clusters. This fact is the primary source of identification driving the main results of this paper, to be discussed further in section 3.4.

3.3 Intra-Brand Competition – A Descriptive Analysis

This section reveals several intriguing observations regarding consumer search patterns that exist among buyers of new vehicles, and explores some of the determinants of search across different local market clusters. Evidence from the sample suggests that a significant portion of consumers end up buying their vehicles from dealerships that are closest to their registered address. At least 60.8% of overall consumers (56.44% in urban and 67.8% in rural areas) buy at the closest dealership which sells their particular model of choice. Consumers who buy a particular brand at a location beyond the dealership closest to their registered address are more likely to pay a lower price. A reasonable assumption is that the people who buy at distant market clusters also exercise more search, but many of those who buy a vehicle at the closest dealerships that sells their brand of choice may have also engaged in some search, and decided to buy locally. Since a large concentration of consumers do buy locally, it is possible that a significant portion of these buyers signal an aversion to search as well bargaining disutility. If the majority of consumers consider the local market as their default, then local market concentration is likely affect dealers' pricing decisions more so than intra-brand competition.

Consumers who engage in sequential search first choose their brand and then pick the dealership at which they will buy. Upon deciding which vehicle to purchase, sequential shoppers research across dealership clusters to find the lowest price among independent dealers who sell the same identical product. In this manner, consumers who engage in sequential search choose from a set of available vehicles in accordance with their preferences, and then find the best price for that vehicle to maximize their utility. The geographical distance between independent dealers of the same franchised brand will be a factor in the sequential shopper's decision of whether or not to conduct additional search. While search costs in terms of time and travel distance across dealerships have been reduced with the addition of internet referral services into new car sales, most consumers must still conduct some of their search at the physical dealerships (Scott Morton, Zettelmeyer, & Silva-Risso, 2001 and 2006, Kuruzovich et al 2008, Sewell & Bodkin, 2009 [63, 74, 43, 66]). Therefore, the level of intra-brand competition faced by dealerships depends on the degree of concentration of same-brand dealerships around them, which is correlated with the population density in those areas.

A study by the Phoenix Center (Beard, Ford, & Spiwak, 2015 in [6]), has been cited by detractors of direct distribution as evidence that intra-brand competition by independent dealerships significantly decreases prices for consumers. The researchers concluded that increasing the distance between Honda dealerships by thirty miles raises the price for a Honda Accord by about $500. First, if this result is correct, then it would imply the unlikely case that consumers' search costs increase exponentially with the distance between same brand dealerships. Second, these results are inconsistent with findings of other research; for example, when asked how many miles consumers are willing to drive in order to save $300 on the purchase of a car, the mean among 712 respondents to the survey was 67.14 miles with a standard deviation of 162.48 miles (Sewell & Bodkin, 2009 [66]). In other words, consumers on average are willing to travel more than double the distance in order to save less money than the parameters in the Phoenix Center's study. The source of this discrepancy is likely due to the fact that the Phoenix Center's study does not use a plausibly causal method of identification, and it fails to properly control for the differences between metropolitan and rural markets. Higher geographic density among same-brand dealerships occurs in markets that are also very competitive on an inter-brand basis, whereas the authors do not isolate this source of endogeneity.

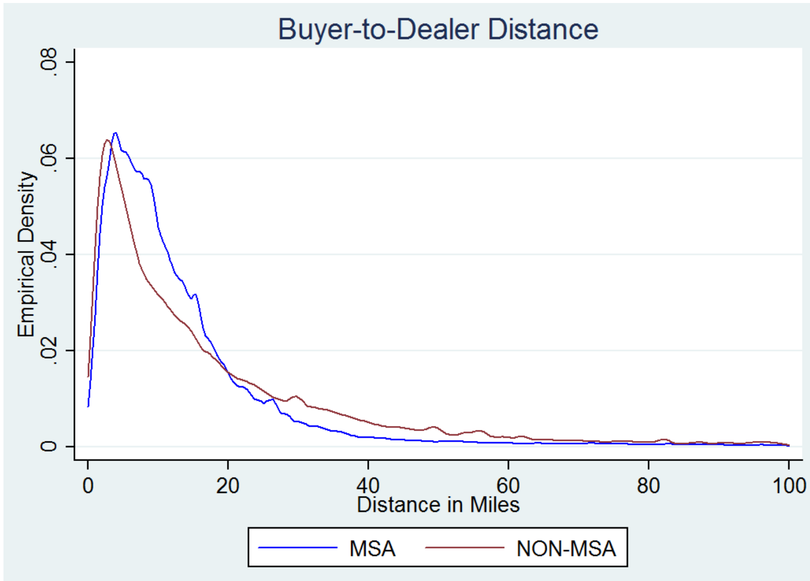
The DMV registration data analyzed in this paper provides some insight into intra-brand competition, focusing on the distance (as the crow flies) between the buyers' residence addresses (title address) and the locations of the dealerships where the transactions were made. Table 3.2 and figure 3.3 illustrate the distribution of buyer-to-seller distance. With a mean of 26.29 and a standard deviation of 51.65 miles, the distribution is skewed to the right. A large concentration of consumers purchase their cars within a 50 mile radius, and nearly half the total of consumers buy their vehicles within a 10 mile radius of their titled address. The pattern of this distribution is not very different across metropolitan and rural consumers, with the exception that the non-MSA buyers must travel a farther distance from one local market area to another. The distances between buyers and sellers tend to be shorter around MSAs where the density of consumers and dealers is higher; however, the median distance among non-MSA buyers is smaller, indicating a higher portion of consumers who buy at the closest dealership in those areas.

Table 3.2: Summary Statistics - Distance between Buyer and Seller (Miles)

	Full Sample	MSA	Non-MSA
Mean	26.27	24.23	29.54
Standard Deviation	51.65	48.12	56.68
Median	10.93	11.01	10.77
75th Percentile	22.97	21.59	26.11
90th Percentile	51.95	42.73	69
95th Percentile	114.27	91.1	142.07
Observations	5,737,603	3,530,525	2,207,078

The average distance between two competing same-brand dealerships across all brands is 29.02 miles, with a standard deviation of 41.46 miles. These numbers vary across different brands, as the number of local markets serviced by a particular brand depends on the timing of the brand's introduction to the Texas market. For instance, with presence in 276 local markets, the average distance between two Ford dealerships is 16.43 miles with a standard deviation of 11 miles. In

Figure 3.3: Buyer-Dealer Distance in Miles



contrast, servicing only 61 local markets, the distance between two Honda dealerships averages 31.09 with a standard deviation of 31.52 miles. Regardless, the average distance between two same-brand dealerships is significantly higher than the average distance among dealerships within a local market cluster. Figure 3.1 illustrates this close proximity of dealerships to one another within local market area clusters, where the average distance between dealerships and the center of their cluster is 1.28 miles and the standard deviation is 1.5 miles. Over 97% of dealerships are located within five miles of their cluster's center.

Table 3.3 shows the portion of customers among the entire sample who bought their vehicles from the first, second, third, fourth, and fifth closest dealerships to their registration address. Over 60% of purchasers in the sample buy at the first closest dealership, and over 90% buy within the first five closest dealerships that offer their vehicle of choice. The likelihood of purchasing a vehicle at the first closest dealership decreases when considering only transactions within large metropolitan (MSA) areas where the travel distance across market clusters is shorter than rural (non-MSA) locations. For rural buyers, the likelihood of purchasing at the closest dealership increases by more than 10% over metropolitan buyers. In parentheses, table 3.3 reports the percentage of buyers out of each group who paid a price lower than the lowest average price across the first five immediate dealerships. As consumers expand the range of their search, they are more likely to pay a lower price for their vehicle of choice in both MSA and non-MSA locations; however, it is more likely that customers pay the lowest price if they purchase their vehicle within MSA as opposed to non-MSA dealerships.

Table 3.3: Portion of Consumers who Buy Locally

Order of Dealership Proximity	Full Sample	MSA	Non-MSA
1st	60.80%	56.44%	67.80%
	(18.05%)	(18.83%)	(17%)
2nd	15.77	16.44	14.70
	(20.7)	(21.17)	(19.86)
3rd	7.23	8.01	5.99
	(22.52)	(22.98)	(21.55)
4th	4.06	4.72	2.99
	(23.21)	(23.53)	(22.42)
5th	2.53	3.06	1.69
	(23.59)	(23.90)	(22.69)

Number in parentheses represents the portion of consumers within the group who paid a price lower than the lowest average price across sales in the 5 closest dealerships occurring up to one week before and after the transaction.

Table 3.4 shows the distances between buyers and sellers among those who bought their cars at the first, second, third, fourth, and fifth dealerships closest to their registered address, and includes the distances to other dealerships that sold the exact vehicle around the same time of purchase,[11] in order to illustrate the other available options regarding the place of purchase. For buyers who purchased their vehicle at the first closest dealership, the average distance they would have needed

[11]For each individual observation, I compare the purchase to other transactions of vehicles with the same exact make, model, year and MSRP, which occurred up to one week before and after the date of purchase

to travel in order to visit the next closest dealership is 52.77 miles, an increase of over 40 miles from the nearest dealership. However, among buyers who actually bought at the second closest dealership, this average increase in travel distance is only 8.68 miles. It is evident throughout table 3.4 that buyers who choose to expand their search of dealerships are located in places with a higher density of dealerships who sell their vehicle.

Table 3.4: Distance between Buyers and Sellers - by Order of Dealership Proximity

Dealership Order	Distance to the 1st	2nd	3rd	4th	5th
1st - Mean	**11.96**	52.77	77.69	95.44	111.46
(Standard Deviation)	(19.79)	(72.88)	(90.97)	(100.49)	(106.73)
[Observations]	[3,474,800]	[3,429,945]	[3,379,623]	[3,326,936]	[3,271,975]
2nd	13.41	**22.09**	46.32	64.69	81.68
	(22.67)	(30.75)	(62.19)	(76.89)	(87.22)
	[901,303]	[901,303]	[897,315]	[891,857]	[884,982]
3rd	13.91	22.79	**29.67**	45.83	61.88
	(24.71)	(33.17)	(40.32)	(55.82)	(66.72)
	[413,285]	[413,285]	[413,285]	[411,671]	[409,724]
4th	14.26	23.68	30.75	**37.41**	50.66
	(25.39)	(34.98)	(42.27)	(49.25)	(58.27)
	[231,795]	[231,795]	[231,795]	[231,795]	[231,795]
5th	14.64	24.81	32.20	39.23	**46.08**
	(26.57)	(37.03)	(44.59)	(51.43)	(58.49)
	[144,694]	[144,694]	[144,694]	[144,694]	[144,694]

From table 3.3, we see that the likelihood for a consumer to purchase a vehicle at the dealership closest to their address is related to the proximity of other same brand dealerships to their area; in table 3.5, we observe that this likelihood varies with brands as well. Buyers of European brands are more than 8% likely to purchase at the nearest dealership than buyers of American or Asian brands. Interestingly, the portions of consumers on each order of dealership proximity are similar across American and Asian brands, despite the larger number and higher concentration of dealerships selling American compared to Asian brands. European and Asian branded dealer-networks are much more consolidated than those of American brands. This is due to the timing of entry to each local market – dynamic adjustments are difficult because of the industry's franchise laws, as discussed above and in Lafontaine & Scott-Morton 2010 [45]. This difference between European and other brands should not be surprising if we believe that consumers who are less price sensitive tend to default to buying at the closest dealership, since European cars are more expensive on average and their average same-brand dealership distance is higher.

Table 3.5: Portion of Consumers who Buy Locally - by Brand Region

Order of Dealership Proximity	European	American	Asian
1st	68.95%	60.43%	60.35%
	(20%)	(15.7%)	(21.04%)
2nd	15.48	15.09	16.75
	(21.92)	(17.78)	(24.21)
3rd	6.84	7	7.6
	(25.7)	(19.36)	(26.22)
4th	2.83	4.01	4.26
	(23.01)	(20.05)	(27.36)
5th	1.47	2.64	2.51
	(22.85)	(20.74)	(27.81)

95.55% of European, 89.18% of American, and 91.47% of Asian cars are sold in one of the five closest dealers to the registration address.
Number in parentheses represents the portion of consumers within the group who paid a price lower than the lowest average price across sales in the 5 closest dealerships occurring up to one week before and after the transaction.

The most interesting piece of information reported in table 3.6 reveals the comparative differences in prices paid by consumers who bought farther and those who bought nearer to their registered address. Concerning the mean and median differences between the average price of identical vehicles (up to the same VIN pattern, sold around the same time of the transaction) across the five closest dealerships to the buyer, it appears that consumers who defaulted to their closest dealership also paid the higher prices. The mean difference shows that consumers pay more than the computed average price across all five locations only at first closest dealerships. There is a noticeable disparity between the mean and median measures – which suggests that consumers who pay more than the average for their vehicle do so at larger distances from the mean than consumers who pay less than the average. In other words, there is more price dispersion on the upper end of the price distribution than the lower end. The pattern seen in table 3.6 indicates that significant savings are extracted by consumers who buy at the second and third dealerships, with very little incremental savings for consumers buying at the fourth and fifth dealerships. In both MSA and non-MSA areas, expanding the search from the first to the second dealership is associated with around $60 ($130) in average (median) savings, and going from second to third is associated with an additional $80-$90 in average and median savings. Expanding search beyond the third dealership, to the fourth and fifth, is associated with very modest incremental savings.

Table 3.6: Difference between Avg. Price Across 5 Closest Dealers and Price Paid

Order of Dealership Proximity	Full Sample	MSA	Non-MSA
1st	-$32.87	-$49.93	$-10.11
	($100.47)	($94.63)	($107.97)
2nd	$35.23	$21.79	$59.30
	($230.64)	($224.16)	($242.4)
3rd	$119.39	$105.61	$148.87
	($318.17)	($310.26)	($334.51)
4th	$131.16	$115.71	$170.22
	($341.55)	($334.94)	($357.55)
5th	$156.21	$122.19	254.97
	($367.79)	($348.57)	($422.98)

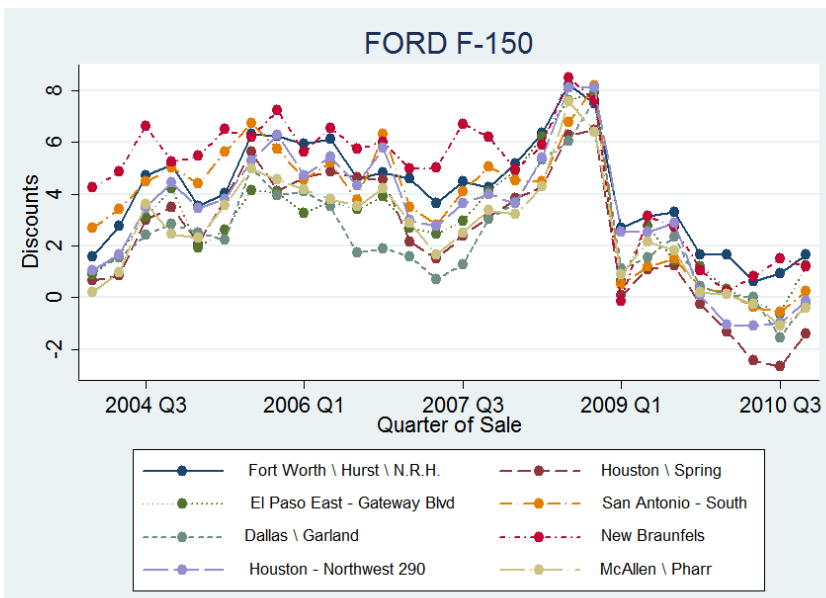
Mean (Median) difference within the group.
Negative sign $\implies$ price paid is higher than average (median)

The lesson learned from this section is twofold. First, it is evident that some intra-brand competition exists and that buyers of new vehicles who engage in price search across independent dealerships that sell identical products are rewarded for their search and they can extract savings of a few hundred dollars. Second, this section reveals some of the determinants of price search and shows that a significant majority of consumers are plausibly defaulting to buying locally, thereby not taking full advantage of intra-brand competition. It is clear that price search across same-brand dealerships is more likely when these dealerships are closer geographically, and therefore much more prevalent in urban areas. This means that consolidation of dealership networks from rural into urban areas is likely to enhance intra-brand competition as well. Rural consumers thus face local markets which are more concentrated both in terms of inter-brand competition and intra-brand competition. It seems that if rural local RMAs would consolidate, although rural consumers may have to travel farther to their nearest local markets, they would enjoy higher levels of competition and a richer variety of alternatives.

3.4 Model

In the following two sections I analyze the pricing response by automotive dealerships to changes in competition within their local market area clusters. I examine whether decreased competition causes dealers to increase prices of new automobiles, and if so, I ask how this effect may vary in different segments of the distribution of prices. Next, I differentiate the source of price changes distinguishing between dealership discounts and the composition of MSRPs, again exploring their incidence in the price distributions. Lastly, I investigate whether decreased competition leads to a different price dispersion and measure the effect on quantity sold at each dealership at each quarter. Throughout all specifications, I control for common shocks across time periods, geographies, vehicle brands and body-types, such that the price distribution for similar alternatives of similar brands is analyzed. This helps in accounting for permanent pricing differences that may exist between a Ford pickup truck sold in Houston and a Toyota sedan sold in Dallas, and maintains an apples-to-apples comparison of prices. I include dummies to control for geographic and temporal fixed effects, along with dummies for vehicle make and body-type to eliminate any biases that may result from different concentration levels of brands and vehicle types in the local markets. I construct the sample to be analyzed by focusing on transactions of relatively popular vehicles occurring at dealerships that never experienced a disruption to their operation during the sample period. I restrict the analysis to three vehicle body types – pickups, sedans, and SUVs, which comprise 83% of all observed new car transactions. I also exclude luxury cars that have a list price higher than $80,000 and I remove observations in which the buyers are not private households, as well as those which contain systematic errors and missing values.

Figure 3.4: Discounts for Ford F-150 by Individual Dealerships

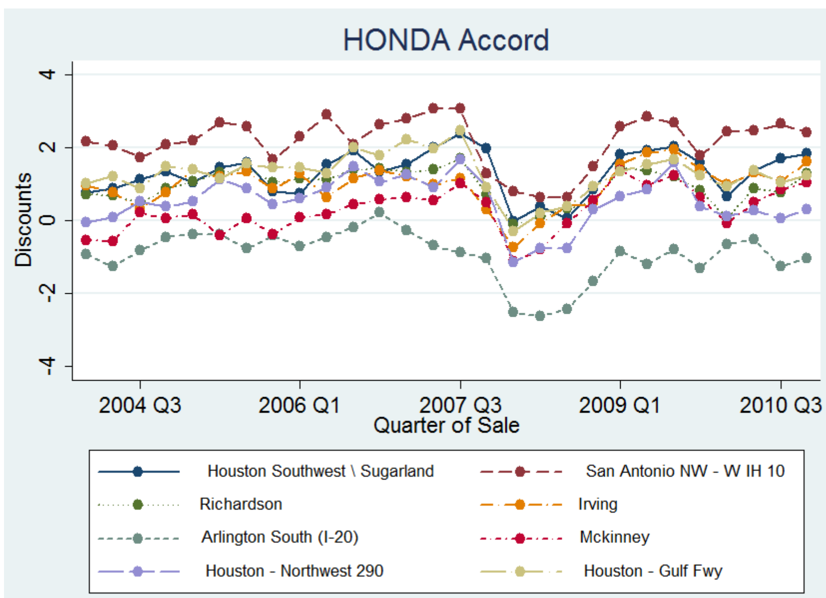


Figures 3.4 and 3.5 illustrate the motivation for the empirical identification strategy used throughout the next two sections. It depicts dealership "discounts" (the difference between the MSRP and vehicle sales price) for the popular Ford F-150 and Honda Accord, averaged for each quarter from 2004-Q1 to 2010-Q4, comparing among eight dealerships that sold the highest volume of these cars.[12] The eight locations in these figures represent dealerships in one of the 312

[12]The reader may notice that some of these discounts are negative; this implies that the transaction price is higher than the MSRP and it is possible due to unobserved "dealership add-ons" – additional options that are added at the

local markets who sell the specific brands. The figures show that discounts for the same make-model and across different locations track in a similar pattern over time, with noticeable periods in which all discounts either increase or decrease simultaneously across the different locations. In addition, it shows that some dealers consistently offer lower or higher discounts than average, and often these locational differences are permanent over time. I explore the differentiation among market clusters over time and find that a significant number of them experienced shocks to their competitive environment from competitors that enter or exit the local market.

Figure 3.5: Discounts for Honda Accord by Individual Dealerships



I exploit exogenous dealership exits which reduce the level of inter-brand competition in local markets. Generally, the decision of whether or not to enter or exit a local market is endogenous to conditions which affect all dealerships' pricing behavior, including that of the competitors. In particular, entry is more likely to occur in booming markets, during times in which they are experiencing increased sales, while exits by dealerships happen when local markets are in decline. Thus,

point of purchase and do not appear on the vehicle profile as it is transported from the manufacturing facility to the dealership. Examples of add-on may include luggage racks, tinted windows, technology and navigation systems, additional warranty, etc., and their incremental prices are factored into the transaction price, but not the MSRP.

we are more likely to see entry (or exit) when average prices increase (or decrease) at competing dealerships, such that a naive approach to estimating the effects of competition without controlling for the endogeneity of entry and exit decisions will cause mitigation bias that undervalues the true effect. Therefore, I will concentrate on particular exit decisions which occurred for reasons unrelated to the dynamics of local supply and demand.

From mid 2008 and through 2009, financial and economic pressure caused specific automotive manufacturers to make drastic changes to their divisions and dealership networks. Starting at the end of 2008, the first wave of GM franchised dealers had their franchise contracts discontinued, which inevitably led to their closures. In April of 2009, after a short lived independent operation separated from DaimlerChrysler, Chrysler LLC. had declared bankruptcy after a period of global losses; this led many franchisees of Chrysler, Jeep, and Dodge to close their doors also. The most dramatic changes were caused by the discontinuation by GM of two entire brand divisions: Saturn and Pontiac. This led to an additional wave of GM dealership closures – shutting down all of the Saturn dealerships, a large portion of dealerships that sold the Buick-GMC-Pontiac combination, and other dealerships selling the Chevrolet, Cadillac, and Hummer brands. Additionally, two Japanese brands – Isuzu (a subsidiary of GM and which was owned for a brief time by Chrysler LLC) and Suzuki – have ceased operations in North America, closing a great majority of their dealerships at one time.

The causes for the above mentioned exits were nationwide and not dependent on market-specific performance by the dealerships which were shut down. Therefore, for a dealership competing with GM or Chrysler, what determined whether or not it would be affected by a rival's exit during the bailouts was its relative proximity to an exiting dealership. Due to the bankruptcy status of these two major auto manufacturers, limitations on dealership terminations were not as binding during the bailouts as they normally would be. Suddenly, GM and Chrysler were given a unique opportunity to sever franchise agreements with many dealerships without the challenge from the state franchise laws, and it is very likely that the dealerships which were chosen for termination had been candidates for termination for quite some time. This should mitigate any concerns regarding selection bias – as while GM and Chrysler may have had some discretion over which dealerships would be shut down during the bailouts, it is the *timing* of these closures that makes them exogenous to local market conditions. Additionally, since the general threat to identification in this setting arises from mitigation bias, we should only be concerned that supposed bias by GM and Chrysler's 'selection into treatment' would mitigate rather than overstate the true effect, since it is very unlikely that these manufacturers would strategically choose to shut down dealerships in booming markets. I proceed by outlining the empirical approach: first, I measure the general effects of local brand competition on the distribution of prices using the HHI as explanatory variable, with the plausibly exogenous exits and brand closures used as instrumental variables. I then proceed to estimate the response of dealers to a single exit event in their local market, in order to analyze the intensity of the pricing response as it varies with the distance to the exiting dealership.

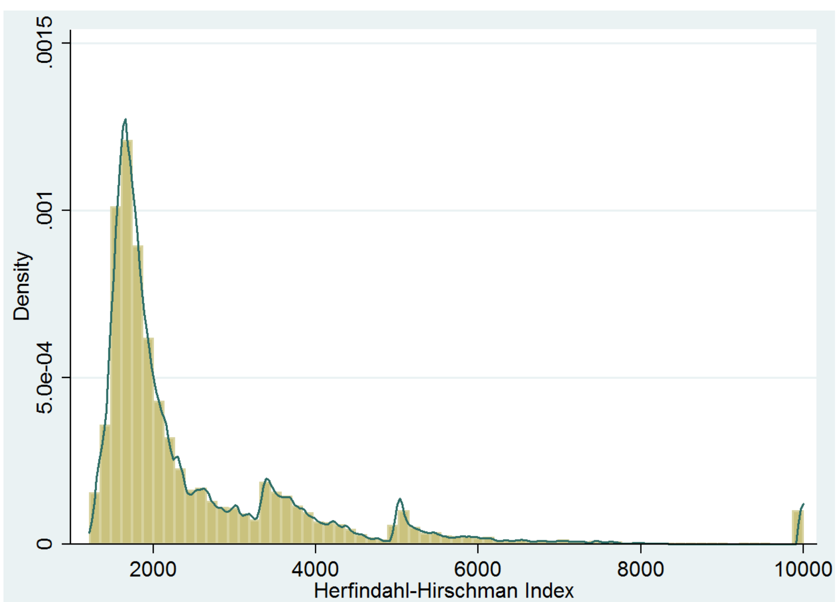
Table 3.7: Sales Under Different Market Concentration Levels

HHI (computed with shares by parent company)	Unconcentrated (HHI <= 1500)	Moderately Concentrated (1500 < HHI <= 2500)	Highly Concentrated (2500 < HHI)
Entire Sample	9.22%	60.79%	29.99%
European Brands (4.74% Share in Sample)	18%	66.86%	15.14%
American Brands (55.5% Share in Sample)	6.4%	49.51%	44.09%
Asian Brands (39.77% Share in Sample)	12.09%	75.82%	12.08%

3.4.1 The Effects of Market Concentration – Instrumental Variables Approach

In this subsection, I estimate an equation in which outcome variables respond to changes in the Herfindahl-Hirschman Index as a measure of market concentration. The HHI is one of the primary tools used by the Department of Justice and the Federal Trade Commission to evaluate the level of competition in merger investigations (DOJ Horizontal Merger Guidelines [37]). It is computed by summing up all squared market shares of firms in a defined local market – i.e. shares of sales occurring at each of the 312 dealership clusters (in which dealerships are at most within a five mile radius of the cluster center) for each quarter from 2004-Q1 to 2010-Q4. Market clusters are defined on a geographical and temporal basis – computing a separate HHI for each local market at each quarter. The shares which factor into the HHI are those of brand parent companies (e.g. Ford, Lincoln, and Mercury would be considered one 'brand', the same as Toyota, Scion, and Lexus; Chrysler, Jeep, and Dodge; all of GM's divisions – Chevrolet, Cadillac, GMC, Buick, etc.) I compute market shares between zero and one to generate HHI's between zero and one to be used in estimation. I report the raw coefficients of HHI when it is between zero and one, but discuss the HHI in the presentation of tables and graphs between zero and 10,000.[13]

Figure 3.6: Distribution of Sales in HHI Levels According to Parent Company



[13]This is a mere rescaling which does not affect the results but handles the HHI in a more convenient scale for estimation; yet it is preferable to discuss the HHI with the common scale of 0-10,000

Table 3.7 shows the percentages of transactions in the sample that fall under each of the market concentration categories as traditionally defined by the DOJ. As evident in table 3.7, 90.78% of the total transactions in the sample occur within markets that are moderately or highly concentrated. Figure 3.6 plots the distribution of all transactions as they occur in markets with varying HHI's, and shows that a significant majority of transactions occur in moderately concentrated markets, in which the HHI is between 1,500 and 2,500. European and Asian are more likely than American brands to be located in unconcentrated (competitive) markets, since these dealership networks tend to be located in central locations which are relatively more populated. Overall, despite the existence of over 40 different brands in the new cars market, which are mere divisions of larger corporations, the actual level of local competition is consistent with the traditional classification of the industry as an oligopoly.

I collapse the data on each geographic market, quarter of sale, brand and vehicle body type. Only observations of transactions occurring in dealerships that never experienced a change to their normal operation during the sample period are included in this sample. I explicitly avoid a structural modeling framework and do not propose to derive an equation from a theoretical model. Rather, I specify the following reduced form equation for estimation:

$$y_{bsmt} = \alpha + \delta_t + \gamma_m + \beta_b^1 + \beta_s^2 + \lambda_1 HHI_{mt} + \lambda_2 HHI_{mt}^2 + \epsilon_{bsmt} \tag{3.1}$$

where $y_{bsmt} \in (\text{VSP}_{bsmt}, \text{MSRP}_{bsmt}, \text{'Discount'}_{bsmt})$, δ_t = represents quarter of sale fixed effects, γ_m = corresponds to local market fixed effects, and β_b^1 and β_s^2 = are the vehicle make and body type fixed. y_{imt} may represent the mean price, MSRP, or discount, as well as several percentiles of their distribution. I also include some measures of price dispersion within the collapsed units, such as the standard deviation, inter-quantile range (the difference between the 75th and 25th percentiles), and the difference between the price that a consumer paid for a vehicle and the lowest price which was paid for that same vehicle at the same dealership within the same quarter of sale. Lastly, I estimate the effect of HHI on the count of sales per dealership per quarter. Given the range of dependent variables of interest, equation 3.1 clearly suffers from omitted variable bias caused by reverse causality. Suppose for example that a demand shock occurs in a market segment that is less price elastic – such as luxury European cars; then a portion of the market which previously experienced relatively low shares will increase its sales – causing the HHI to decrease. Then we might wrongly conclude that a decrease in HHI caused higher prices. Suppose on the other hand that a government program encourages buyers to purchase more fuel efficient cars by offering them a rebate, but at the same time requires that the car be under a certain MSRP to qualify;[14] then, an increase in the market share of cheap vehicles will cause an increase in HHI – which would be connected to lower average prices. Due to the obvious limitation that can be expected in estimating equation 3.1, I include an estimation procedure that utilizes quasi-random exogenous variation in HHI. Exogenous exits by dealers clearly cause changes in local HHI (an average exit increases HHI by between 100 to 200 points), and as long as these exits are not systematically related to the pricing behavior of competitors, dummy variables that indicate when a market cluster experienced an exogenous exit are valid instruments for the changes in local competition that are orthogonal to the pricing dynamics across affected and unaffected local markets. Formally, I define the following instrumental variables: $\mathbf{z}^i_{mt_h} = 1$ if local market m experienced an exogenous dealership or brand closure at time $t - h$ ($h \in \{0, 1, 2\}$), as a result of event i, and $\mathbf{z}^i_{mt_h} = 0$ otherwise. The explicit identification assumption is therefore:

$$E(\epsilon_{bsmt} | \delta_t, \gamma_m, \beta^1_b, \beta^2_s, \mathbf{Z}_{mt}) = 0$$

that is, conditional on fixed effects, vehicle make and body type, exits due to bailouts by competing dealerships are orthogonal to own prices.

The main events that induced plausibly exogenous dealership exits were: (1) GM closing multiple dealerships in two waves, at the end of 2008 and 2009, after suffering losses worldwide; (2) Chrysler LLC announcing bankruptcy in April 2009, followed by a large exit by dealers selling

[14] See the details of the Cash for Clunkers program

the Chrysler, Dodge, and Jeep brands,[15] (3) GM Closing the Saturn brand at the end of 2009 and dropping Pontiac from all dealerships – leaving only GMC, Buick, and Cadillac to accompany the Chevrolet flagship brand; and (4) Suzuki and Isuzu leaving the North American market. These are coded into six separate events that are utilized in varying the local competition index. I include indicators for (a) an exit by dealership selling the Pontiac brand, (b) an exit by a dealership selling the Saturn brand, (c) an exit by a GM dealership that sold neither the Pontiac nor the Saturn brands, (d) a case where a dealership ceased selling the Pontiac brand but did not exit entirely, (e) an exit by a dealership selling any of the Chrysler LLC brands, and (f) an exit by a dealership that sold either the Suzuki or Isuzu brands. I use the quadratic specification of the dependence of outcome variables on HHI to better reflect the difference in marginal effects when markets are more or less concentrated. This allows for a more realistic analysis and reporting of these marginal effects than a linear specification. I report the non-linear marginal effects in section 3.5.

I am conscious of the fact that the above quadratic equation is identified through the usage of 24 dummy variables as instruments – that is, for each of the six distinct exit events, a dummy equals one in affected markets at the time of the exit, and two other dummies indicate the two subsequent periods for the same event. Normally, in such cases in which the causal relationship is represented by a nonlinear function of endogenous variables, one would desire to follow the recommendation in Wooldridge 2010 [72] and apply nonlinear functions of the instruments to identify the quadratic term. However, since all instruments are dummies, this is not possible – but the nonlinear parameter is identified nonetheless. To see this, notice first that since each of the exogenous variables vary HHI qausi-randomly, they also vary HHI^2 quasi-randomly. Second, note that this specification allows for each of the six separate events to have its own 'treatment effect', utilizing the heterogeneous effects in the first stage across different brands and across the different time periods to non-parametrically identify a quadratic curve. For instance, the proposed specification was compared with two specifications, one without the quadratic term, and another using a count of exits and their squares. These two specifications limit place limitations on what the

[15] This large exit was then followed by a recovery period in which some of the markets that saw an exit by Chrysler later had it reenter.

model is able to identify - and while the linear equation was able to measure an effect of decreased competition on higher prices through a sales mix mechanism, the specification using exit counts and their squares was only able to identify increased prices through a negotiations mechanism. The method proposed above identifies both mechanisms (more on that in section 3.5). The model is robust to adding both the proposed instruments above in addition to the exit counts and their squares; however, it is not robust to a solution proposed in Wooldridge 2010 [72] in which the square of the predicted term from the first stage on HHI is used as an instrument for HHI^2. In fact, the results of this method were extremely biased and were very similar to applying the actual 'forbidden regression' that uses the squared prediction of HHI, $\hat{HHI}^2$ directly in the second stage. The reason is that the errors in the first stage are heteroskedastic, and thus, utilizing this prediction introduces systematic errors in the second stage. Lastly, after carefully checking the properties of the first stage, and given the treatment of this issue in Angrist and Pischke 2008 [3], I conclude that the quadratic equation satisfactorily identifies the two endogenous variables through the usage of 24 indicator variables which are uncorrelated with the error term.

In evaluating the quality of identification in each of the estimated equations, I consider two primary statistics: the Wald F-statistic, which determines whether the instruments are weak or if they are effective in varying the HHI sufficiently, and the Sargan P-Value which tests the overidentifying restrictions. After numerous trials, I end up using the same set of instruments for all specifications, which include three dummy variables for each of the events listed above – one for the actual period of exit, and one for each of the two following periods, for markets that experienced an exit. Including more post-periods may certainly provide extra variation in HHI, but it resulted in strong rejection of the over-identification hypothesis – which cast doubt on the reliability of the instruments. Including fewer periods or permanent effects resulted in weak identification, which again, caused the estimates to be biased. I also test whether the addition of three more instrumental variables, which indicate whether a local market experienced an exit of *any* dealership, causes a significant change in results. Due to the nature of franchise regulation in the retail auto industry, I observe no significant change by adding these instruments, as it is highly unlikely that dealership exits are correlated with market performance, since termination of dealerships requires a lengthy process in which the manufacturer must provide sufficient evidence that warrant the discontinuation. I maintain the more conservative specification in the remaining analyses.

3.4.2 Dealers' Response to a Sudden Exit: The Cases of Saturn and Pontiac

At the beginning of 2009, GM had already announced that it would cease manufacturing and end all sales of the Pontiac and Hummer brands by the end of the year. This affected all 160 (out of 312) Texas local market clusters in which a GM branded dealership sold the Pontiac brand. Of the 160 such dealerships, 18 exited entirely, while the remaining 142 continued selling the other GM brands – GMC and Buick. Though market shares of the Pontiac brand alone averaged 2.09% in the markets where it was sold, together with the accompanying brands, Buick and GMC, dealerships selling the Pontiac brand averaged 9.16% in shares of total local sales. Therefore, it was uncertain ex-ante which dealerships would close and which would remain in business, and what potential impact this change would have on local markets and on competitors.

While the discontinuation of the Pontiac brand was a well anticipated event, GM initially had a different plan for its Saturn division and was engaged in negotiations to sell the brand to Penske Automotive, an international transportation services company that also operates car dealerships. The sale of the brand was meant to assure the continuation of its production line for at least two additional years; after which, production would be picked up by a different manufacturer. Unlike Pontiac or Hummer, Saturn's retail network of dealerships sold only the Saturn brand, whereas Pontiac was sold alongside GMC and Buick, and Hummer typically with Cadillac or Saab.[16] Throughout the sample, 29 Texas dealerships sold the Saturn brand only, 12 of which were closed prior to the events of 2009. On September 30th, 2009, the negotiation efforts between GM and Penske Automotive failed, and it was suddenly announced that the Saturn brand would also be discontinued by the end of 2009. This announcement delivered a shock to the 19 local markets that still had an operational Saturn dealership. However, unlike Pontiac dealerships, dealers selling the Saturn

[16]Exceptions are The "Classic" and the "Covert" dealer networks in Texarkana and Austin, respectively, who operated other dealerships in parallel to the Saturn dealership

brand enjoyed a modest average of 3% market share, and it was uncertain whether or not their competitors considered the Saturn exit to have a significant impact on local competition.

The immediate closure of the Saturn and Pontiac brands offers a unique opportunity to study the response of dealerships to changes in local competition. By separating local markets to "treatment" and "control" groups, I am able to exploit a difference-in-differences research design on individual transactions in which "treated" sales are transactions that occurred at a competing dealership (to one that sold Saturn or Pontiac) located within a certain distance from a dealership that either experienced an involuntary closure, or dropped the Pontiac brand but continued selling the GMC and Buick brands. I begin by defining the treatment groups in both cases as including all sales that occur in dealerships that are within one mile (as the crow flies) from the exiting Saturn or Pontiac dealership. I construct a control group composed of sales in all 152 markets that did not have a dealership which sold the Pontiac brand, and which occurred at least 10 miles away from such dealership. For the Saturn case, I cannot define the control group in a similar way since that introduces bias from events that happened simultaneously to the Saturn exit (such as a high incidence of Pontiac, Chevrolet, or Chrysler exits in control markets). Instead, I construct a control group from the 12 local markets in which the Saturn brand was sold in the past, but where the Saturn dealership had to exit in the past for various reasons. This way, I ensure that dealers both in the treatment and control groups are similar, especially in the fact that they have possibly considered Saturn to be a rival at some point.

For both the Saturn and Pontiac cases, I estimate the following two reduced-form difference-in-differences regression equations, measuring both the permanent effects as well as dynamic effects:

$$y_{imt} = \alpha + \delta_t + \gamma_m + \beta X_i + \tau D^p_{it} + \epsilon_{imt} \tag{3.2}$$

where y_{imt} is the dependent variable of interest – vehicle sales price, MSRP, or discount; δ_t are quarter-specific fixed effects; γ_m are market specific geographic fixed effects; X_i's are dummies for make and body type, and ϵ_{imt} is an error term that is allowed to be correlated within the same dealership at any given quarter (using clustered standard errors throughout these estimations). The dummy $D^p_{i,t} = 1$ if transaction i is treated at period t, and $D^p_{i,t+h} = 1 \ \ \forall h > 0$; that is, $D^p_{i,t}$ indicates whether the vehicle was sold at a dealership whose one of its rivals shut down due to the Pontiac or Saturn closures, after the actual exit took place. Therefore, τ is the estimate of the *permanent* local average treatment effect that measures dealers' response to an exit by a competitor. Then, for each of the Saturn and Pontiac cases, I decompose the local average treatment effect by quarters before and after the actual exit, to estimate the following dynamic equation:

$$y_{imt} = \alpha + \delta_t + \gamma_m + \beta X_i + \tau^0 D^q_{it} + \tau^{pre} Pre_{it} + \tau^{post} Post_{it} + \epsilon_{imt} \tag{3.3}$$

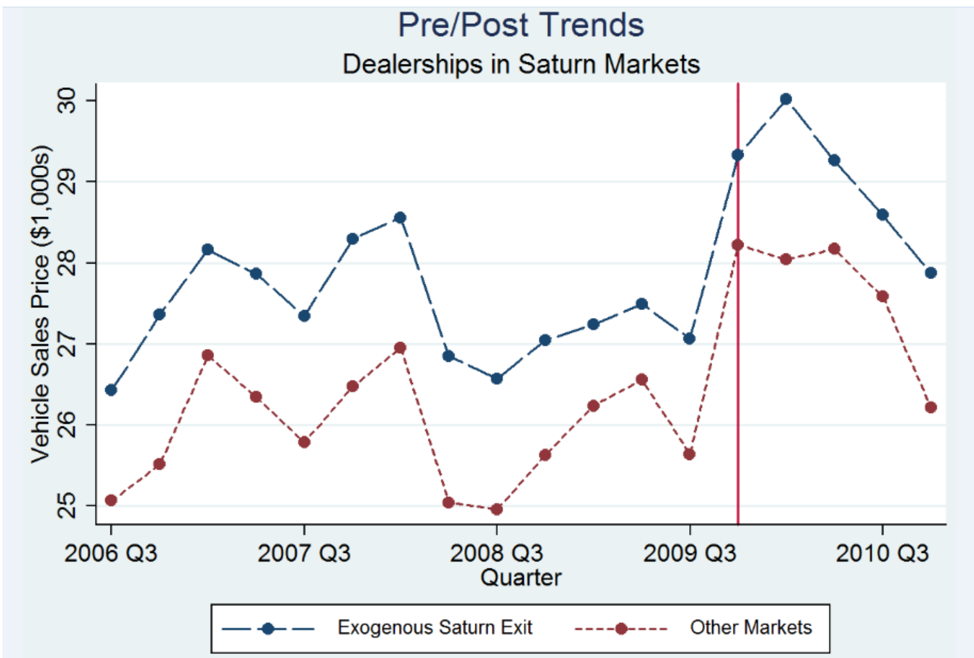
in which $y_{imt} \in (\text{VSP}_{imt}, \text{MSRP}_{imt}, \text{'Discount'}_{imt})$, δ_t = represents quarter of sale fixed effects, γ_m = stands for local market fixed effects, and X_i = is a set of vehicle characteristics (make & body type). Since both specifications utilize individual transactions, standard errors are clustered at m and t. The dummy variable $D^q_{i,t} = 1$ if transaction i is treated at period t, and $D^q_{i,t+h} = 0 \ \ \forall h > 0$. $Pre_{i,t_h} = 1$ only if transaction i is treated at period $t + h$, for $h \in \{1, \ldots, 8\}$; $Post_{i,t_h} = 1$ only if transaction i is treated at period $t - h$, for $h \in \{1, \ldots, 4\}$. In both cases, an individual sale is affected if it occurs within the particular treatment radius: $R \in \{1, 2, 3, 4, 5\}$ miles, while a sale is fixed in the control group for Pontiac if it is at least 10 miles away from any Pontiac/GMC/Buick dealership. The formal identification assumption is therefore:

$$E(\epsilon_{imt} | \delta_t, \gamma_m, X_i, D_i) = 0$$

which means that conditional on fixed effects, vehicle make and body type, prices would not have differed in the absence of treatment due to bailouts.

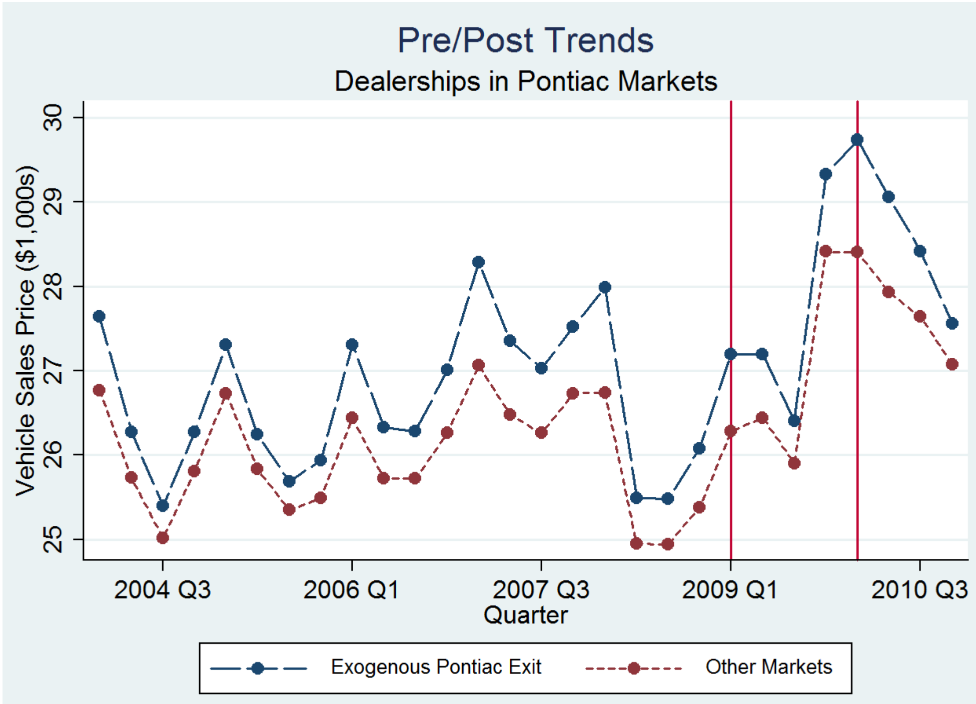
The last specification is similar to equation 3.2 except that the dummy D_{imt} consists of an indicator regarding whether the vehicle was sold at a dealership whose one of its rivals shut down in the previous quarter. The vectors Pre_{imt} and $Post_{imt}$ consist of dummy variables for up to four quarters before and three quarters after the actual exit. With the specification in equation 3.3, I am able to track the timing of the first treatment effect, and to examine the gradual anticipation to and recovery from the actual exit.

Figure 3.7: Pre-Post Trends; Dependent Variable – Vehicle Sales Price



Figures 3.7 and 3.8 help to graphically illustrate the validity of the identification assumptions in this section, as the response to the disappearing Saturn and Pontiac brands was starkly visible in the immediate quarter after these brands exited the market. These figures show a close parallel in the pricing trends between the treatment and control groups prior to the affected periods, as all quarterly shifts follow along in similar directions up until the point of the actual dealership exits. Then, immediately a sharp differential change in average prices is evident. In particular, average vehicle sales prices increase sharply during the first quarter of 2010 for the treatment groups while decreasing for the control groups. The similarities between treatment and control markets in both the Saturn and Pontiac cases confirm that the identification strategy should deliver a credible local

Figure 3.8: Pre-Post Trends; Dependent Variable – Vehicle Sales Price



average treatment effect, and corroborate the a priori presumption that exits during the bailouts period were exogenous to local market conditions.

3.5 Results

This section outlines the estimation results of all specifications mentioned above. The consistent pattern of evidence shows that average prices of new vehicles have increased at the remaining dealerships after some of their rival brands or entire dealers exited their local market. This pattern stands in contrast to a scenario in which exit is endogenous to market conditions, because in that situation we would expect to see exits occurring as a response to a decline in demand along with decreasing prices. In both of the following subsections, it appears that the overall increase in prices as a result of decreased competition is driven both by having a more expensive sales mix as well as by an adjustment of price negotiations. There is substantial variation in the incidence of price effects with regards to (a) the placement of a transaction in the price distribution given the make and body type, (b) whether or not consumers used a trade-in toward partial payment, (c) whether the transaction was for a pickup truck, SUV, or a sedan, and (d) how close the transaction is to an exiting rival dealership or brand in terms of physical proximity. This variation in incidence is consistent with a behavioral explanation in which new-car sellers perceive new consumers joining their residual demand after the exit of a rival dealership, and respond strategically by adjusting their pricing behavior to a new distribution of willingness-to-pay.

3.5.1 The Effects of the Herfindahl-Hirschman Index on Prices

Table 3.8: Comparison of the Effects of HHI on the Mean, 1st, and 3rd Quartiles of Vehicle Sales Price

	OLS			IV1[a]			IV2[b]		
	Mean	1st	3rd	Mean	1st	3rd	Mean	1st	3rd
HHI[c]	3.38	3.52	3.19	15.46	9.89	22.43	15.63	10.67	21.39
	(1.23)	(1.22)	(1.58)	(9.2)	(9.18)	(11.87)	(9.31)	(9.3)	(12.02)
HHI^2	-3.16	-2.86	-3.09	-15.89	-5.82	-27.21	-15.88	-5.93	-25.81
	(1.16)	(1.16)	(1.5)	(12.18)	(12.16)	(15.71)	(12.3)	(12.28)	(15.86)
R^2	0.857	0.836	0.812	0.857	0.836	0.811	0.857	0.836	0.812
Sargan P-Value		-		0.984	0.926	0.892	0.96	0.853	0.876
LM Statistic		-			298.69			295.06	
Wald F-Statistic		-			12.465			14.073	
Marginal Effect:									
(HHI=1500)									
ΔHHI = 100	$24.01	$26.37	$22.37	$105.37	$82.86	$140	$107.05	$88.37	$133.86
(P-value)	(0.008)	(0.003)	(0.055)	(0.074)	(0.161)	(0.067)	(0.074)	(0.14)	(0.083)
ΔHHI = 200	$47.39	$52.17	$44.13	$207.56	$164.69	$274.56	$147.42	$151.84	$159.3
(P-value)	(0.008)	(0.003)	(0.056)	(0.074)	(0.156)	(0.067)	(0.074)	(0.136)	(0.84)
Marginal Effect:									
(HHI=2500)									
ΔHHI = 100	$17.68	$20.65	$16.2	$73.58	$72.49	$85.58	$75.3	$76.52	$82.23
(P-value)	(0.014)	(0.004)	(0.081)	(0.084)	(0.088)	(0.119)	(0.08)	(0.075)	(0.139)
ΔHHI = 200	$34.73	$40.72	$31.78	$143.99	$143.94	$165.72	$147.42	$151.84	$159.3
(P-value)	(0.015)	(0.004)	(0.083)	(0.086)	(0.086)	(0.126)	(0.082)	(0.073)	(0.146)
HHI s.t. ME=0:	5343.68	6157.4	5173.55	4864.91	9539.34	4122.76	4921.53	9004.57	4142.85

[a] Variation in HHI induced by select exits (including Pontiac) during the 2008-2009 period, and any other exit.
[b] Variation in HHI induced by select exits (and dealers dropping Pontiac) during the 2008-09 period only.
[c] All specifications include quarter, market, make, and body type fixed effects.

Table 3.9: Effect of Local Competition - Shares by Brand Parent Company

Dependent Variable	Mean	1st Decile	1st Quartile	Median	3rd Quartile	9th Decile
Vehicle Sales Price						
β_{HHI}	15.46	7.28	9.89	8.49	22.43	29.06
	(9.20)	(9.21)	(9.18)	(10.05)	(11.87)	(14.26)
β_{HHI^2}	-15.89	0.07	-5.19	-6.05	-27.21	-42.71
	(12.18)	(12.19)	(12.16)	(13.30)	(15.71)	(18.88)
R^2	0.8569	0.8245	0.8355	0.8325	0.8114	0.7739
Sargan P-Value	0.9837	0.7584	0.9258	0.9926	0.8922	0.9423
Marginal Effect at HHI=1500:						
ΔHHI = 100 points	$105.37	$73.04	$82.86	$66.11	$140.0	$158.18
(P-value)	(0.075)	(0.217)	(0.161)	(0.306)	(0.067)	(0.085)
ΔHHI = 200 points	$207.56	$146.1	$164.69	$131.01	$274.56	$307.81
(P-value)	(0.074)	(0.21)	(0.156)	(0.303)	(0.067)	(0.088)
Marginal Effect at HHI=2500:						
ΔHHI = 100 points	$73.58	$73.18	$72.49	$54.02	$85.58	$72.76
(P-value)	(0.084)	(0.086)	(0.088)	(0.245)	(0.119)	(0.27)
ΔHHI = 200 points	$143.99	$146.37	$143.94	$106.83	$165.72	$136.97
(P-value)	(0.086)	(0.081)	(0.086)	(0.243)	(0.126)	(0.292)
HHI at which ME is zero:	4864.91	-	9539.34	7017.59	4122.76	3401.72

Wald F-Statistic for the first stage: 12.465 ; LM Statistic: 298.687.

The first set of results reported in this section shows the difference between the Naive OLS estimation, and the approach using instrumental variables to vary the HHI exogenously. In table 3.8, the first panel reports the effect of HHI and HHI^2 on the mean, first quartile, and third quartile of prices for each market-quarter-make-body type combination in the analysis group, using an OLS regression. Though the marginal effects (reported at the bottom of the table) are strongly statistically significant, their values are significantly attenuated and are not very economically significant. This is consistent with the attenuation bias discussed in section 3.4. Panels IV1 and IV2 reveal the magnitude of the attenuation bias present in the OLS, as the marginal effect more than quadruples in size, albeit the statistical significance diminishes. Panel IV1 uses three more instrumental variables than IV2 that indicate an exit of any kind, not just exits during the financial crisis. The results are not very different across the specifications in IV1 and IV2, and I proceed with the method in IV2 as it provides slightly more conservative estimates for the marginal effects at the higher end of the price distribution. In both IV1 and IV2 panels, it is clear that the instruments are relevant and do not exhibit weak-instruments properties. Also we are reassured that the model is not over-identified, as instruments seem to provide sufficient identification power. This pattern is consistent along the remaining results, which reassures that the reported estimates are credibly identified with the Instrumental Variables model.

Tables 3.9 and 3.10 report the main results of this paper in tabular format, while the remaining results from the IV model will be reported in graphs that depict the marginal effect, which is non-linear in HHI levels. Each panel lists the distributional effects on the mean, first decile, first quartile, median, third quartile, and ninth decile of the dependent variable. At the bottom of each panel, I include the estimate of the marginal effects of an increase in HHI (which indicates decreased competition) by 100 and 200 points, in markets where the HHI is 1,500 and 2,500. I also include at the bottom row the level of HHI at which the marginal effect would be zero (due to the quadratic specification, certain regions of HHI may have a negative marginal effect). From table 3.9, we learn that the marginal effect of an increase in HHI is higher at the upper side of the price distribution when markets are more competitive. This means that in relatively competitive markets, a decrease in competition will lead to a response by dealers that increases prices for consumers who are relatively less price sensitive and who already pay a higher than average price for their vehicles. As markets become less competitive, however, the significance of the effect shifts to the lower end of the price distribution. Table 3.10 reports the decomposition of the effect on prices through two mechanisms by which prices increase at the lower and higher ends of the price distribution. First, it is seen that discounts diminish significantly at the lower end of the discount distribution – meaning that consumers who typically receive a low discount now receive an even lower one, after a decrease in local competition. This effect is consistent in relatively competitive and moderately concentrated markets. Secondly, we learn that the source of the price increase for the lower end of the price distribution was an increase in MSRP.

Table 3.10: Effect of Local Competition - Shares by Brand Parent Company

Dependent Variable	Mean	1st Decile	1st Quartile	Median	3rd Quartile	9th Decile
MSRP						
β_{HHI}	7.63	8.87	5.56	2.20	-1.44	18.60
	(8.89)	(9.49)	(9.75)	(10.54)	(11.85)	(13.58)
β_{HHI^2}	-6.02	-1.52	0.90	1.24	-0.34	-31.08
	(11.76)	(12.56)	(12.91)	(13.96)	(15.70)	(17.98)
R^2	0.8481	0.8072	0.8030	0.7963	0.7862	0.7577
Sargan P-Value	0.9757	0.9792	0.9901	0.9812	0.7395	0.4993
Marginal Effect at HHI=1500:						
ΔHHI = 100 points	$57.67	$83.99	$58.37	$25.87	-$15.39	$89.63
(P-value)	(0.313)	(0.169)	(0.352)	(0.703)	(0.84)	(0.305)
ΔHHI = 200 points	$114.14	$167.67	$116.92	$51.99	-$30.85	$173.05
(P-value)	(0.31)	(0.162)	(0.343)	(0.697)	(0.837)	(0.314)
Marginal Effect at HHI=2500:						
ΔHHI = 100 points	$45.63	$80.96	$60.18	$28.36	-$16.06	$27.47
(P-value)	(0.267)	(0.065)	(0.182)	(0.561)	(0.770)	(0.662)
ΔHHI = 200 points	$90.05	$161.61	$120.53	$56.96	-$32.19	$48.72
(P-value)	(0.266)	(0.062)	(0.175)	(0.554)	(0.766)	(0.694)
HHI at which ME is zero:	6338.56	-	-	-	-	2991.91
MSRP-Price						
β_{HHI}	-7.75	-22.15	-12.82	-5.48	-3.36	2.71
	(5.11)	(6.98)	(5.76)	(5.34)	(5.94)	(6.79)
β_{HHI^2}	9.82	29.34	16.04	6.55	3.84	-3.94
	(6.77)	(9.25)	(7.63)	(7.07)	(7.86)	(8.99)
R^2	0.4169	0.3191	0.3643	0.4106	0.3979	0.3791
Sargan P-Value	0.0341	0.8464	0.8566	0.0324	0.0014	0.0000
Marginal Effect at HHI=1500:						
ΔHHI = 100 points	-$47.07	-$130.52	-$78.41	-$34.48	-$21.74	$14.86
(P-value)	(0.152)	(0.004)	(0.034)	(0.315)	(0.569)	(0.734)
ΔHHI = 200 points	-$92.18	-$255.17	-$153.61	-$67.65	-$42.72	$28.92
(P-value)	(0.154)	(0.004)	(0.035)	(0.317)	(0.569)	(0.736)
Marginal Effect at HHI=2500:						
ΔHHI = 100 points	-$27.43	-$71.84	-$46.31	-$21.39	-$14.06	$6.97
(P-value)	(0.246)	(0.026)	(0.082)	(0.386)	(0.609)	(0.824)
ΔHHI = 200 points	-$52.90	-$137.81	-$89.41	-$41.47	-$27.36	$13.15
(P-value)	(0.256)	(0.03)	(0.089)	(0.394)	(0.613)	(0.832)
HHI at which ME is zero:	3946.89	3774.2	3992.9	4183.65	4381.94	3434.26

Wald F-Statistic for the first stage: 12.465 ; LM Statistic: 298.687.

Figure 3.9: Marginal Effects of Decreased Competition on the Price Distribution

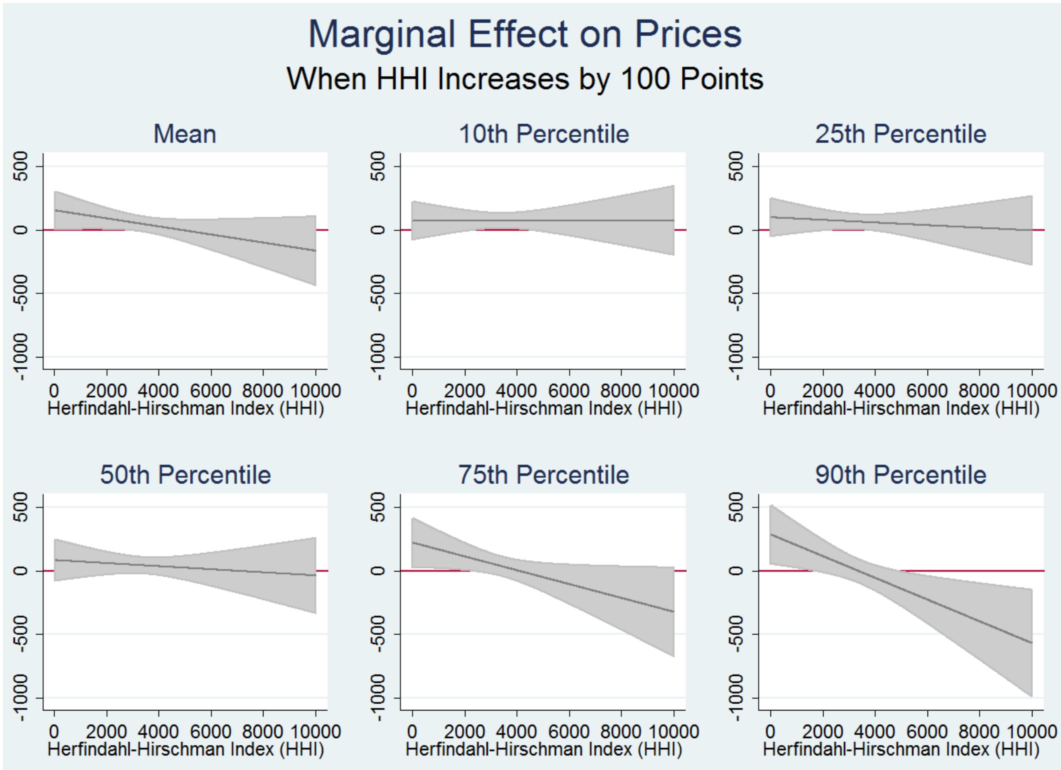
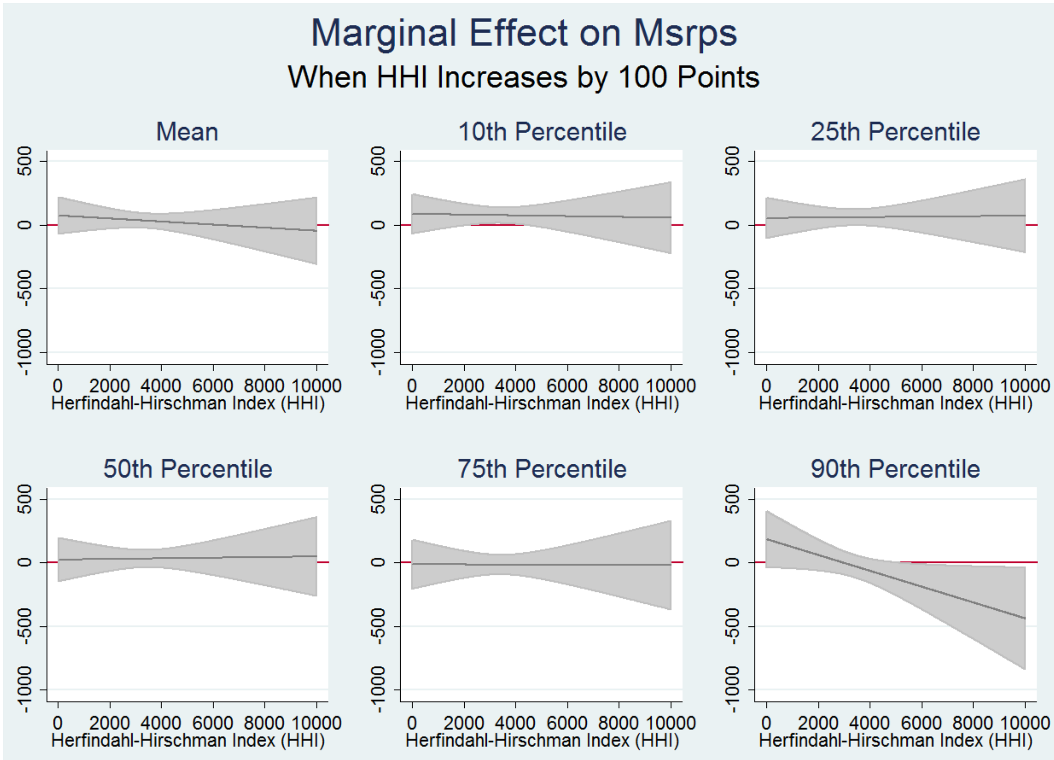


Figure 3.9 depicts the same results reported at the panel of table 3.9 in graphic form. In each panel of figure 3.9, the 'Y' axis represents the marginal effect of a 100-point increase in HHI on average prices paid by consumers. A 90% confidence interval is drawn around the point estimate, and areas in which the entire confidence interval is above (or below) the 'X' axis are statistically significant at the 10% level. The graphs show that it is rare for the marginal effect to be negative, and the depiction on the graph is done by extrapolation. A negative effect is only documented in markets which are very concentrated and only for the customers buying the most expensive products. Decreased competition causes higher mean prices, with consumers of expensive products are affected in the more competitive environments, while purchasers of less expensive products being affected in moderately concentrated markets.

Figure 3.10: Marginal Effects of Decreased Competition on the MSRP Distribution



Estimation of the model on the decomposition of the final transaction price into MSRP and 'discount' reveals further information about the type of sales response applied to different consumers. In figure 3.10, we observe that the increase in average prices for buyers of less expensive vehicles, in markets which are relatively concentrated, is driven by an increase in MSRP. This type of response indicates that dealers are selling a more expensive sales mix, or higher trim lines given specific models. The fact that this influence is seen at the lower end of the price distribution indicates that dealers have influenced the choice set available to these consumers by ordering more expensive vehicles from manufacturers. Consumers interested in the less expensive alternatives do not have the option to purchase them at their local market. It is also seen that the projected negative effect on prices at the higher end of the price distribution is attributed entirely to a sales mix; simply stated – decreased competition in areas which are already concentrated will cause the remaining dealerships to fill their lots with a more even mix of the higher trim line options (possibly to accommodate a demand shift).

Figure 3.11: Marginal Effects of Decreased Competition on Negotiation Outcomes

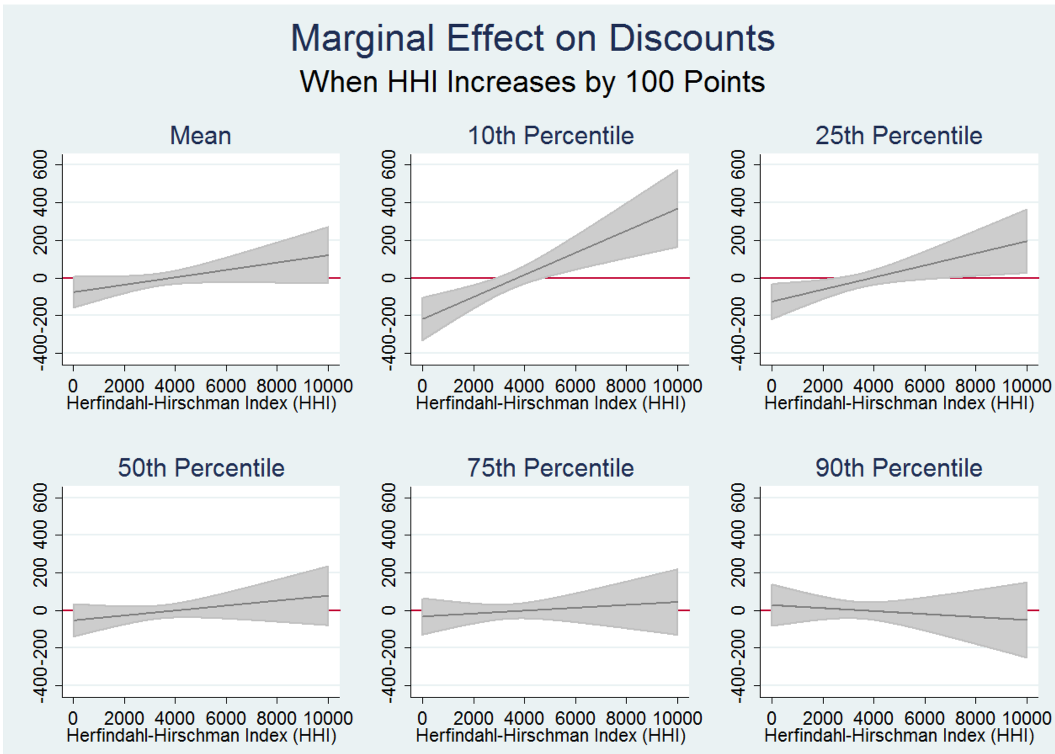
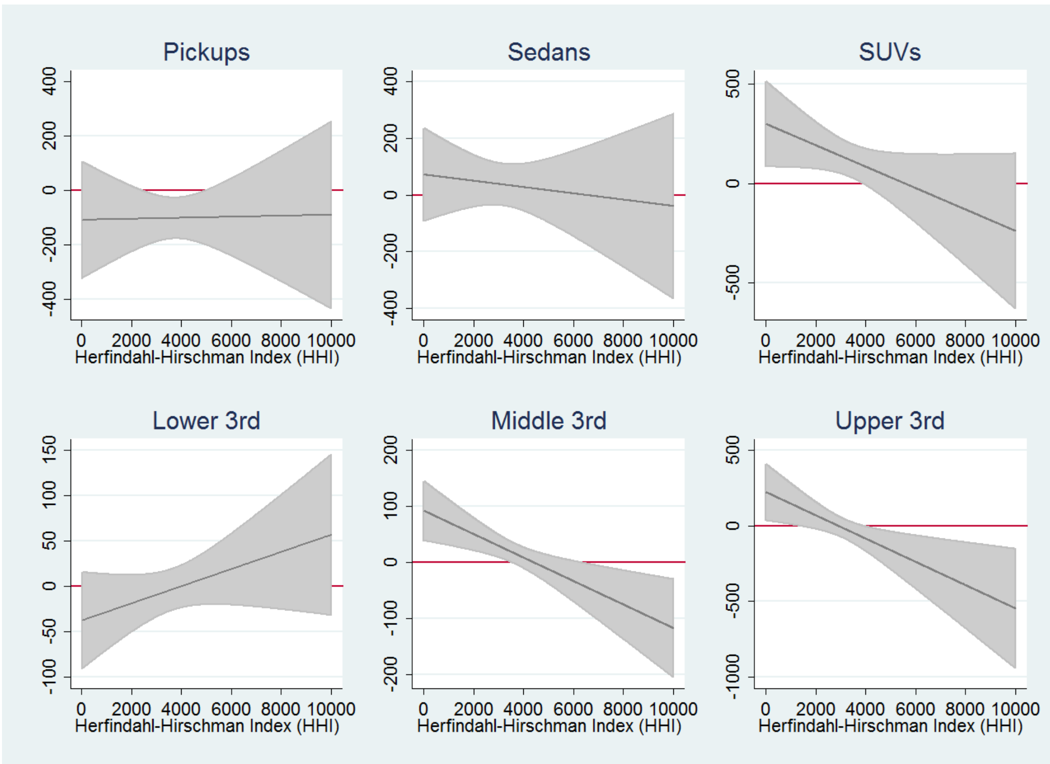


Figure 3.11 shows the effects of a 100-point HHI increase on dealer 'discounts' measured by the difference between the MSRP and the transaction price. I am unable to distinguish which portion of this difference was driven by rebates to consumers as opposed to additional sales of options which are added-on to the sale at the dealership. Both mechanisms operate in a similar direction – the higher the final transaction price is relative to the MSRP, the happier the seller. We learn from figure 3.11 that for the portion of consumers who either receive lower discounts or who buy many add-ons, the difference between MSRP and the transaction price decreases at competitive and moderately concentrated markets, while it is projected to be increasing at very concentrated markets. This is the portion of consumers who is most likely to include individuals with bargaining disutilities and an aversion to search, which shows a negotiation outcome more

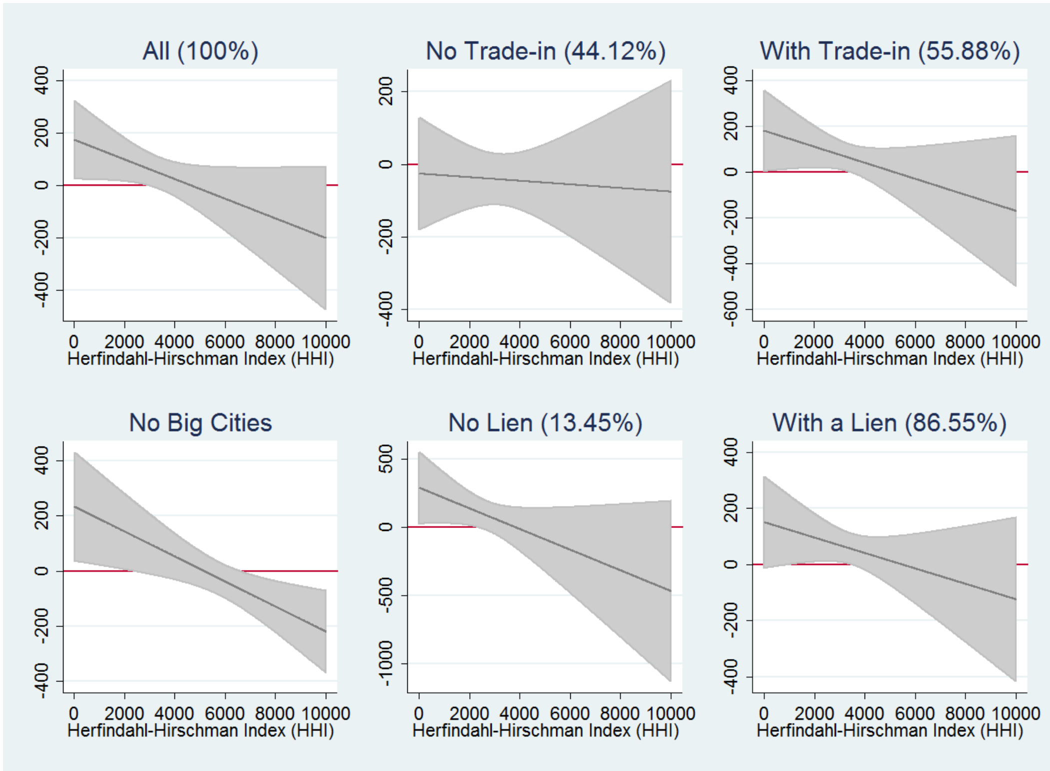
favorable to the seller. The fact that decreased competition causes these individuals to pay higher prices by means of negotiation outcomes indicates that sellers are strategically choosing where to exercise their market power.

Figure 3.12: Breakdown of the Marginal Effect on Average Prices Based on Vehicle Type



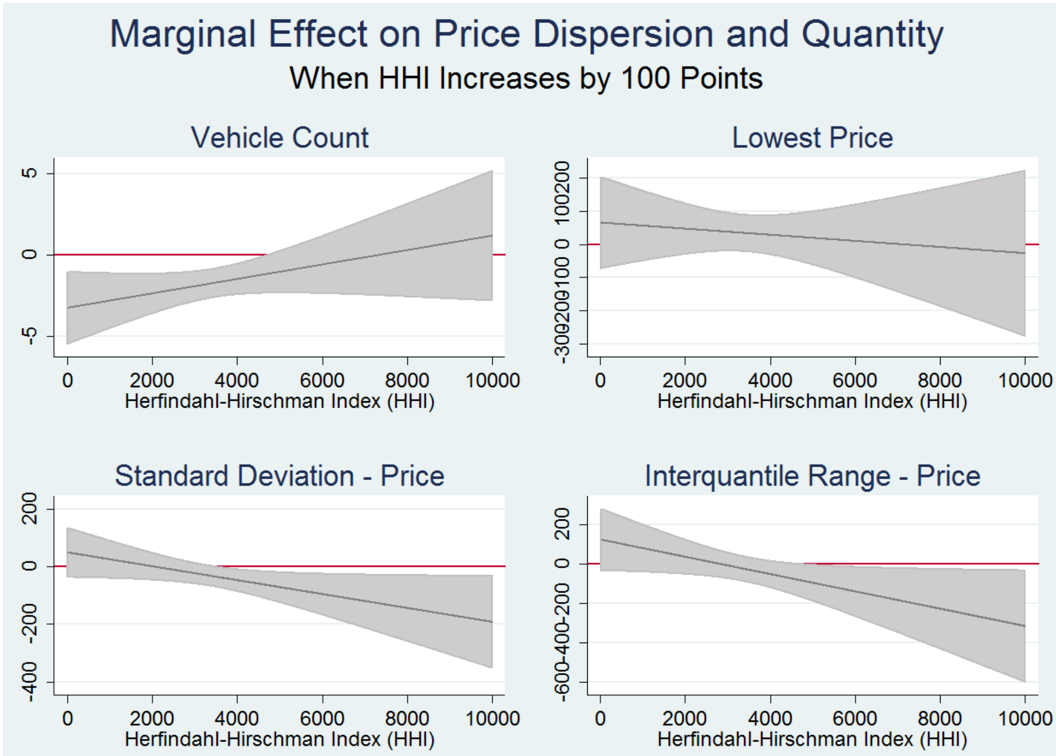
I proceed to outline a further breakdown of the effect of reduced competition on average transaction prices in figures 3.12 and 3.13. In figure 3.12, I split the sample and estimate the model separately for each of the three most popular vehicle body types – pickups, SUVs, and sedans – and separately collapse each of the three thirds of price ranges conditional on vehicle make and body type. I find that almost the entire incidence of the effect on average transaction prices falls on buyers of SUVs, with a negative effect on buyers of pickups. This is not surprising if we consider that the majority of exiting dealerships, especially carrying the discontinued GM brands, were primarily selling sedans and SUVs (Saturn and Pontiac had no pickups in their production lines).

Figure 3.13: Breakdown of the Marginal Effect on Average Prices Based on Payment Method



In addition, we see that the price effect was exclusively concentrated in the middle to higher price ranges of these vehicles. This is again consistent with an explanation that sellers choose to exercise their market power strategically. Figure 3.13 shows another interesting outcome. First, we notice that when we exclude large metropolitan areas from the sample we still obtain a statistically significant estimate of the marginal effect, netting out any spillovers which may occur among urban local markets which are close to one another. Moreover, we see that both consumers who finance their purchase with a lien on the vehicle and those who do not, experience a positive marginal effect. Most interestingly, the incidence of the average price increase as a result of decreased competition seems to fall almost entirely on consumers who partially finance their purchase with a trade-in. This result comes in a striking resemblance to the finding in Kwon et al 2015 [44], which shows that dealers charge higher prices to customers who trade-in used cars, further solidifying the impression that the price effect is explained by seller behavior.

Figure 3.14: Marginal Effects of Decreased Competition on Quantity and Price Dispersion



Lastly, figure 3.14 illustrates the three measures of dispersion considered: the standard deviation of prices, inter-quantile range of prices, and the difference between price paid and lowest price accepted for each particular subset of vehicles. These measures do not point to significant price dispersion resulting from decreased competition, and instead suggest that price dispersion conditional on make and body type declines in markets which are already concentrated. The first panel of figure 3.14 depicts the effect of decreased competition on the sales count, and shows that quarterly sales decrease by three-to-four vehicles per dealership in affected markets (the baseline of the number of sales depends on the size of the dealership; the average quantity of vehicles sold, conditional on make and body type per dealership, ranges between 40-50 units).

3.5.2 Difference-in-Differences

Table 3.11 reports the estimates of the permanent average treatment effect derived in the difference-in-differences estimation, with treatment defined when a transaction occurs at a dealer-

Table 3.11: Difference-in-Difference Estimation Results - Saturn and Pontiac Exit

	Radius around Saturn in "Treated" Markets				
	1 Mile	2 Miles	3 Miles	4 Miles	5 Miles
Vehicle Sales Price	$286.08	$233.42	$79.12	$152.89	$163.64
	(225.73)	(157.70)	(150.08)	(144.36)	(144.79)
MSRP	$182.72	$13.45	$60.32	$184.92	$180.63
	(159.68)	(116.90)	(103.12)	(112.79)	(113.58)
MSRP-Price	-$103.36	-$219.97**	-$18.80	$32.03	$16.99
	(150.50)	(111.99)	(103.24)	(111.45)	(110.67)
N	576,946	871,722	1,094,416	1,233,068	1,264,024
	Radius around Pontiac in "Treated" Markets				
	1 Mile	2 Miles	3 Miles	4 Miles	5 Miles
Vehicle Sales Price	$237.2**	$251.68***	$285.28***	$272.51***	$293.5***
	(102.07)	(94.02)	(90.35)	(88.50)	(87.72)
MSRP	$238.58***	$225.71***	$195.85***	$149.72**	$163.64**
	(77.52)	(70.50)	(66.89)	(64.31)	(63.86)
MSRP-Price	$1.38	-$25.97	-$89.43	-$122.80*	-$129.86**
	(81.66)	(71.39)	(68.65)	(66.86)	(66.19)
N	1,976,250	2,470,968	2,771,318	2,986,926	3,035,969

All specifications include market, quarter, make, and body-type fixed effects
Standard errors clustered at the dealership level for each quarter.

ship which is located within a specified mile radius from another dealership that previously sold the Saturn or Pontiac brands and no longer does, due to mass closures. The first panel is defined by a one-mile radius around the exiting dealership, and then the radius is gradually increased to two, three, four, and five miles. The outcome variables analyzed throughout these specifications are the average vehicle sales price, the average vehicle MSRP, and the average difference between the MSRP and the sales price. The first measures the overall effect of the response by dealerships on the prices that consumers pay for their cars, and the latter two differentiate the source of the price change. If there is a change in vehicle prices due to a change in MSRP, this is attributed to a different product mix offered by the dealership; and if the change is due to the change in the difference between MSRP and prices, then that is attributed to difference in negotiation. The top panel presents the results for the Saturn exit, which shows an increase in average prices in the one-mile radius, driven by both a higher MSRP and lower discounts; however, none of these effects are statistically significant. When expanding the treatment group to two miles, the reduction in discounts becomes significant but the overall increase in price is not. Going further away from the exiting Saturn, the effects become much less pronounced or stable, with the effect on discounts changing its sign at the four-mile range. The bottom panel of table 3.11 shows that competing dealers responded to the Pontiac exit much more than tha Saturn exit, with statistically significant price and MSRP increases. It appears that dealerships which were closer to the affected locations responded more with higher MSRP's than other dealerships located in the same market cluster, who responded with lower discounts.

Table 3.12: Difference-in-Difference Estimation Results - Saturn Exit

Dependent Variable	**Radius around Saturn in "Treated" Markets**				
	1 Mile	2 Miles	3 Miles	4 Miles	5 Miles
Vehicle Sales Price					
T_{-4}	-\$471.45	-\$516.71	-\$433.64	-\$418.1	-\$412.61
	(497.12)	(376.69)	(331.15)	(323.26)	(324.58)
T_{-3}	-\$202.81	-\$210.54	-\$75.88	\$46.43	\$50.19
	(416.56)	(283.2)	(250.87)	(246.66)	(247.49)
T_{-2}	\$291.02	\$78.06	\$113.12	\$196.83	\$204.12
	(348.21)	(236.5)	(213.7)	(209.22)	(211.38)
T_{-1}	\$488.48	\$121.34	-\$74.05	\$36.1	\$61.58
	(502.62)	(359.89)	(344.25)	(333.21)	(337.71)
T	**\$835.35***	**\$387.25**	**\$264.52**	**\$343.1**	**\$331.79**
	(485.41)	(359.95)	(327.39)	(320.15)	(320.1)
T_{+1}	\$162.31	\$185.69	\$110.14	\$215.39	\$222.06
	(413.07)	(284.71)	(276.73)	(267.51)	(269.01)
T_{+2}	\$242.79	\$159.9	\$123.01	\$195.31	\$210.43
	(346.78)	(272.77)	(261.46)	(255.63)	(257.18)
T_{+3}	\$152.8	\$239.14	-\$169.72	-\$124.33	-\$84.7
	(531.83)	(330.07)	(323.98)	(296.88)	(296.48)
N	576,946	871,722	1,094,416	1,233,068	1,264,024

Breaking down the permanent effects of the single event, in tables 3.12 and 3.13, I report the effects of being near a Saturn dealership up to four quarters prior to its exit, at the quarter immediately following its exit, and up to three quarters after that. Tables 3.14 and 3.15 report the same thing for the Pontiac exits. A significant increase in the average vehicle sales price exists at the quarter immediately after the Saturn exit among dealerships located within one mile of the Saturn dealership. This is the most pronounced price increase of over \$800 occurring at the quarter which followed immediately after the Saturn dealerships' ceased operation. Half of this increase is attributed to higher MSRP, the other half to a decrease in discounts. This breakdown shows a mixed response by dealers who are near a competitor – anticipating a higher ability of selling more expensive vehicles and ordering a product mix with a higher MSRP – while at the same time exhibiting less bargaining flexibility. At the bottom panel, it is clearly noted that the average treatment effect in terms of reducing discounts is mitigated as we expand the treatment group to include dealerships that are farther from the Saturn location. Overall, tables 3.11, 3.12, and 3.13 report a very modest response by competitors to the sudden exit by Saturn. However, due to the stark difference between the effects when the treatment group is composed of sales within one mile around the exiting dealership, as opposed to two miles or higher, it is clear that the closest dealerships certainly anticipated an increased ability to sell more expensive vehicles while offering lower discounts.

The same decomposition of temporal effects is reported for the Pontiac exits in tables 3.14 and 3.15, where an increase in average prices is documented as soon as sales for the Pontiac brand ceased, lasting for two more quarters afterwards. Similar to the Saturn exits, a large component of the price increase is due to dealerships selling vehicles with a \$200-\$400 higher MSRP; however, unlike the Saturn exits, there is little response in terms of discounts, and the recorded estimate is not statistically significant. It also appears that the response to the Pontiac exits took place in the entire relevant local market area and not only among dealerships closest to a Pontiac seller; though it is evident that the response patterns last longer, and are stronger in terms of MSRP, at the locations that are physically closer to the exiting Pontiac brand. The fact that none of the effects (with two exceptions) in any of the panels is significant for the periods leading to the Pontiac exit, and that statistically significant effects lasted no longer than two periods after the exit, strengthens the interpretation that the reported results are caused by the period of decreased competition after the exogenous exits took place. The fact that the effect on MSRP was more pronounced than the effect on discounts, teaches us that dealerships may have ordered more expensive vehicles from manufacturers, filling their lots with higher trim-line models, in anticipation of reduced competition. Since all vehicles in dealers' inventories must eventually be sold, this may explain a lasting effect on MSRP for two more periods, accompanied with modest effect on discounts.

Table 3.13: Difference-in-Difference Estimation Results - Saturn Exit

Dependent Variable	**Radius around Saturn in "Treated" Markets**				
	1 Mile	2 Miles	3 Miles	4 Miles	5 Miles
MSRP					
T_{-4}	-$597.66	-$633.33*	-$467.53	-$462.87	-$472.55
	(476.34)	(361.51)	(318.52)	(309.70)	(311.34)
T_{-3}	-$313.32	-$487.92*	-$272.07	-$209.82	-$207.96
	(333.10)	(265.26)	(243.85)	(237.14)	(239.29)
T_{-2}	$72.70	-$169.12	$22.32	$84.01	$87.20
	(251.17)	(210.02)	(195.93)	(189.21)	(189.68)
T_{-1}	$291.18	-$113.73	-$114.08	-$39.95	-$25.53
	(319.19)	(289.74)	(275.12)	(268.82)	(275.49)
T	**$398.24**	**-$16.93**	**$61.77**	**$153.85**	**$144.03**
	(306.99)	(236.13)	(204.07)	(217.11)	(217.9)
T_{+1}	$8.34	-$130.29	$17.72	$192.64	$193.64
	(267.42)	(182.71)	(164.91)	(191.36)	(193.4)
T_{+2}	$189.34	-$3.83	$132.7	$246.38	$239.68
	(299.27)	(235.88)	(213.26)	(232.01)	(233.95)
T_{+3}	$148.47	$80.1	-$38.24	$80.55	$80.08
	(316.13)	(234.99)	(206.8)	(224.32)	(224.67)
MSRP-Price					
T_{-4}	-$126.21	-$116.62	-$33.89	-$44.78	-$59.94
	(184.06)	(172.09)	(151.1)	(144.62)	(143.14)
T_{-3}	-$110.51	-$277.38	-$196.19	-$256.24	-$258.15*
	(208.89)	(194.7)	(165.73)	(157.28)	(156.66)
T_{-2}	-$218.32	-$247.17	-$90.8	-$112.82	-$116.91
	(247.65)	(190.95)	(173.17)	(164.57)	(164.54)
T_{-1}	-$197.3	-$235.07	-$40.02	-$76.06	-$87.11
	(263.69)	(201.27)	(183.62)	(174.88)	(174.23)
T	**-$437.11**	**-$404.18***	**-$202.75**	**-$189.25**	**-$187.77**
	(282.62)	(225.08)	(213.8)	(212.2)	(211.29)
T_{+1}	-$153.97	-$315.98	-$92.42	-$22.75	-$28.42
	(261.07)	(207.58)	(198.95)	(219.4)	(218.25)
T_{+2}	-$53.44	-$163.73	$9.69	$51.07	$29.26
	(234.14)	(190.2)	(179.41)	(197.87)	(196.42)
T_{+3}	-$4.32	-$159.04	$131.48	$204.88	$164.78
	(396.53)	(237.88)	(206.52)	(228.85)	(226.26)

Table 3.14: Difference-in-Difference Estimation Results - Pontiac Exit

Dependent Variable	Radius around Pontiac in "Treated" Markets				
	1 Mile	2 Miles	3 Miles	4 Miles	5 Miles
Vehicle Sales Price					
T_{-4}	-$55.34	-$150.79	-$76.09	-$124.17	-$116.57
	(213.85)	(187.04)	(174.5)	(165.42)	(164.24)
T_{-3}	$56.56	-$70.37	$49.53	-$32.39	-$9
	(183.88)	(170.59)	(163.75)	(156.25)	(155.08)
T_{-2}	-$1.97	-$84.86	-$11.24	-$53.2	-$44.41
	(139.98)	(127.13)	(122.97)	(117.97)	(116.87)
T_{-1}	$188.42	$39.1	$159.78	$124.91	$131.64
	(219.56)	(191.3)	(185.32)	(178.95)	(176.46)
T	**$289.04**	**$291.31**	**$357.07***	**$324.89***	**$344.09***
	(224.92)	(194.19)	(185.97)	(185.7)	(184.18)
T_{+1}	$201.82	$175.09	$221	$163.81	$198.1
	(178.11)	(166.73)	(162.24)	(156.57)	(155.69)
T_{+2}	$342.16**	$288.08*	$312.23**	$261.02*	$283.13**
	(164.86)	(156.32)	(149.27)	(145.11)	(143.46)
T_{+3}	$135.03	$203.53	$256.07	$283.47	$289.17
	(218.3)	(208.05)	(189.91)	(185.68)	(182.58)
N	1,976,250	2,470,968	2,771,318	2,986,926	3,035,969

3.5.3 Discussion

Consumers who were most affected by the decreases in local competition were purchasers of mid to higher trim lines of SUVs, who may be more averse to bargaining and search (indicated by their being on the lower end of the discount distribution), who utilize a trade-in transaction toward partial payment, reside around local market areas which are relatively competitive or moderately concentrated, and who purchased their vehicle in close proximity (in terms of time and geography) to an exit by a rival dealership. The duration of the price effects as a result of this temporary reduction in local competition lasted up to nine months before returning to a new equilibrium. The type of pricing response differed for transactions at the extreme ends of the price distribution; the sales-mix response affected buyers of less expensive vehicles, conditional on brand and body-

Table 3.15: Difference-in-Difference Estimation Results - Pontiac Exit

Dependent Variable	**Radius around Pontiac in "Treated" Markets**				
	1 Mile	2 Miles	3 Miles	4 Miles	5 Miles
MSRP					
T_{-4}	\$58.97	\$69.77	\$70.4	\$5.98	\$27.95
	(211.27)	(179.31)	(165.98)	(156.7)	(155.67)
T_{-3}	\$121.64	\$46.52	\$73.24	-\$5.19	\$14.22
	(168.78)	(156.09)	(147.78)	(140.66)	(139.58)
T_{-2}	\$128.53	\$120.32	\$106.67	\$29.82	\$32.32
	(131.46)	(112.27)	(104.3)	(99.66)	(98.81)
T_{-1}	\$198.89	\$101.49	\$127.21	\$67.75	\$74.95
	(175.79)	(148.42)	(138.5)	(130.92)	(129.35)
T	**\$262.21***	**\$284.32****	**\$271.89****	**\$202.4***	**\$208.21***
	(155.79)	(130.24)	(121.64)	(117.16)	(116.24)
T_{+1}	\$271.9**	\$225.32*	\$198.78*	\$144.95	\$164.59
	(129.36)	(119.2)	(111.93)	(105.8)	(105.35)
T_{+2}	\$400.99***	\$314.89**	\$255.76**	\$180.75	\$203.21*
	(140.57)	(124.61)	(118.52)	(112.13)	(111.29)
T_{+3}	\$107.09	\$157.44	\$134.77	\$85.69	\$94.21
	(146.93)	(127.38)	(117.67)	(111.69)	(109.95)
MSRP-Price					
T_{-4}	\$114.31	\$220.56**	\$146.49	\$130.15	\$144.52
	(119.61)	(108.57)	(102.69)	(95.93)	(95.12)
T_{-3}	\$65.08	\$116.9	\$23.71	\$27.2	\$23.22
	(113.44)	(104.17)	(103.18)	(98.38)	(97.39)
T_{-2}	\$130.49	\$205.18*	\$117.9	\$83.02	\$76.73
	(115.22)	(105.27)	(101.3)	(98.3)	(97.21)
T_{-1}	\$10.48	\$62.4	-\$32.57	-\$57.16	-\$56.69
	(129.38)	(113.88)	(109.61)	(106.56)	(105.37)
T	**-\$26.83**	**-\$6.99**	**-\$85.17**	**-\$122.49**	**-\$135.88**
	(155.34)	(132.65)	(126.43)	(124.42)	(123.01)
T_{+1}	\$70.08	\$50.23	-\$22.22	-\$18.86	-\$33.51
	(152.69)	(132.23)	(126.07)	(120.82)	(119.36)
T_{+2}	\$58.84	\$26.81	-\$56.47	-\$80.27	-\$79.92
	(141.39)	(124.11)	(119.25)	(116.71)	(115.1)
T_{+3}	-\$27.94	-\$46.09	-\$121.3	-\$197.78	-\$194.96
	(154.96)	(154.94)	(145.26)	(144.25)	(141.93)

type, in markets that tend toward being more than moderately concentrated, while the negotiations based response affected buyers who are both on the higher end of the price distribution *and* on the lower end of the discount distribution in markets that tend toward being relatively competitive. Lastly, we see in the difference-in-differences case studies how the intensity of the pricing response was higher at dealerships which were physically closer to their former rival. All of these results indicate a consistency with strategic price adjustments by sellers, rather than other effects which ascribe a differential demand response. In essence, sellers are responding to a plausible change in their perceived residual demand. The fact that a change in residual demand results in a change in pricing behavior indicates that dealerships exercise strategic pricing in an attempt to utilize any local market power to increase profits from individual car sales as well as increase their returns from subsequent warranty services.

4. SUMMARY AND CONCLUSIONS

Both of the above separate and independent chapters provide new results and answer questions which were previously not well addressed. I have targeted questions with a high impact value addressing two major aspect of the U.S. automotive industry - environmental regulation and retail competition. The results help to inform policy in these areas, and the research presented in this dissertation opens up new questions that should be addressed in future research. I have targeted 'big' questions in the hopes to provide relevant and actionable information that contributes to our understanding of how to do proper policy in the U.S. automotive industry.

4.1 Conclusions regarding Optimal Feebates

We have seen that when non-internalized externalities exist in the utilization of vehicles, a second-best policy that imposes fees on purchasers of low fuel efficiency vehicles and rewards buyers of high fuel efficiency ones can be welfare increasing. I have explored optimal feebates by performing numerical optimizations that seek to find the feebate parameters that maximize an objective social welfare function, comprised of utility from purchasing new cars, firm profits, and social costs of emissions. I specified smooth and continuously differentiable functional forms for the mapping of fuel efficiency ratings into fees and rebates which affect the final prices and shift market shares to a new equilibrium. Using estimates from a theoretical demand and supply model, estimated with random coefficients Logit GMM algorithm, I was able to predict market outcomes that result from price interventions in the form of a feebate. The social welfare function was maximized numerically to identify optimal feebates under several restrictions.

Identification of optimal feebates is made possible by requiring the satisfaction of program constraints which are likely to be real political concerns in the design of actual feebate systems. A constraint which requires budget balance is reasonable and straightforward, and without such constraint the numerical algorithm does not reach a solution. The other main constraint determines the scale of the program by defining a limit on the maximum payment of either a fee or a rebate.

Again, this is a reasonable parameter which ought to be considered against equity considerations. The last constraint is applicable only at the logistic functional form, and it is placed on the proportionality of fee payments to rebates between individuals who are just above and just below the pivot point. A logistic feebate with a large marginal incentive at the pivot point and a small marginal incentives everywhere else, represents a non-equitable distribution of fees and rebates. Placing an upper bound on the slope parameter controls this level of inequity. This again ought to be evaluated against potential savings in emission costs that can be obtained from inequitable logistic feebates.

I conclude that optimal feebates are welfare increasing in the presence of any non-internalized environmental externality. In addition, I conclude that functional form matters in that choosing an appropriate logistic function that balances efficacy and equity concerns well is the most appropriate tool among the alternatives which were evaluated in this paper. Where marginal incentives are high, outcomes are more pronounced, and placing relatively higher and smooth marginal incentives on a large portion of consumers will lead to more pronounced increases in fuel economy. Lastly, given the literature which demonstrates the importance of having incentives salient to consumers (Busse et al 2006 [13]), and since feebates provide consumers with much more salient information about their marginal incentives than the CAFE regulation, I conclude that the adoption of optimal logistic feebates could have a high potential to increase total welfare even in the presence of gasoline taxation and fuel economy standards regulation.

4.2 Conclusions regarding Competition among Local Dealerships and the Automotive Distribution Franchise Laws

The results from this paper indicate that local brand competition is relevant to pricing decisions made by retail dealerships selling new cars under franchised licenses. Results are consistent with dealerships exercising a degree of market power, and differentiating their consumers according to willingness to pay. As market concentration increases locally, dealers may extract higher profit margins by raising prices on vehicles at the higher end of the price distribution, as such customers are less likely to be price sensitive. Moreover, it appears that dealers target consumers with an aversion to search and who may have bargaining disutilities in exercising market power strategically.

The marginal effect of decreased competition on the distribution of prices varies across markets with different levels of concentration. Dealers cause consumers to pay higher prices both by ordering more expensive vehicles from manufacturers, and by adjusting their negotiation behavior.

Descriptive evidence suggests that a majority of consumers default to purchasing their cars at the closest dealership at which their vehicle of choice is available. Limited search by consumers across different market clusters may contribute to the view by car sellers that they mainly need to be concerned with local brand competition. In addition, local brand competition should matter to dealers more than intra-brand competition in price negotiations because it is more important to gain a customer who otherwise would buy another brand than a customer who will buy an identical product from another seller, since dealers are interested in the flow of revenues from service and warranty repairs from people who buy the brands that they service.

This study is the first to provide recent causal empirical evidence of retail competition dynamics of new car sales. Findings inform the important public policy debate concerning the removal of state bans on direct distribution by auto manufacturers. If double marginalization offsets any potential benefits from intra-brand competition, then there is little reason to ban direct distribution in the name of protecting consumer benefits.

4.3 Challenges and Further Study

It is my hope that further study will be informed by the results obtained in this dissertation. First, regarding feebate policies, much more can be learned by applying the logistic functional form and finding the proper way to calibrate the program parameters, such as the maximum allowable payment and the maximum marginal incentive (determined by the slope parameter τ). It is thus a further challenge to correctly model social welfare in additional distributional terms that will also factor in politically acceptability. Further, it would be of additional interest to explore trade-offs in logistic feebates that are defined separately for different classes of vehicles (i.e. cars vs. light trucks), or alternatively, to study optimal feebates that are defined as a function of an additional parameter (such as footprint based etc.).

Secondly, concerning policies related to franchise regulation and local competition, the challenge of assessing the impact of eliminating state bans on direct distribution still remains as long as these bans are in effect. A counter-factual experiment to the effect that measures outcomes when direct distribution is allowed does not yet exist; however, further study to determine the accurate trade-off between inter-brand and intra-brand competition could assist in understanding whether such a policy would be appropriate in the near future. The most obvious challenge to removing state bans is the effective automotive dealers lobby, which has thus far been able to secure dealer protection laws in many states. Additional study into the political economy surrounding automotive distribution franchise laws could illuminate proper public policy in the future.

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APPENDIX A

PROOF: MATHEMATICAL PROPERTIES OF THE PROPOSED FEEBATE FUNCTIONS

In this appendix, I show how marginal incentives differ across feebate functional specification and across the support used for measuring fuel efficiency, distinguishing between miles per gallon (MPG) and gallons per 100 miles (GPM).

A.0.0.0.0.1 Linear: The linear function is defined as

$$FB_j^{linear} = \tau \cdot (GPM_0 - GPM_j)$$

for GPM, and as

$$FB_j^{linear} = \tau \cdot (GPM_0 - \frac{100}{MPG_j})$$

for MPG. Taking the derivatives with respect to the fuel efficiency rating of vehicle j, we have:

$$\frac{\partial FB^{linear}}{\partial GPM_j} = -\tau \quad \text{and} \quad \frac{\partial FB^{linear}}{\partial MPG_j} = \tau \cdot \frac{100}{MPG_j^2}$$

thus, the linear feebate is decreasing with GPM and increasing with MPG, indicated by the positive-everywhere derivatives, and while the marginal incentive is constant at τ for GPM, it is decreasing for MPG as MPG increases. The second derivative w.r.t MPG is easily shown to be negative.

A.0.0.0.0.2 Exponential[1] - Marginal Incentives Increase with GPM: To show this, recall the first exponential feebate as follows:

$$FB_j^{exp1} = S \cdot [1 - exp^{-\tau \cdot (GPM_0 - GPM_j)}]$$

for GPM and

$$FB_j^{exp1} = S \cdot [1 - exp^{-\tau \cdot (GPM_0 - \frac{100}{MPG_j})}]$$

for MPG. Taking the derivatives with respect to the fuel efficiency rating of vehicle j:

$$\frac{\partial FB^{exp^1}}{\partial GPM_j} = -exp^{-\tau\cdot(GPM_0-GPM_j)}\cdot S\cdot\tau \quad \text{and} \quad \frac{\partial FB^{exp^1}}{\partial MPG_j} = exp^{-\tau\cdot(GPM_0-\frac{100}{MPG_j})}\cdot S\cdot\tau\cdot\frac{100}{MPG_j^2}$$

we again notice the opposing signs, as all other terms are positive, the marginal incentive will always be in the direction of increasing fuel economy. It is certainly a desirable requirement for feebates to maintain monotonicity. To show the increasing marginal incentives w.r.t GPM, I take the second derivative of the marginal incentive's absolute value and show that it is positive:

$$\frac{\partial^2 FB^{exp^1}}{\partial GPM_j^2} = \frac{\partial|-exp^{-\tau\cdot(GPM_0-GPM_j)}\cdot S\cdot\tau|}{GPM_j} = exp^{-\tau\cdot(GPM_0-GPM_j)}\cdot S\cdot\tau^2 > 0$$

applying the same for the marginal incentive w.r.t MPG:

$$\frac{\partial^2 FB^{exp^1}}{\partial MPG_j^2} = -\frac{200S\tau}{MPG_j^4}exp^{-\tau\cdot(GPM_0-\frac{100}{MPG_j})}\cdot(50\tau+MPG_j) < 0$$

which indicates decreasing marginal incentives with MPG, most likely at a higher rate than w.r.t GPM, but that depends on the relationship between MPG and τ.

A.0.0.0.0.3 Exponential[2] - Marginal Incentives Decrease with GPM: Following a similar procedure for the second exponential formulation:

$$FB_j^{exp2} = S\cdot\left[exp^{\tau\cdot(GPM_0-GPM_j)}-1\right]$$

for GPM and

$$FB_j^{exp2} = S\cdot\left[exp^{\tau\cdot(GPM_0-\frac{100}{MPG_j})}-1\right]$$

for MPG. Taking the derivatives with respect to the fuel efficiency rating of vehicle j:

$$\frac{\partial FB^{exp^2}}{\partial GPM_j} = -exp^{\tau\cdot(GPM_0-GPM_j)}\cdot S\cdot\tau \quad \text{and} \quad \frac{\partial FB^{exp^2}}{\partial MPG_j} = exp^{\tau\cdot(GPM_0-\frac{100}{MPG_j})}\cdot S\cdot\tau\cdot\frac{100}{MPG_j^2}$$

which are very similar to the marginal incentives arrived at with the former exponential specification, the only difference being the sign of the exponent which is flipped. The signs of the marginal incentives are monotonic in the direction of increasing fuel economy. To show the decreasing marginal incentives w.r.t GPM, I take the second derivative of the marginal incentive's absolute value and show that it is negative:

$$\frac{\partial^2 FB^{exp^2}}{\partial GPM_j^2} = \frac{\partial|-exp^{\tau\cdot(GPM_0-GPM_j)}\cdot S\cdot\tau|}{GPM_j} = -exp^{\tau\cdot(GPM_0-GPM_j)}\cdot S\cdot\tau^2 < 0$$

applying the same for the marginal incentive w.r.t MPG:

$$\frac{\partial^2 FB^{exp^2}}{\partial MPG_j^2} = \frac{200S\tau}{MPG_j^4}exp^{\tau\cdot(GPM_0-\frac{100}{MPG_j})}\cdot(50\tau - MPG_j)\overset{?}{\lesseqgtr} 0$$

shows that it is uncertain how the decreasing marginal incentives w.r.t GPM and fuel costs translate to changing marginal incentives w.r.t MPG. Again, this depends on the relative size of τ compared to the range of fuel economy ratings.

A.0.0.0.0.4 Logistic Recall the functional form:

$$FB_j^{logistic} = S\cdot\left[\frac{1}{1+exp^{-\tau(GPM_0-GPM_j)}} - 1\right]$$

and

$$FB_j^{logistic} = S\cdot\left[\frac{1}{1+exp^{-\tau(GPM_0-\frac{100}{MPG_j})}} - 1\right]$$

The first derivatives preserve the monotonicity toward increased fuel economy:

$$\frac{\partial FB_j^{log}}{\partial GPM_j} = -S\cdot\left[\frac{exp^{-\tau(GPM_0-GPM_j)}}{\left(1+exp^{-\tau(GPM_0-GPM_j)}\right)^2}\right]\cdot\tau$$

and

$$\frac{\partial FB_j^{log}}{\partial MPG_j} = S\cdot\left[\frac{exp^{-\tau(GPM_0-\frac{100}{MPG_j})}}{\left(1+exp^{-\tau(GPM_0-\frac{100}{MPG_j})}\right)^2}\right]\cdot\frac{100\tau}{MPG_j^2}$$

The second derivative with respect to GPM is:

$$\frac{\partial^2 FB_j^{log}}{\partial GPM_j^2} = -S \cdot \tau^2 exp^{-\tau(GPM_0 - GPM_j)}\left(1 - exp^{-\tau(GPM_0 - GPM_j)}\right)\left[\frac{1}{\left(1 + exp^{-\tau(GPM_0 - GPM_j)}\right)^3}\right]$$

which equals zero when

$$exp^{-\tau(GPM_0 - GPM_j)} = 1$$

This happens at the pivot point where $GPM_j = GPM_0$. Without taking a third derivative, in order to show that the pivot point is where the marginal incentive is maximized, we observe that the term in parentheses for $\frac{\partial FB_j^{log}}{\partial GPM_j}$ can be re-written as $f(t) = \frac{t}{(1+t)^2}$, and we can show that this term is maximized at $t = 1$:

$$\frac{\partial f}{\partial t}\Big|_{t=1} = \frac{1-t}{(1+t)^3} = 0 \quad \text{and} \quad \frac{\partial^2 f}{\partial t^2} = -\frac{t^2 + 4t + 3}{(1+t)^4} < 0$$

APPENDIX B

DEMAND ELASTICITIES TABLES

Own and Cross Elasticities - Random coefficients Specification (3)

		Pick Up Trucks			SUVs						Sedans					
	Average Markups	Ford F-150	Chevrolet Silverado 1500	Toyota Tundra	Honda CR-V	Toyota 4Runner	Chevrolet Tahoe	Ford Escape	Lexus RX-350	BMW X5	Mercedes-Benz C-Class	Cadillac CTS	Volkswagen Jetta	Nissan Altima	Honda Accord	Chevrolet Malibu
F-150	$6723	-3.578	0.025	0.030	0.032	0.016	0.024	0.010	0.110	0.020	0.025	0.025	0.029	0.042	0.041	0.006
Silverado 1500	6,698	0.056	-3.634	0.029	0.034	0.017	0.029	0.010	0.117	0.022	0.030	0.035	0.025	0.032	0.044	0.007
Tundra	6,435	0.051	0.022	-3.807	0.037	0.016	0.028	0.009	0.092	0.013	0.016	0.030	0.021	0.034	0.047	0.006
CR-V	6,574	0.049	0.023	0.025	-3.216	0.014	0.023	0.008	0.101	0.016	0.024	0.028	0.025	0.034	0.042	0.006
4Runner	6,602	0.045	0.022	0.028	0.031	-4.213	0.025	0.008	0.085	0.019	0.015	0.036	0.019	0.031	0.044	0.006
Tahoe	7,122	0.050	0.029	0.027	0.035	0.015	-4.732	0.010	0.104	0.029	0.039	0.045	0.026	0.033	0.045	0.007
Escape	6,346	0.053	0.023	0.029	0.031	0.016	0.024	-3.114	0.100	0.019	0.023	0.026	0.026	0.041	0.039	0.006
RX-350	7,008	0.048	0.023	0.016	0.040	0.010	0.033	0.010	-5.087	0.017	0.046	0.033	0.025	0.027	0.037	0.006
X5	8,325	0.048	0.021	0.020	0.025	0.012	0.030	0.008	0.116	-6.476	0.025	0.042	0.022	0.030	0.026	0.005
C-Class	7,446	0.041	0.028	0.020	0.020	0.012	0.041	0.006	0.136	0.026	-5.065	0.055	0.018	0.029	0.026	0.007
CTS	7,385	0.051	0.025	0.026	0.030	0.016	0.027	0.008	0.147	0.026	0.036	-4.737	0.027	0.037	0.038	0.006
Jetta	7,022	0.038	0.021	0.021	0.030	0.012	0.020	0.007	0.101	0.022	0.013	0.043	-3.168	0.033	0.046	0.006
Altima	6,672	0.047	0.024	0.022	0.028	0.012	0.025	0.008	0.101	0.016	0.018	0.016	0.021	-3.216	0.039	0.006
Accord	6,637	0.048	0.024	0.025	0.031	0.013	0.025	0.008	0.092	0.016	0.023	0.030	0.024	0.033	-3.237	0.006
Malibu	6,398	0.052	0.027	0.027	0.037	0.015	0.025	0.011	0.108	0.018	0.034	0.034	0.028	0.035	0.045	-2.952

Own and Cross Elasticities - Random Coefficients Specification (6)

		Pick Up Trucks			SUVs						Sedans					
	Average Markups	Ford F-150	Chevrolet Silverado 1500	Toyota Tundra	Honda CR-V	Toyota 4Runner	Chevrolet Tahoe	Ford Escape	Lexus RX-350	BMW X5	Mercedes-Benz C-Class	Cadillac CTS	Volkswagen Jetta	Nissan Altima	Honda Accord	Chevrolet Malibu
F-150	$5,881	-4.060	0.029	0.036	0.039	0.019	0.029	0.011	0.132	0.023	0.030	0.031	0.035	0.050	0.049	0.007
Silverado 1500	5,835	0.068	-4.146	0.035	0.041	0.020	0.035	0.011	0.139	0.026	0.036	0.043	0.030	0.038	0.053	0.008
Tundra	5,652	0.061	0.026	-4.303	0.044	0.019	0.035	0.011	0.111	0.015	0.019	0.036	0.025	0.041	0.056	0.007
CR-V	5,678	0.059	0.028	0.030	-3.707	0.016	0.028	0.010	0.119	0.018	0.029	0.034	0.030	0.041	0.050	0.008
4Runner	5,869	0.055	0.027	0.034	0.036	-4.710	0.031	0.009	0.104	0.022	0.018	0.045	0.023	0.037	0.053	0.007
Tahoe	6,441	0.060	0.035	0.033	0.042	0.018	-5.193	0.012	0.129	0.037	0.048	0.056	0.030	0.039	0.053	0.008
Escape	5,448	0.063	0.028	0.034	0.037	0.019	0.028	-3.611	0.116	0.021	0.027	0.031	0.031	0.050	0.047	0.008
RX-350	6,230	0.058	0.027	0.019	0.047	0.012	0.041	0.011	-5.617	0.022	0.056	0.041	0.029	0.031	0.044	0.007
X5	7,894	0.056	0.024	0.024	0.027	0.015	0.038	0.008	0.143	-6.767	0.031	0.051	0.024	0.033	0.029	0.005
C-Class	6,712	0.049	0.033	0.025	0.023	0.014	0.050	0.007	0.167	0.033	-5.558	0.068	0.021	0.034	0.031	0.008
CTS	6,570	0.063	0.031	0.032	0.036	0.020	0.034	0.009	0.179	0.032	0.045	-5.283	0.033	0.044	0.046	0.007
Jetta	6,095	0.046	0.026	0.025	0.037	0.015	0.024	0.009	0.117	0.024	0.015	0.052	-3.643	0.040	0.055	0.007
Altima	5,759	0.056	0.029	0.027	0.034	0.015	0.030	0.010	0.117	0.018	0.022	0.019	0.026	-3.707	0.047	0.007
Accord	5,747	0.058	0.029	0.029	0.037	0.016	0.030	0.010	0.108	0.018	0.028	0.037	0.028	0.040	-3.720	0.007
Malibu	5,467	0.062	0.032	0.032	0.045	0.018	0.029	0.013	0.124	0.019	0.040	0.040	0.034	0.043	0.054	-3.443