Essays in Industrial Organization

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
Doctor of Philosophy

Amil Petrin, Advisor

May, 2020

Acknowledgments

I am very grateful to my advisor, Amil Petrin, and my committee members, Thomas J. Holmes, Joel Waldfogel and Aaron Sojourner, for their continued advice and support. Their guidance has provided me with an invaluable blueprint for choosing and approaching research questions.

Additionally, my research has benefited from conversations with Jonathan Borowsky, Mark Ponder, Aradhya Sood, Kevin Williams, members of the University of Minnesota Applied Microeconomics workshop, and participants of conferences and seminars at which I have presented while attending the University of Minnesota.

I acknowledge the financial support of the Graduate School of the University of Minnesota. I also acknowledge support from the Minnesota Supercomputing Institute for providing computational resources. Finally, I would like to thank the Department of Economics staff, especially Caty Bach and Wendy Williamson.

Dedication

To my family. To Nadiia for her unwavering patience and support.

Abstract

This dissertation is comprised of three essays. The first one studies the valuation of novel safety technologies such as airbags and anti-lock brake systems by consumers using real-world data on car purchases. The second essay looks at the interaction between government regulation and adoption of airbags by car manufacturers, as well as the welfare implications for the market. Finally, the third chapter utilizes the data on car sales to study the evolution of markups and concentration in the US automobile industry throughout the last 24 years.

In the first chapter I study the economic value of the new safety technologies that were introduced in automobiles in the 1990's. While these features reduce the risk of death and injury in traffic accidents they are often expensive and not all consumers are willing to pay for them. I find that an average consumer values driver airbags at the level of $861, anti-lock brake system - at $1,043, and side airbags - at $1,633. Overall, the introduction of frontal airbags improved consumer welfare by an equivalent of about $1,345, however it affected the consumers differently based on their characteristics. Understanding the value that consumers place on these technologies is helpful in guiding the policy related to regulation of car safety standards.

The second chapter studies the effects of technology-forcing regulation that was announced in 1991 and required all new cars to be equipped with airbags starting in 1998. This government intervention forced firms to adopt new technology earlier that they found optimal, creating a market distortion. I develop and estimate a structural model of consumer vehicle choice and dynamic airbag adoption decision of the firms in the presence of a deadline. I construct a detailed data set of car sales for more than 2,600 car models and 16 distinct car features over 13 years. The results show that government regulation was a major driver of airbag adoption. The mandate forced 100% of cars to have dual airbags by 1998; however, in the counterfactual, without the airbag mandate, only 60% of new cars would have dual airbags in 2002. I also find that the regulation had heterogeneous effect on consumers. When comparing the world without the airbag mandate to the world with the airbag mandate, consumers experienced an average welfare gain of 1.7% because airbags were available earlier and cheaper. However, the airbag mandate reduced welfare for consumers with high price-sensitivity and low valuation of airbags by 5.2%. Firms that adopted airbags before the regulation requirement experience 1.3% lower profits compared to the world without the mandate because the mandate limited their ability to differentiate themselves from the competition.

In the third and final chapter I investigate the development of markups and firm concentration in the automobile market from 1990 to 2014. I estimate markups for all the firms active in the market in these years using a structural model of consumer car choice. The findings show that the markups have slightly decreased by during the period covered in my dataset. This confirms the findings in the literature for the markups in the automobile industry.

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Chapter 1

Consumer Valuation of Safety Technologies in Automobiles

1.1 Introduction

Car manufacturers have added a significant array of features to their vehicles over the last decades. In the 1990's car companies widely adopted airbags, anti-lock brakes, automatic headlamps, as well as, simple electronics such as powered windows, locks, and seats. In the 2000's electronic stability control, keyless entry, side airbags, rear object sensors, and remote start became common. After 2010 backup cameras, automatic braking, and lane-keeping joined the list of marketed features. In this paper, I study the value that consumers put on these new technologies with particular focus on airbags. I choose to focus on airbags since they are one of the most well-known automobile safety features and were a subject of a heated policy debate in the 1970's and 1980's. Furthermore, I briefly discuss the valuation of other safety technologies: anti-lock brake system (ABS) and side airbags.

I construct a structural model of consumer vehicle choice where consumers are heterogeneous in their preference for airbags and income. I estimate consumer preference parameters for specific car features including airbags, as well as measures of consumer heterogeneity using the methodology outlined in Berry et al. [1995]. This allows me to estimate consumer readiness to pay for airbags and other features. Finally, I calculate how much the consumers value the airbag technology as a whole by calculating compensation for having to live in a world without airbags using the methodology from Petrin [2002].

Understanding the value that consumers place on car features is important due to two factors. First, safety technologies are often a subject of government regulation. Government has regulated the use of seatbelts, as well as, installation of airbags, electronic stability controls, tire pressure monitoring, and backup sensors. Second, quality changes are one of the factors that affects the calculation of Consumer Price Index[1].

The dataset that I use covers over 95% of all mainstream cars that were sold in the US from 1990 to 2002. It provides basic descriptives such as horsepower, fuel efficiency, and size, as well as other multiple features, prices, and sales. The novelty of the dataset comes from the fact that it includes additional information on over a dozen extra features that range from airbags and anti-lock brakes to rear defogger and adjustable steering column. Inclusion of these additional features allows me to better identify the preference for airbags by avoiding omitted variable bias. Since airbags first appear in luxury cars along with a slew of other features it is important to control for them in order not to overestimate the preference parameter for airbags.

I find that consumers have statistically significant preference for airbags and the average willingness to pay for an airbag is about $900[2]. However, the willingness to pay varies across consumers depending on their preference for airbags and income. I find that there is relatively little heterogeneity in preferences for airbags but income plays a large role in determining willingness to pay. I also study the differences in preference for driver and passenger airbags. The results show that consumers value driver airbags much higher than passenger airbags. I also investigate the presence of a trend in preferences of airbags and find that it is not significantly different from zero. Finally, I evaluate how much the consumers valued the airbag technology overall. The estimates show that on average a consumer would need to be compensated over $440 in order to have the same expected utility level when living in a world where no cars have airbags.

There were several attempts to quantify the value of the safety equipment, as well as airbags. Jones-Lee et al. [1985] used a survey to elicit consumer willingness to pay for marginal improvement in traffic safety. Uri [1988] studied the market valuations of car with respect to their quality as measured by reliability, and safety as measured by crashworthiness. Mannering and Winston [1995] use a discrete choice logit framework and apply it to a dataset covering households and their car purchases between 1990 and 1993. However, they do not account for price endogeneity in their regression of car sales on prices and car features. Berry et al. [1995] showed that such

[1]For example, see Bureau of Labor Statistics [2014].

[2]Here and henceforth all dollar values are measured in equivalents of 2017 US dollars.

approach is likely to underestimate price sensitivity of consumers, which would cause the estimates of readiness to pay for airbags to be biased as well. Dunham [1997] studied the effect of new vehicles with safety equipment on prices of used vehicles lacking such equipment. He found that regulations requiring new vehicles to install safety equipment depressed prices of used vehicles, which suggests that consumers, in fact, value additional safety. Andersson [2005] and Andersson [2008] studied the value of safety equipment using the hedonic price regressions.

Another set of papers studied the value of new products and improvements in a more general setting. Trajtenberg [1989] calculated gains in social welfare from introduction of computer tomography scanners. Greenstein [1996] looked at the development of computing capabilities of computers and corresponding benefits to consumers. Petrin [2002] considered the value that consumers derived from the introduction of minivans, a new product, to their choice set.

1.1.1 Outline

The paper proceeds as follows. Section 1.2 describes the dataset. Section 1.3 presents the model. Section 1.4 discusses the estimation methodology. Section 1.5 presents the results of the estimation. Section 1.6 uses the results to discuss the consumer valuation of the technology. Finally, section 1.7 concludes.

1.2 Data and Preliminary Analysis

1.2.1 Data

I constructed my dataset using information reported in Ward's Automotive Yearbook, an automobile magazine that collects and publishes automobile news as well as data on the car market. While some exotic cars are excluded the dataset covers over 95% of all cars that are sold in the US and provides data for years between 1990 and 2002. Apart from the data on sales, it also provides coverage of the characteristics and features of the car models. The data is provided on a model level, i.e. one observation corresponds to one car model in a given year (for example, Ford F-150 or Dodge Charger).

For each model the dataset captures some general characteristics such as horsepower-to-weight ratio, fuel efficiency as measured by mile-per-gallon, physical size of the car, manufacturer's suggested retail price (MSRP) and unit sales. I report all monetary values including prices in 2017 US dollars. MPG is measured in 0.1*miles/gallon and

Table 1.1: Descriptive statistics for years 1990-1998

Year	1990	1991	1992	1993	1994	1995	1996	1997	1998
MSRP	28.4	28.4	29.8	30.4	30.7	32.0	32.2	32.8	33.9
HP/Weight	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
MPG	2.4	2.4	2.3	2.3	2.3	2.3	2.3	2.3	2.3
Space	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.2	1.2
Airbag (Driver)	21.7	20.7	39.0	40.7	25.8	34.8	31.2	14.2	0.0
Airbag (Dual)	0.0	0.0	0.0	7.3	40.7	59.3	68.2	84.5	100.0
Airbag (Side)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.7	7.7
All-Wheel Drive	5.7	8.0	9.2	10.0	11.3	13.0	15.8	17.1	23.7
Power Brakes	74.9	66.3	56.0	50.6	31.9	31.5	29.7	27.1	22.6
Anti-Lock Brakes	25.1	33.8	44.0	49.4	68.1	68.5	70.3	72.9	77.4
Automatic AC	12.1	11.6	9.1	7.7	7.6	7.9	7.7	7.6	11.5
Automatic Lights	0.0	0.0	0.0	0.0	0.0	0.0	0.0	14.4	14.48
Adjust. Steering	75.9	74.6	77.4	77.4	79.3	82.8	82.0	84.6	89.8
Cruise Control	67.7	70.1	74.8	74.8	74.6	78.0	80.2	82.5	83.3
Keyless Entry	0.0	0.0	0.0	0.0	0.0	11.9	22.9	33.1	40.7
Rear Defogger	72.1	79.5	75.5	75.7	73.4	76.5	78.7	74.8	71.2
Power Equipment	45.2	40.1	46.8	51.0	54.6	59.1	61.0	63.2	67.1
Total Models	212	216	220	219	205	207	202	199	195
Total Sales (M.)	12.4	12.7	12.2	13.1	13.9	14.9	13.6	14.6	14.7

Note: All variables except Total Models and Total Sales are sales-weighted averages. MSRP is given in 2017 dollars. Total Sales are given in million units. Power Equipment is a sum of Power Windows, Power Seats, and Power Locks. Data for years 1990-2002 can be found in Table A.1 in Appendix.

HP/Weight is measured in 10*HP/pounds. Space captures the size of a car and is equal to Length*Height/10,000 in inches.

Additionally, the dataset reports the share of the cars of a particular model that were equipped with additional features[3][4]. These features include airbags, anti-lock brakes (ABS), automatic air conditioning (AC) etc. The full list of the additional features can be found in table 1.1.

The detailed coverage of the car features is an important advantage of this dataset. Most of the literature studying the car market used only a limited number of characteristics such as horsepower, fuel efficiency, and size[5]. While such approach may be

[3] For example, it could show that 20% of all Ford Fiesta models had ABS installed at the factory. However, these values are most often either 0% or 100% so I treat them as dummy variables. A histogram of the values of factory-installed equipment can be found in Appendix in table A.1.

[4] While it would be helpful to observe sales and prices of two identical models where one is equipped with airbags and the other one is not such data is not available. However, this dataset still allows for precise identification of airbag parameters by comparing an airbag-equipped model to a similar car without airbags in the same or previous year.

[5] For example, see Verboven [2002], Berry et al. [2004], Schiraldi [2011], Blonigen et al. [2017]. Berry et al. [1995] also controlled for air conditioning as a proxy for luxury level of a car.

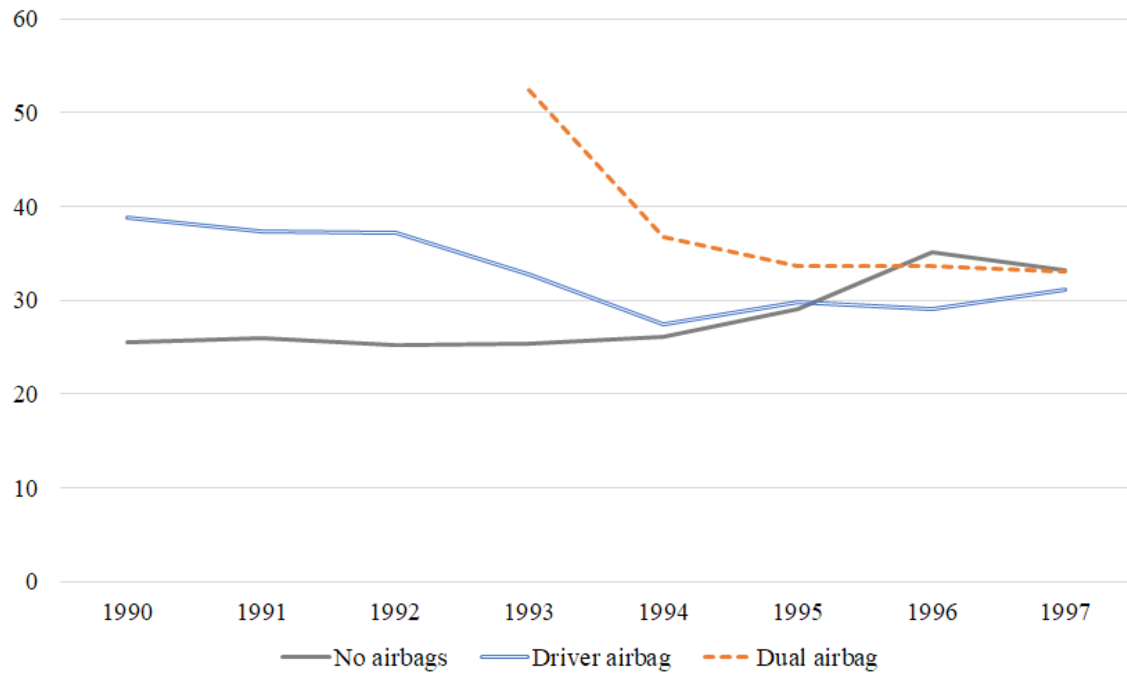
sufficient to accurately identify the price sensitivity of the consumers, the identification of consumer preference for airbags requires more information. New features tend to appear in luxury cars first, often at the same time with other desirable features. Unless these additional features are controlled for, the preference parameters may exhibit an omitted variable bias by picking up consumer preference for the features. This would lead to overestimating consumer preference for the variable of interest which is, in our case, airbags.

Table 1.1 shows how the car characteristics and features changed over time. Prices, horsepower, fuel efficiency, and physical size have changed little during the 1990's. Most of the improvements in cars came from adding new features, in particular those that were related to safety and electronics. Driver airbags appeared a few years before the start of the dataset but were quickly replaced by dual airbags[6]. Once airbag technology became mature enough, car manufacturers went beyond frontal airbags and introduced side airbags, and later curtain airbags to cars. Anti-lock brakes (ABS) were quickly replacing power brakes as well. Keyless entry and power equipment such as power locks, power windows, and power seats became more common as well. Adoption of some minor features such as automatic AC (also known as climate control), rear defogger, or adjustable steering was somewhat slower. As it is outlined in Sperling et al. [2004] proliferation in new features in cars over time is likely due to decreasing costs of these features as technology become more mature and, sometimes, improved consumer awareness about their benefits. While the sales of new cars increased over the same period the number of available models has slightly declined.

Figure 1.1 shows the average price of cars that had no airbags, only driver airbag, or dual airbags. Cars with driver airbag command a significant premium at the beginning of the 1990's which reflects the fact that more expensive, luxury cars adopt new desirable features first. For example, Audi, BMW, Mercedes, and Volvo, which mostly produce luxury cars, equipped 100% of their models with driver airbags already in 1990. This observation holds for cars with dual airbags as well. However, as more models adopt airbags the average prices conditional on the type of airbags converge until year 1998 when dual airbags become mandatory. Curiously, the average price of cars without airbags seems to increase late into the period. However, this is driven almost exclusively by Ford F-150, a large truck that was equipped with airbags only in 1998, that had above average price and was historically one of the

[6]Dual airbag is a system that includes both driver and passenger airbags. One of the reasons for such quick replacement of driver airbags by dual airbags was the government mandate that made dual airbags mandatory in all new cars by 1998. I study the effects of this mandate in Chapter 2.

Figure 1.1: Mean car prices by airbag type ($1,000)



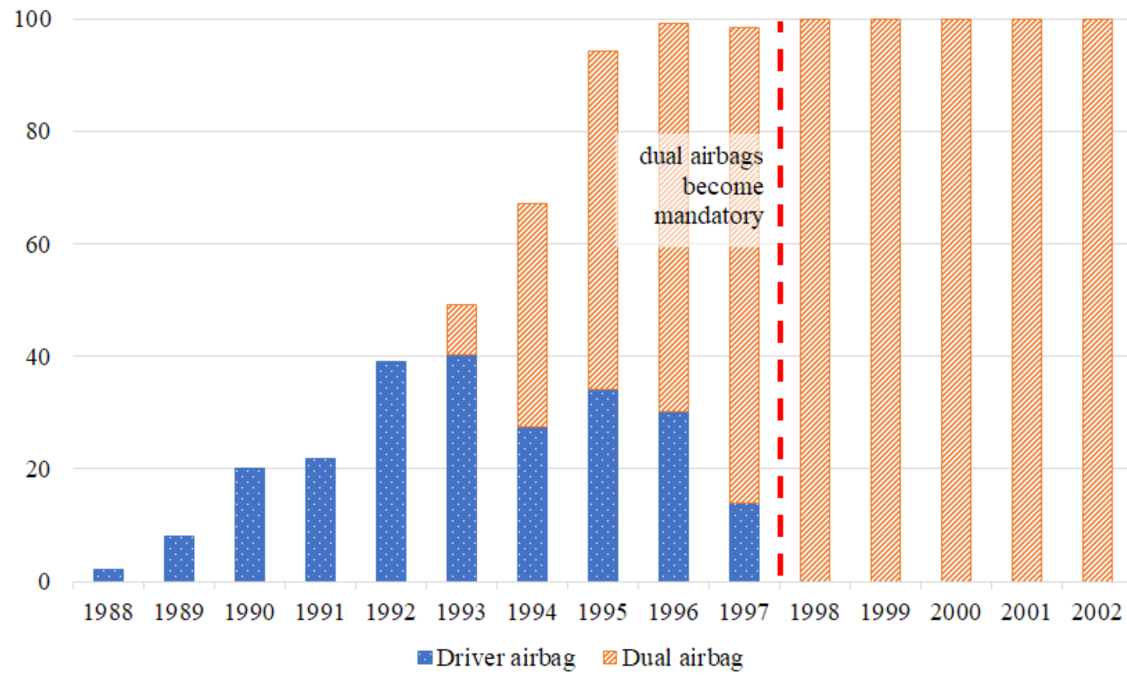
Note: Prices are given in 2017 dollars.

best-selling cars in the US.

The adoption of airbags is shown in Figure 1.2. Driver airbags were adopted rather rapidly at the beginning of the 1990's. Dual airbags were fully adopted even faster - all cars were equipped with them by year 1998. One of the main drivers of adoption was the government regulation that was passed in 1991 and required all new cars to have dual airbags by 1998. However, such gradual adoption allows for better identification of consumer preferences for the airbags as it becomes possible to observe consumer behavior in different situations: when airbags are a feature of luxury cars only, and when airbags are ubiquitous.

Finally, I also utilized St. Louis FRED database to get the number of households and consumer price index (CPI). These two variables are used to calculate the US market size for cars and convert prices to their equivalents of 2017 dollars. Since consumer are likely to react to gasoline prices MPG is divided by the cost of gasoline to obtain miles-per-dollar (MPD). Mean and variance of household income is used to proxy for consumer heterogeneity with respect to income.

Figure 1.2: New car sales by airbag type (%)



Note: Data for years 1988 and 1989 comes from additional Ward's Automotive Yearbook reports not included in the main dataset.

1.2.2 Hedonic Analysis

For the purposes of preliminary investigation of the valuation of airbags I conduct a hedonic regression. A hedonic regression has price as the dependent variable and studies what product characteristics contribute to it. Tables 1.2 and 1.3 report the results of the hedonic regression of car prices on product characteristics and features under different specifications. These results are of particular interest because they can suggest an approach how to specify airbags in the main model. First, it is interesting to explore what role the additional features that are used as controls play in the analysis. Furthermore, recall that the airbags in question were not, in fact, a single feature but had to versions: driver and dual. It is not immediately clear whether consumers would value both driver and passenger airbags equally or whether they would cost the same. Moreover, it is reasonable to assume that the cost of a novel feature such as airbag might decrease over time. In order to understand how important these factors may be I run the hedonic regression under several specifications.

Specifications i-iv in Table 1.2 report the results for the total number of frontal airbags (between 0 and 2). The first specification utilizes a very modest set of controls that is commonly used in the literature. Specification ii adds additional features as controls, and specification iii adds year and brand fixed effects. Finally, the last regression adds a trend to the airbag variable. Specifications v-viii in Table 1.3 show the same regressions in a similar fashion however they treat driver and passenger airbags separately.

In specification i the coefficient on driver airbag is positive and statistically significant. Since it is a linear regression the interpretation of the coefficient is straightforward. In this case, addition of a driver airbag to a model corresponds to price increase of $1,720. Adding some additional features as controls in specification ii lowers the coefficient on airbags and makes it not significant. The reason behind it could be wide-spread adoption of airbags by cheaper cars in the later years. Controlling for the year and brand fixed effects makes the coefficient on airbags much higher and statistically significant. Once I allow the effect of airbags on price to vary over time the coefficients remain high and significant. Moreover, the estimates suggest that the effect of airbags on price decreases by $510 every year.

While driver and passenger airbags utilize the same technology it is not immediately clear whether they were priced the same. To determine it I treat them separately in the regressions reported in Table 1.3. In specification iv the coefficient on driver airbag is notably higher. However, the coefficient on passenger airbag is negative and not significant. The reason why this estimate is high is omitted variable bias. Here airbag coefficient captures the effect not only of airbags but also other features on prices. After I add side airbags, anti-lock brakes, automatic AC, all-wheel drive, and power equipment into the regression in specification v the corresponding coefficient for driver airbag decreases to 1.45 (which is equivalent to $1,450). The coefficient on passenger airbags has a coefficient that is very close to zero. The difference in estimates between these two specifications highlights the importance of controlling for additional features. Regression vii controls for year and brand fixed effects. In this specification both types of airbags are positive and statistically significant. Finally, the interaction with trends suggest that there may be some variation in prices of driver and dual airbags over time.

The results of hedonic regressions suggest that installation of airbags in cars is associated with higher price, even after controlling for differences in luxury status and other features. The price increase is driven by two factors: additional costs associated with airbags (e.g. components and labor) and firm markup, that the firm charges for an airbag. Understanding the cost structure of airbags is helpful for evaluating the change in consumer welfare that comes from the introduction of airbags[7]. The econo-

[7] I will use it when calculating a new price equilibrium in a world without airbags in section 1.6.

Table 1.2: Hedonic regression results with total airbags

Price ($1,000)	i	ii	iii	iv
# Airbags	1.72***	0.66	2.98***	4.87***
	(0.42)	(0.41)	(0.61)	(1.20)
# Airbags × Trend				-0.51*
				(0.28)
Airbag (Side)		7.39***	1.96*	2.01**
		(1.04)	(1.01)	(1.01)
Anti-Lock Brakes		3.79***	0.83	0.76
		(0.76)	(0.74)	(0.74)
Auto AC		17.60***	12.69***	12.65***
		(0.84)	(0.81)	(0.81)
All-Wheel Drive		0.17	1.21	1.24
		(0.85)	(0.83)	(0.83)
Auto Headlamps		-3.92***	-0.85	-0.80
		(0.86)	(0.85)	(0.85)
Adj. Steering		-4.86***	-2.00**	-1.95**
		(0.93)	(0.86)	(0.86)
Cruise Control		-0.54***	-0.57	-0.57
		(1.08)	(0.97)	(0.97)
Keyless Entry		-6.84***	-3.68***	-3.49***
		(0.81)	(0.80)	(0.80)
Rear Defogger		0.79	1.09	1.14
		(0.74)	(0.70)	(0.70)
Power Equipment		3.78***	2.97***	2.92***
		(0.51)	(0.46)	(0.46)
MPG	-22.69***	-12.42***	-9.25***	-9.16***
	(0.89)	(0.88)	(0.84)	(0.84)
HP/Weight	74.35***	61.08***	66.85***	66.95***
	(3.22)	(2.94)	(2.80)	(2.80)
Space	-6.56***	-6.09***	5.75***	5.99***
	(2.29)	(2.14)	(2.09)	(2.09)
Constant	60.97***	33.22***	7.81	11.69**
	(4.82)	(4.63)	(5.01)	(5.45)
Truck FE	yes	yes	yes	yes
Year FE			yes	yes
Brand FE			yes	yes

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.3: Hedonic regression results with driver and passenger airbags

Price ($1,000)	v	vi	vii	viii
Airbag (Driver)	5.11***	1.47*	3.30***	4.54***
	(1.01)	(0.87)	(0.86)	(1.42)
Airbag (Dr.) × Trend				-0.68
				(0.50)
Airbag (Passenger)	-1.18	-0.07	2.60***	5.81***
	(0.89)	(0.82)	(0.96)	(1.71)
Airbag (Pass.) × Trend				-1.40***
				(0.68)
Airbag (Side)		7.42***	1.94*	2.07**
		(1.04)	(1.01)	(1.01)
Anti-Lock Brakes		3.75***	0.82	0.75
		(0.76)	(0.74)	(0.74)
Auto AC		17.58***	12.69***	12.63***
		(0.84)	(0.81)	(0.81)
All-Wheel Drive		0.22	1.23	1.19
		(0.85)	(0.83)	(0.83)
Auto Headlamps		-3.87***	-0.84	-0.78
		(0.86)	(0.85)	(0.85)
Adj. Steering		-4.80***	-1.98**	-2.00**
		(0.93)	(0.86)	(0.86)
Cruise Control		-0.57	-0.58	-0.52
		(1.08)	(0.97)	(0.97)
Keyless Entry		-6.69***	-3.64***	-3.46***
		(0.82)	(0.80)	(0.80)
Rear Defogger		0.77	1.10	1.14
		(0.74)	(0.70)	(0.70)
Power Equipment		3.75***	2.96***	2.91***
		(0.51)	(0.46)	(0.46)
MPG	-22.01***	-12.30***	-9.21***	-9.28***
	(0.91)	(0.89)	(0.84)	(0.84)
HP/Weight	76.19***	61.38***	66.98***	66.41***
	(3.25)	(2.96)	(2.82)	(2.83)
Space	-5.96***	-5.97***	5.84***	5.78***
	(2.29)	(2.15)	(2.09)	(2.10)
Constant	56.71***	32.45***	7.59	16.20***
	(4.95)	(4.69)	(5.03)	(6.28)
Truck FE	yes	yes	yes	yes
Year FE			yes	yes
Brand FE			yes	yes

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

metric model that I lay out in the next section provides a framework for estimating costs of airbags.

1.3 Model

1.3.1 Consumer Problem

My approach follows closely to Berry et al. [1995]. In every period each agent chooses whether to buy a car out of the set of available cars or whether to choose an outside option. In my setting, an outside option is not to buy a new car. This includes buying a used one or keeping the one that he already has. I make several assumption. First, every consumer can only buy one car in a given period. Second, he cannot choose specific features separately from a car - that is, the only way to have airbags in his car is to buy a car that has them already installed.

Then, consumer i's utility from buying a car j in year t is:

$$U_{ijt} = \delta_{jt} - \alpha \log(y_{it} - P_{jt}) + \mu_{jt} + \varepsilon_{ijt}$$

The notation is as follows. I use δ_{jt} to denote the part of utility that is common to all consumers. The term $\alpha \log(y_{it} - P_{jt})$ captures consumer disutility from having to pay price P_{jt}, where y_{it} denotes a measure of consumer income. The term μ_{ij} captures consumer i's idiosyncratic preference for airbags. Finally, ε_{ij} is a random shock from Extreme Value Type I distribution. δ_{jt} and μ_{jt} are given below:

$$\begin{aligned} \delta_{jt} &= \beta_A A_{jt} + \beta_X X_{jt} + \xi_{jt} \qquad (1.1) \\ \mu_{jt} &= \sigma_A A_{jt} \nu_{iA} \end{aligned}$$

Variable A_{jt} captures the presence of airbags in the model j. X_j describes other characteristics and features. Following already established notation from Berry et al. [1995] I use ξ_{jt} to denote the characteristic that influences consumer decision but is not captured in my dataset. Examples of such a feature include how stylish the car is or what is its general appeal to buyers. ξ_{jt} is assumed to be independent of X_{jt} but may be correlated with product price P_{jt}. The reasoning behind it is that the manufacturer observes the realization of ξ_{jt} and adjusts his price accordingly. Hence, products with higher values of the unobserved characteristics are likely to have higher prices. Ignoring this problem can lead to biased and inconsistent estimates of the price sensitivity parameter α by introducing omitted variable bias. Berry et al. [1995]

suggested using instrumental variables to tackle this problem which will be discussed below.

The above specification translates into the probability that consumer i purchases car j that is given as follows:

$$\Pr(i \text{ purchases } j|A, X, P) = \frac{\exp(\delta_i - \alpha \log(y_i - P_j) + \mu_{ij}(\nu_i))}{1 + \sum_{k=1}^{N} \exp(\delta_k - \alpha \log(y_i - P_k) + \mu_{ik}(\nu_i))}$$

Here N represents the number of models that available in a given year. I suppress the year subscript t from the equation for better tractability. Aggregating consumers allows to calculate the market share for any given model:

$$\begin{aligned} s_j(A, X, P) &= \int \frac{\exp(\delta_j - \alpha \log(y_i - P_j) + \mu_{ij}(\nu_i))}{1 + \sum_{k=1}^{N} \exp(\delta_k - \alpha \log(y_i - P_k) + \mu_{ik}(\nu_i))} f(\nu_i) d\nu_i \\ &= \frac{1}{N_d} \sum_{i=1}^{N_d} \frac{\exp(\delta_j - \alpha \log(y_i - P_j) + \mu_{ij}(\nu_i))}{1 + \sum_{k=1}^{N} \exp(\delta_k - \alpha \log(y_i - P_k) + \mu_{ik}(\nu_i))} \end{aligned}$$

N_d corresponds to the number of consumers.

1.3.2 Firm Problem

I assume that firms are profit-maximizing and have knowledge of the unobserved characteristic ξ_{jt}. Let F_f denote all products of a firm f, and M be the market size (which is defined as number of households in the US).Then the problem of a firm f is:

$$\max_{p_{j \in F_f}} \sum_{j \in F_f} (P_j - MC_j) \cdot M_t \cdot s_j \tag{1.2}$$

MC_j denotes the marginal cost of car j. Note that since several car companies own multiple brands[8], I assume that a firm chooses how to price products that belong to all the brands it owns.

Following the approach outlined in BLP I assume that the marginal costs depend linearly on product characteristics X_j:

$$\log MC_j = X_j \gamma + \omega_j \tag{1.3}$$

[8]For example, General Motors owned Buick, Cadillac, GM, Chevrolet, Oldsmobile, Pontiac, and Saturn brands. Ford owned Lincoln and Mercury brands. Toyota owned Daihatsu, Lexus, and Scion brands.

I will impose an assumption that ω_j has to be independent of the regressors X_j. This equation will be used later in estimation to help with identification.

1.4 Estimation

1.4.1 Mean Utility

The estimation procedure is based on the General Method of Moments. The first set of restrictions utilizes the values of δ as defined in Equation 1.1. However, δ is unknown and will need to be calculated iteratively using contraction mapping as suggested in BLP. For any given value of (α, σ) and any starting value of δ I calculate δ' as follows:

$$\delta' = \delta + \log(s) - \log(\hat{s}(X, P, \delta; \theta))$$

s represents market shares as observed in the data, and $\hat{s}$ are fitted values based on the current values of δ. Then I iterate this procedure until $\delta' - \delta$ takes a value less than $1.0e - 14$. Once the procedure stops I use these values to run the regression below and calculate $\hat{\xi}$:

$$\delta_{jt} = \beta_A A_{jt} + \beta_X X_{jt} + \xi_{jt}$$

This regression returns the estimates of β, and $\hat{\xi}$ is used to construct the first set of moment restrictions that are discussed at the end of this section.

Since firms know ξ_j when pricing their products but I may not observe these values this may lead to an omitted variable bias when determining the price coefficient α. BLP suggest to use product j's characteristics X_j, sum of characteristics of other products that belong to the same firm $\sum_{r \neq j, r \in F_f} X_r$, and, finally, sum of characteristics of products of other firms $\sum_{r \neq j, r \notin F_f} X_r$ as instruments. The interaction of instruments and the residuals will form the moment conditions. The more detailed discussion of the moment conditions used to estimate the rest of the parameters follows below.

1.4.2 Marginal Costs

Another set of restrictions that assists with identification comes from the supply side. Using the firm problem specified in Equation 1.2 I can apply first order condition with respect to price P_j. This FOC for a product j is given by:

$$s_j(P) + \sum_{r \in F_f} (P_r - MC_r) \frac{\partial s_r(P)}{\partial P_j} = 0$$

Applying this FOC to every product in a given year yields J first order conditions. This set of FOC's can be expressed in a matrix form:

$$s(P) - \Delta(P)[P - MC] = 0$$

Here each element of Δ is defined as:

$$\Delta_{jr} = \begin{cases} -\frac{\partial s_r}{\partial P_j} & \text{if } r \text{ and } j \text{ belong to the same firm;} \\ 0 & \text{if } r \text{ and } j \text{ otherwise.} \end{cases}$$

Then MC can be found by solving the above system of linear equations. The solution is then given by:

$$MC = P - \Delta^{-1}(X, P) \cdot s(X, P)$$

Prices P and shares s come from data. Δ and Δ^{-1} can be computed for any given values of the demand parameters.

After computing MC I move onto estimating the regression equation 1.3 which gives me the estimates of γ and ω. With the knowledge of $\hat{\xi}$ and $\hat{\omega}$ the moment restrictions of the form $G_1 = E[Z_1^T \xi]$ and $G_2 = E[Z_2^T \omega]$ are constructed. Here Z_1 and Z_2 represent the instruments for the demand and marginal cost equations respectively. Finally, combining the moment restrictions into an objective function and minimizing it allows to recover the parameters $\hat{\theta}$.

1.5 Results

1.5.1 Demand Parameters

The results from the estimation are reported below. In order to better understand consumer willingness to pay for airbags I conduct the estimation under two different specifications (unrelated to those in section 1.2.2). The first specification (I) assumes that the cost of airbags stays the same over time. In the second specification (II) I introduce an interaction term between the number of airbags and years in order to capture whether the airbag cost has changed over time.

My decision to explore the latter specification is motivated by two factors. First, the literature on airbag adoption suggests that the airbag industry has benefited massively from the economies of scale and learning-by-doing as the production volumes have increased[9]. While I do not aim to establish the causal link between the production volumes and airbag cost in this paper, my hedonic regressions in Section 1.2.2 suggest that the prices of cars with airbags were indeed decreasing over time even controlling for other features. Second, understanding the cost structure of the airbags is important for quantifying the welfare effects of airbags on consumers which I do in Section 1.6.

For the purposes of tractability I reduce the total number of regressors by grouping similar features into two groups: comfort features and power equipment. Also, this allows me to avoid possible issues with collinearity when constructing instruments for the endogenous variables, as described in the previous section. More details how features were categorized can be found in Table A.2 in Appendix.

Table 1.4 reports the estimates of consumer preference parameters. Estimates of β_k capture the mean level of corresponding parameters, and estimates of σ_k serve a measure of heterogeneity in tastes. The results have largely the expected sign and are in line with the literature[10]. Most of the parameters are also statistically significant with the exception of the all-wheel driver (AWD) and luxury brand dummy in specification II. One possible explanation for this could be that consumers value the additional features of cars rather than the brand luxury status per se. The standard deviations are also of expected magnitude.

The coefficients on all safety features, which are frontal airbags, side airbags, and anti-lock brake system (ABS), are positive and significant in both specifications.

Since our regression is non-linear the interpretation of parameters is rather non-trivial. To deal with this issue I report mean willingness-to-pay (WTP) for product characteristics in Table 1.5. WTP is calculated by finding a price decrease that would leave a buyer of a certain product just as well off as before once a certain feature of his car is taken away[11]. For example, the results from specification I show that removing one frontal airbag from a car would need to be accompanied by price decrease of $932 to leave an average consumer just as well off as before. Since the WTP estimates are a function of demand parameters reported in Table 1.4 their statistical significance levels are identical to those of corresponding parameters in Table 1.4.

Overall the willingness-to-pay for different features is in line with expectations.

[9] See Sperling et al. [2004].

[10] For example, see Berry et al. [1995] and Berry et al. [2004].

[11] A similar approach was also used by Mannering and Winston [1995]

Table 1.4: Demand estimates

		I	II
Means (β_k)	log(Price)	-65.503***	-53.846***
		(5.044)	(4.132)
	HP/Weight	1.233***	1.342***
		(0.303)	(0.305)
	MPD	0.211*	0.289**
		(0.162)	(0.160)
	Space	2.176***	2.315***
		(0.188)	(0.189)
	# Frontal Airbags	0.249***	0.189***
		(0.050)	(0.050)
	Airbag (Side)	0.356***	0.358***
		(0.080)	(0.078)
	ABS	0.188***	0.229***
		(0.068)	(0.069)
	AWD	-0.136**	-0.159**
		(0.076)	(0.076)
	# Comfort Features	0.327***	0.359***
		(0.028)	(0.029)
	# Power Equipment	0.370***	0.416***
		(0.046)	(0.048)
	Truck	0.418***	0.547***
		(0.102)	(0.104)
	Luxury Brand	0.113**	0.030
		(0.066)	(0.065)
	Constant	-5.758***	-7.418***
		(0.531)	(0.545)
Std. Dev. (σ_k)	# Frontal Airbags	1.297***	1.904***
		(0.133)	(0.153)
	Constant	2.205***	4.192***
		(0.439)	(0.424)

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The difference between specifications I and II is in how the corresponding marginal cost equation is written. See Table 1.6 for more details.

On average consumers are ready to pay about $1,226 for an additional comfort feature (such as automatic air conditioning), $704 for an anti-lock brake system (ABS), and $1,389 for another piece of power equipment. Willingness to pay for side airbags is about $1,335. Furthermore, average consumer is ready to pay additional $1,567 for a truck and $422 for a luxury brand. These estimates are higher than those reported in previous literature. Mannering and Winston [1995] reported consumer WTP ranging

Table 1.5: Willingness-to-pay estimates ($1,000)

	I	II
HP/Weight	4.623	6.126
MPD	0.793	1.319
Space	8.158	10.564
# Frontal Airbags	0.932	0.861
Airbag (Side)	1.335	1.633
ABS	0.704	1.043
AWD	-0.509	-0.724
# Comfort Features	1.226	1.639
# Power Equipment	1.389	1.898
Truck	1.567	2.494
Luxury Brand	0.422	0.137

Note: While standard errors are not reported in this table they are equivalent to those of the corresponding parameters in Table 1.4.

between $527 and $868[12].

1.5.2 Cost Parameters

I also report the cost parameters that were estimated jointly with the demand parameters. Cost side estimates for all specifications are found in Table 1.6. The results are largely robust to the specification of airbags. Most of the estimates have the expected sign except log(MPG) and log(Space) as is common in the literature[13]. Furthermore, most of the estimates are statistically significant with the exception of all-wheel drive (AWD), the number of comfort features, and truck dummy. One possible explanation is that the model is already saturated and there may not be enough variation to identify these parameters precisely.

The above results indicate that one airbags adds about $3,126 to the marginal cost of an average car[14]. While this estimate is high, it is worth noting that the cost of airbags has experienced a significant decrease between 1990 and 1996[15]. The high cost of airbags at the beginning of the 1990's is driving this high estimate. I study the cost evolution of airbags in much more detail in Chapter 2.

[12]These values were calculated by translating the original values from their paper that were reported in 1993 dollars into their equivalents in 2017 dollars.
[13]See Berry et al. [1995].
[14]Full table with dollar equivalents can be found in Table A.3 in Appendix.
[15]See Sperling et al. [2004].

Table 1.6: Cost estimates

		I	II
Means (γ_X)	log(HP/Weight)	0.488***	0.456***
		(0.033)	(0.030)
	log(MPG)	-0.974***	-0.878***
		(0.052)	(0.047)
	log(Space)	-0.456***	-0.444***
		(0.048)	(0.044)
	# Frontal Airbags	0.139***	0.204***
		(0.012)	(0.016)
	# Frontal Airbag × Trend		-0.015***
			(0.003)
	Airbag (Side)	0.093***	0.101***
		(0.017)	(0.016)
	ABS	0.044***	0.035***
		(0.013)	(0.012)
	AWD	0.002	0.001
		(0.013)	(0.012)
	# Comfort Features	0.005	0.004
		(0.005)	(0.005)
	# Power Equipment	0.084***	0.066***
		(0.009)	(0.008)
	Truck	0.007	0.017
		(0.019)	(0.018)
	Luxury Brand	0.229***	0.211***
		(0.014)	(0.013)
	Trend	-0.021***	-0.006***
		(0.002)	(0.003)
	Constant	3.938***	3.854***
		(0.056)	(0.054)

Note: Standard errors are given in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

1.6 Welfare Impact of Safety Technologies

While willingness-to-pay is a useful measure of how much consumers value airbags it does not necessarily represent all the change in consumer welfare due to introduction of airbags in cars. Adding airbags to a product puts pressure on competing models to which they may react by lowering prices. Hence, consumers who do not purchase or value airbags can still benefit from introduction of airbags by enjoying lower prices due to competition. In order to study these effects I use compensating variation. I construct an equilibrium where no cars have airbags and calculate consumer welfare in this new setting. Then, I ask how much a consumer would have to be compensated in order to have the same welfare as in the world where cars have airbags.

I make several assumptions while calculating the equilibrium in a world without airbags. I assume that no cars have any airbags at any point in time and that all other car features remain unchanged. Furthermore, I assume that the structure of airbag marginal cost across years is unchanged as well[16]. Since the absence of airbags would affect marginal cost I re-calculate the marginal costs for each model using the estimates obtained from my model. Given the estimated parameters I compute optimal prices for all models in the new Bertrand-Nash equilibrium. In order to do so I iterate on firm FOCs until I find a fixed point. Finally, I compute consumer welfare in this setting using the formula for consumer surplus in logit setting:

$$CS_i = \frac{1}{\tau_i} \cdot \log\left(\sum_{j=1}^{J} \exp(\delta_{jt} - \alpha \log(y_{it} - P_{jt}) + \mu_{jt})\right)$$

where τ_i is the marginal utility of income of consumer i. The next step is to calculate a flat change in income such that consumer surplus of agent i in the new equilibrium equals the consumer surplus in equilibrium with airbags[17].

I start the exploration of the effects of frontal airbags with exploring how they affected the market equilibrium. On average, prices are lower when no airbags are installed[18]. The difference in mean prices in the two scenarios amounts to about \$2,570. However, it is not constant over time and increases as more and more models adopt airbags in the baseline scenario. This difference is primarily driven by the marginal cost of airbags. However, not all models experience price decrease in the world without airbags. I find that 542 out of 2,707 models in my sample are priced higher in the world without airbags due to the lack of competitive pressure from airbag-equipped models. However, such price increases are rather small and are on average about \$334.

I report summary statistics on welfare changes due to safety technologies in Table

[16] Note that I use the results from specification II to estimate the counterfactual model. While the parameters are similar across different specifications the cost structure of airbags differs. In particular, different estimate of marginal cost of airbags would affect the computation of equilibrium prices in a world without airbags. I choose this specification because it allows the cost of airbags to vary over time and does better job at describing cost evolution of airbags as observed in the real world. See Sperling et al. [2004] for more details on airbag cost. I also study the cost of airbags in more detail in Chapter 2.

[17] Note that this calculation of compensating variation does not require me to account for the change in idiosyncratic taste term as in Petrin [2002], for example. This is because the choice set of consumers remains the same in the counterfactual scenario.

[18] See Figure A.2 in Appendix for an illustration of mean sales-weighted prices of new cars in a world where no cars have airbags.

Table 1.7: Summary statistics for welfare effects of safety technologies

	Frontal airbags	Side airbags	Anti-lock brakes
Compensating variation			
Mean ($)	1,345	157	481
Consumers who are ...			
Better off (%)	15.1		
Worse off (%)	17.6		

Note: I do not report the percentage of consumers who are better or worse off from the introduction of side airbags and anti-lock brakes because my model does not account for consumer heterogeneity in preferences for these two features. Hence, the change in utility from the introduction of these features is uniform for all consumers.

1.7. Mean compensating variation for all consumers in the period from 1990 until 2002 amounts to $1,345. However, it is also not constant over time. For example, an average consumer who finds himself in a world without airbags in 1993 would have to be compensated $545 in order to have the same welfare as in the world with airbags. Compensating variation ranges from $310 in 1990 to about $516 in 1998 and is generally lower at the beginning of the period. This is because airbags are available at a high premium and in a limited set of models at the beginning of the 1990's. Furthermore, the marginal cost of airbags is decreasing over time and thus leads to comparatively lower price of airbag-equipped cars in the later years.

However, the welfare change from the introduction of airbags was not uniformly positive. Compensating variation is, in fact, negative for about 17.6% of consumers, and positive for 15.1% of consumers[19]. On average, the gains of those who benefit outweigh the losses in welfare of those who lose. Conditional on benefiting from airbag the mean welfare increase is $5,880. Conditional on experiencing a decrease in welfare the average welfare loss is -$3,835[20]. The difference in the sign and magnitude of the effect is due to consumer heterogeneity in income and preference for airbags.

Side airbags appeared only in 1997 and are present for 6 years in my dataset. While I do not estimate the random coefficient on side airbags due to computational constraints I can still calculate the mean welfare impact of the introduction of side airbags. As Table 1.7 shows, the mean welfare change due to side airbags is about $157. While this number is very low it is mostly due to their low penetration rates

[19] The remaining 67.3% do not experience a significant change in welfare, that is their compensating variation is less than 10 dollars in absolute terms.

[20] Mean changes in welfare are strongly affected by extreme outliers. For example, the median values for welfare gain and loss conditional on experiencing an increase or decrease in welfare are only $4,647 and -$2,578. The numbers reported above are calculated excluding the top and bottom 5%.

(only 22% in 2002) and their relatively high prices.

Anti-lock brake systems first appeared at the end of 1980 about at the same time as airbags but were regulated only in 2013. They adoption rate varied between 20% and 80% throughout the period covered by my dataset. I find that the introduction of ABS improved consumer welfare by an average of $481.

1.7 Conclusion

In this paper I studied the welfare changes that resulted from the introduction of airbags in cars. The findings suggest that the airbags have increased the consumer welfare overall, however this effect created both winners and losers among consumers. Overall, the positive effects from new technologies was more pronounced for those consumers who had higher incomes (and thus, could afford to pay for them) and higher preference for airbags. This also goes in line with the findings in the public health literature which show that motor vehicle accident deaths are decreasing at higher rate for people with more education (and hence, income)[21].

Another interesting finding is that the marginal costs of airbags were, in fact, higher than the willingness to pay of an average consumer throughout most of the years in my dataset. Yet airbags saw universal adoption by the end of the 1990's. An important factor is the government mandate of 1991 which made airbags required in all new cars by 1998. I study the effects of this mandate on firms and consumers in Chapter 2.

[21] See Harper et al. [2015].

Chapter 2

Technology Mandates and Welfare: The Case of Airbags

2.1 Introduction

After a period of focusing on cutting costs in the 1970's, car manufacturers have been adding new features to cars almost on a yearly basis. These new features have ranged from simple electronic buttons that control windows to automatic lane-keeping. These developments make cars more comfortable, more efficient, and much safer[1]. Yet, it takes a long time for an average consumer to reap the benefits of new features as they appear in high-end luxury vehicles first and can take years to reach mainstream models. The Highway Loss Data Institute [2017] estimates that starting from the moment a feature becomes commercially available it takes almost 30 years for it to become ubiquitous in cars driven on the roads[2]. In the case of safety features, the government has often chosen to regulate their adoption by issuing mandates - regulations that made a specific feature mandatory in all new cars offered for sale. Such mandates required adoption of dual airbags by 1998, tire pressure sensors by 2007, electronic stability control by 2013, and backup cameras by 2018. In this work, I study the effects of such mandates on feature adoption, consumers and firms. I focus on dual airbags, as the airbag mandate was a hotly debated topic throughout almost two decades.

I develop a structural model of consumer vehicle choice and firm airbag adoption decision in presence of a deadline. The model is estimated on a novel detailed data set that covers car characteristics, features, prices and sales. I estimate consumer

[1] See Glassbrenner [2016].

[2] See Gargett et al. [2011], Highway Loss Data Institute [2017].

demand parameters, and marginal cost of cars and individual features, in particular, airbags using the methodology outlined in Berry et al. [1995] (further referred to as BLP). Furthermore, I estimate sunk costs of adoption using a model of dynamic oligopoly that is based on Bajari et al. [2007] (further referred to as BBL). The model and estimates are used to simulate individual firm adoption and prices in the absence of regulation in order to understand how the industry behaves when no mandate is place. This allows me to estimate the welfare impact of the airbag mandate of 1998 on consumers and firms.

Even without regulation, firms often have an incentive to introduce new desirable features in their products. New features allow firms to better differentiate themselves from competition and price discriminate, as consumers vary in their preferences and price sensitivity. The adoption process often follows a pattern where the innovative features appear first in luxury, expensive products and then make their way into mainstream and cheaper products over time. There are two developments that drive such process. First, consumer preferences may change and their willingness to pay may increase over time. Second, the cost of technology decreases as technology becomes more mature. In many cases these processes lead to universal adoption - delay wipers, rear defoggers, adjustable steering columns, and keyless entry are now ubiquitous in most cars.

Government interventions such as mandates force firms to adopt new features earlier than they find optimal, thus creating a market distortion. There may be multiple reasons for such interventions. First, safety technologies may have positive externalities[3]. For example, anti-lock brakes, which became mandatory as a part of electronic stability control in 2013, prevent the driver from losing control on slippery surface, and thus reduce the risk to nearby drivers and property. Second, the government estimates of consumer willingness to pay and cost of features may differ from those of the industry. Lee Iacocca who was the CEO of Ford and later Chrysler was a fervent opponent of airbag regulation. His opinion was that cars with airbags could not be sold profitably, yet it changed in the 1990's and he became a proponent of airbags himself[4]. Finally, the government may pursue paternalistic or political goals by promoting mandatory installation of safety equipment[5].

The market distortions caused by technology mandates are complex and do not affect firms and consumers uniformly. Consider the effects of mandate on firms first.

[3] See Berlemann and Matthes [2014], Edlin and Karaca-Mandic [2006].

[4] See Sperling et al. [2004].

[5] One line of argument is that consumers tend to consistently overestimate their driving abilities and/or underestimate risk. See Greening and Chandler [1997] for more details.

Some firms adopt voluntarily before the mandate is in force. They enjoy competitive advantage over the firms which have not adopted yet. This also allows them to differentiate themselves from the competition and charge higher markup. As the mandate comes into force, every firm is forced to adopt airbags and the markup associated with having airbags in a car evaporates. This leaves the voluntary adopters worse off. Other firms may simply find it unprofitable to adopt costly airbags if, for example, they target particularly price-sensitive consumers or consumers with low preference for safety. The mandate would leave such firms worse off as well.

The sign of the effect depends on consumer price sensitivity and valuation of safety equipment. A consumer with high preference for airbags and low price-sensitivity is likely to get a car with his desired feature earlier and cheaper since the mandate reduces firm ability to charge airbag-specific markups. On the other end of the spectrum, a highly price sensitive consumer with low valuation of airbags is forced to pay for a feature that he may not value enough.

The magnitude of these effects depends on how binding the mandate is - if it comes late, after the costs have fallen low enough and most firms adopted, the distortions will be small. On the other hand, if the mandate is introduced too early, when costs of the mandated technology are still high, the welfare effects will be much more pronounced.

While studying this question, one could be tempted to approach it by looking at the market before and after the regulation. However, such approach would be complicated by the fact that most firms chose to adopt airbags before the mandate was fully in force. In fact, almost 70% of new cars sold in the US[6] already had an airbag in 1994, several years before the mandate was in force. This behavior could be driven by the fact that the mandate makes it profitable to adopt early rather than at the deadline if large sunk costs are present. To illustrate this point, consider an example where the firm finds it profitable to sell cars with airbags but faces large sunk cost of adoption. If sunk costs are larger than the sum of discounted future marginal profits from adoption, then the firm will not adopt. However, in case the firm is exogenously required to adopt at some point in the future and pay the sunk cost anyway, it may be profitable to adopt early and recoup the adoption costs by selling airbag-equipped cars earlier. If a firm adopts at the deadline then it cannot recoup any costs since it has no competitive advantage. This makes it difficult to quantify the effects of the airbag mandate on consumers and firms - in a counterfactual scenario without the airbag mandate of 1998 the world looks different not only after 1998 but

[6]About a third of these cars still had driver-only airbags. The mandate required dual airbags.

also before 1998 since firms anticipated the regulation and optimized accordingly.

I find that government regulation speeds up adoption. The regulation ensured that 100% of new vehicles had dual airbags by 1998. In contrast, I find that in the world without the mandate only 39% of new cars would have dual airbags in 1998 and only 61% - in 2002. The rest of the models would either be equipped with driver-only airbag or none at all. Despite the stark effect on adoption rates, the welfare effects of the mandate are not as pronounced - consumer welfare is only 2.1% higher in the world with the mandate. Most of the consumers (those with high preference for safety and low price sensitivity) benefit from the mandate by getting airbag-equipped cars earlier and cheaper. Yet about 32% of the consumer base is made worse off. A small share of consumer of 0.9% chooses the outside option due to the higher prices caused by the mandate. Firms are made worse off by the mandate with total profits decreasing by about 4.5% on average. Beside the welfare effects the model yields a number of interesting results on consumer valuation of airbags and their marginal costs. An average consumer is estimated to value an airbag at about $1,000[7]. The marginal costs of airbags are falling over time and represent another driver of adoption beside regulations. They are estimated to be around $3,000 in 1990 and fall to less than $1,000 by the end of the decade.

My analysis contributes to literature on government regulation and technology adoption in two important ways. First, government regulation and its dynamic implications for markets were studied in great detail. Ryan [2012] studied the costs of environmental regulation in the cement industry and its implication for entry and exit. Sweeting [2013] analyzed the changes in royalties regulation on positioning of radio stations in a market. A number of papers have also focused on the effects of environmental standards for automobiles. For example, see Gramlich [2009], who studied the trade-offs between car quality and fuel efficiency. Yet a notable difference between adoption of safety features and fuel efficiency is that the latter has been driven almost exclusively by regulation while the former has been driven both by regulation and market forces. A related paper that studies the effects of regulations is Nelson and Drews [2008]. The authors study the effects of liability regulation, which de-facto imposed an extremely strict safety standards on produced aircraft[8], and find that it reduced the sales of new airplanes by over 80%. They show that, despite making brand new airplanes safer, the regulation has made the industry less safe overall

[7]All monetary values here and henceforth are in 2017 USD.

[8]They study general aviation industry. General aviation is the term used to describe non-commercial aircraft primarily used for personal transportation and recreation.

since most plane owners chose to keep on flying older (and less safe) planes. Overall there has been relatively little exposition of the effects of mandates, which are rather drastic government interventions in the functioning of a market. I contribute to the literature by quantifying the effects of mandates on consumers, firms, and industry dynamics.

Second, this paper contributes to the literature on technology adoption. A large body of papers studied firm decisions to invest in improving their products under free market conditions. Igami [2017] studies the decision of incumbent firms to switch to a new technology format in the hard-drive industry. Schmidt-Dengler et al. [2006] looks at the competitive effects that drove hospital decision to adopt MRI machines as they became available. My paper is different as it studies the adoption of new technology in the presence of a deadline imposed by the government.

There are a couple of other papers that are broadly relevant to this topic. Mannering and Winston [1995] use a discrete choice model to estimate consumer willingness to pay for airbags using aggregate data on market shares of airbag-equipped vehicles. However, they do not take into account the dynamic implications of the mandate on firm behavior, and do not control for endogeneity in prices and consumer heterogeneity. In terms of the empirical strategy Blonigen et al. [2017] are very close to my paper. They study car manufacturer decisions to refresh a model line in presence of competition. Their model relies on the BLP approach to calculate the demand side parameters and profits, and on the BBL in order to estimate the sunk costs of a model refresh.

2.1.1 Outline

The paper proceeds in the following fashion. The upcoming section 2.2 provides background information on the car industry and adoption of airbags. Section 2.3 describes the dataset and its constructions. Section 2.4 outlines the model. Section 2.5 discusses the empirical strategy. Sections 2.6 and 2.7 discuss the estimates and welfare implications of the mandate. Section 2.8 concludes.

2.2 Industry Background

2.2.1 History of Airbag Regulation

Airbags were invented in the late 1950's and were adapted for use in automobiles by the early 1970's. Initial adoption of airbags was slow. GM equipped several thousands of its cars in mid-1970's but quickly scrapped the plan citing high cost. However, the regulators have taken notice of airbags and pushed for regulation to make airbags mandatory for all cars[9]. The car industry has been extremely resistant to such regulation. Some company executives even went as far as to say that the airbag mandate would spell the death sentence for the American car industry. However, the regulators were moderately successful in 1981 by passing a law that mandated some form of passive protection in cars by 1991. Car manufacturers could comply either by installing an automatic seat belt, that would wrap around the driver automatically once he is seated, or an airbag. Most of the companies responded by installing automatic seat belts which were cheap and, reportedly, rather inconvenient to use.

Airbags reappeared on the market in 1984 and were mostly offered as an option. Porsche 911 offered for sale in 1988 was the first car to feature a driver airbag as standard equipment. Soon other luxury manufacturers followed. Porsche, Mercedes, and BMW made driver airbags standard equipment by 1990.

In 1991 the regulators have finally succeeded in their push for airbag mandate and the Intermodal Surface Transportation Efficiency Act of 1991 made dual (that is, driver- and passenger-side) airbags mandatory in all vehicles offered for sale on and after September 1st, 1998. The industry has complied with the regulation and all cars were equipped with airbags as standard equipment in model year 1998.

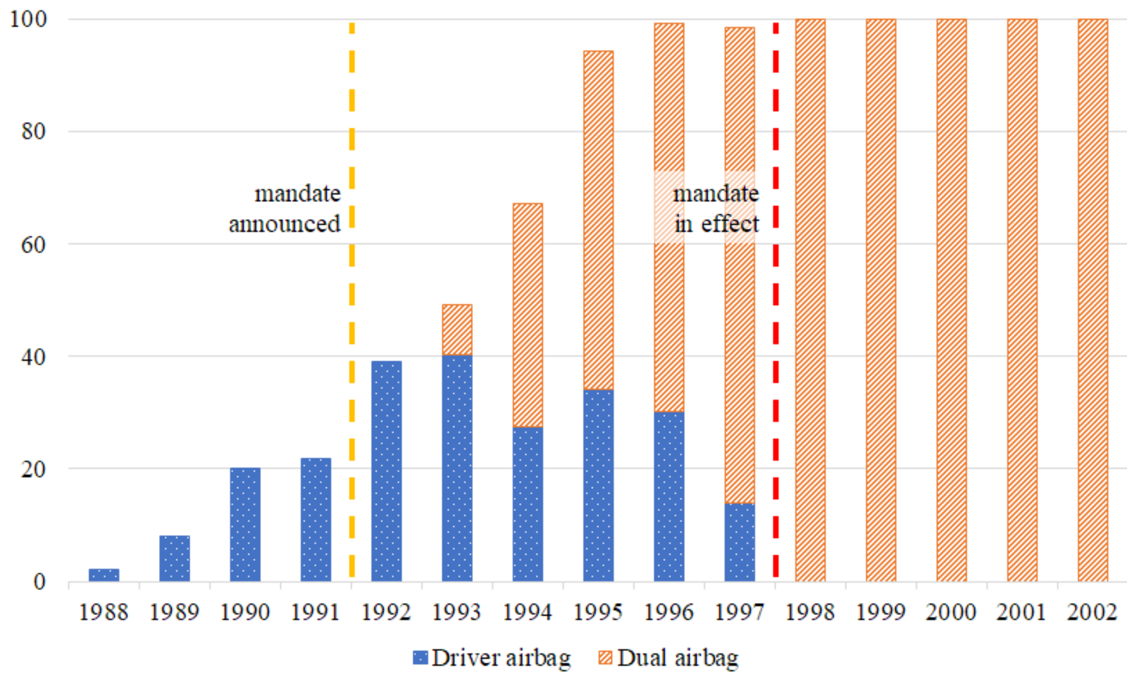
2.2.2 Airbag Adoption

Figure 2.1 shows the adoption rates of driver and dual airbags in the industry. Installations of driver airbags almost double in 1992, one year after the mandate was announced. Yet driver airbags are quickly phased out and are replaced by dual airbags, with firms achieving 100% in 1998. The cars that were not equipped with airbags were still equipped with automatic seatbelts to comply with the previous regulation.

Since I am primarily interested in the effect of the mandate on adoption, it is helpful to look at other safety features which were not regulated. There are good examples. Side airbags are designed to protect a passenger's side, shoulder, and neck from a side impact. Figure 2.2 below shows the adoption rates for non-regulated side airbags. The adoption rate is notably slower in the case of side airbags. After 10 years their adoption rate is around 50%, and it takes 16 years for them to achieve 90% adoption rate.

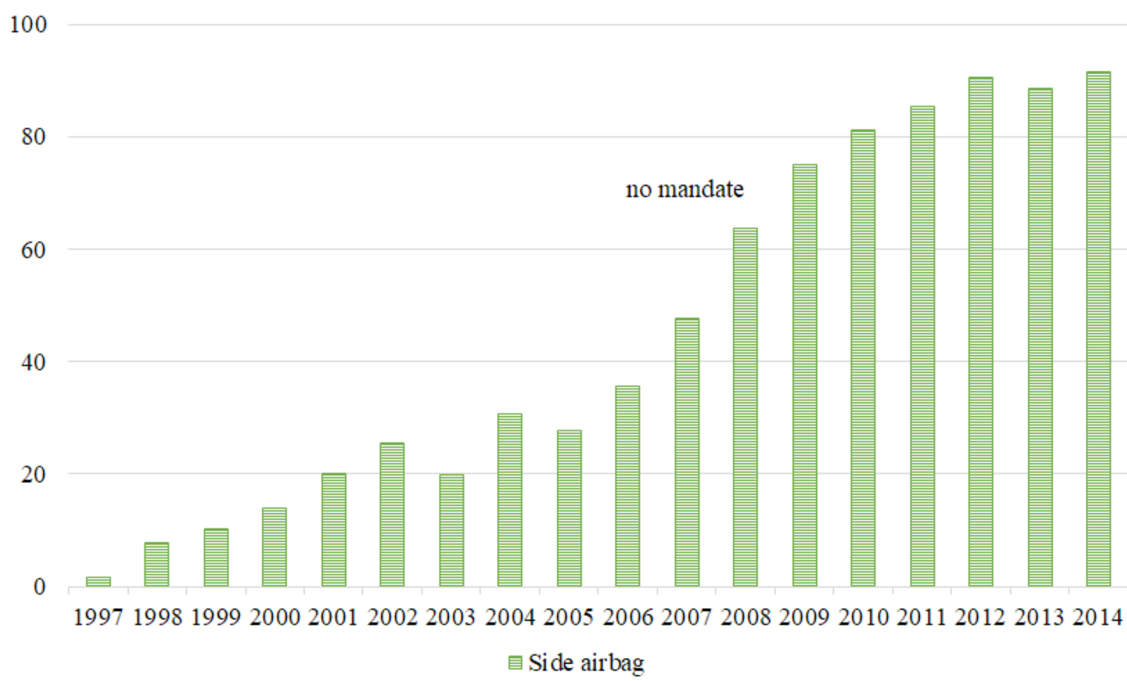
[9]It was also due to the very low usage rates of seat belts.

Figure 2.1: New car sales by airbag type by year (%)



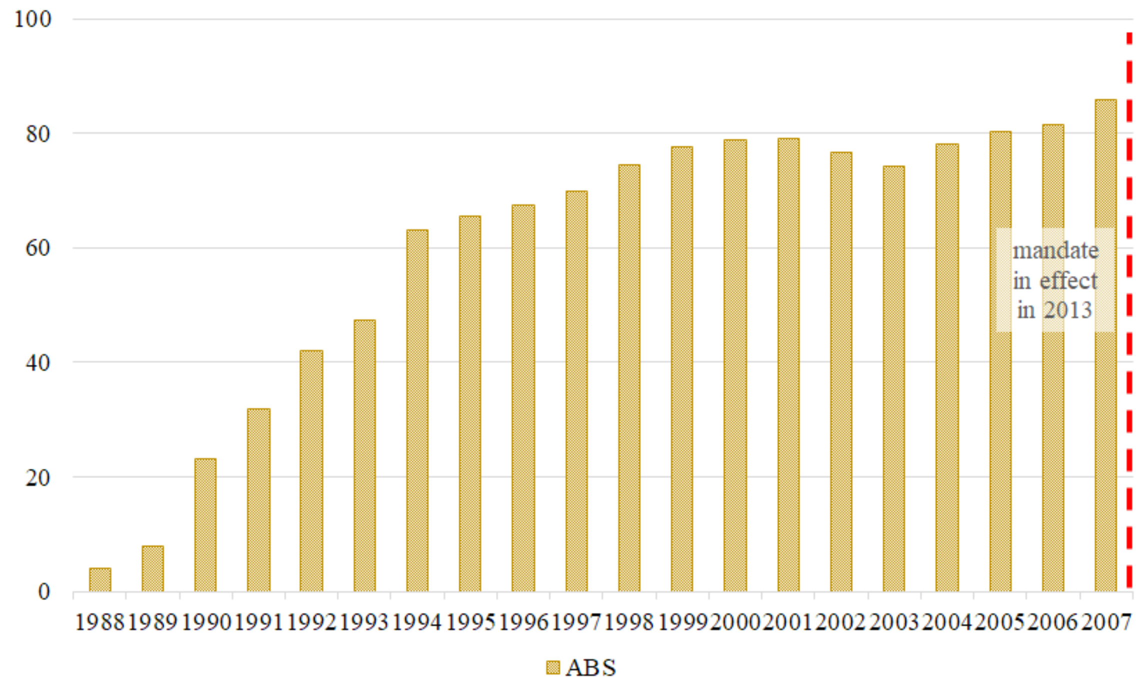
Note: Data for years 1988 and 1989 comes from additional Ward's Automotive Yearbook reports not included in the main dataset.

Figure 2.2: New car sales with side airbags by year (%)



Note: Data for years beyond 1990-2002 comes from additional Ward's Automotive Yearbook reports not included in the main dataset.

Figure 2.3: New car sales with ABS by year (%)



Note: Data for years beyond 1990-2002 comes from additional Ward's Automotive Yearbook reports not included in the main dataset.

Another example is the anti-lock brake system (ABS) that prevents the driver from losing traction on a slippery road. ABS was invented and became commercially available in the late 1980's, about the same time as airbags. Its adoption rate is reported in Figure 2.3. However, they were not regulated until 2013, when they also became mandatory as a part of electronic stability control. Their installation rates hovered around 50% for most manufacturers well into the 2000's.

However, it is worth noting that the adoption of airbags was not evenly spread out between firms. The early adopters were the brands that were generally considered to be luxury brands. For example, in my dataset companies such as Audi, BMW, and Mercedes already had driver airbags in all of their US models in 1990. A snapshot of adoption rates for selected brands is reported in Table 2.1. Large American brands were the ones to adopt at a more moderate pace, and large Asian brands were the slowest ones to adopt. However, once the differences in adoption between the brands are accounted for, there does not seem to be any particular pattern to adoption decisions within a firm. This observation tentatively suggests that the adoption decisions are not coordinated within a firm to occur at the same time.

Table 2.1: Number of models with airbags by brand

Brand	Models	1990	1991	1992	1993	1994	1995	1996	1997	1998
Audi	Driver	6	6	4	1	0	0	0	0	0
	Dual	0	0	0	3	4	2	3	4	4
	Total	6	6	4	4	4	2	3	4	4
Chrysler	Driver	7	5	7	7	3	1	1	0	0
	Dual	0	0	0	1	7	9	8	8	7
	Total	13	8	9	10	11	10	9	8	7
Ford	Driver	2	3	6	6	5	7	7	2	0
	Dual	0	0	0	0	6	10	10	15	12
	Total	17	17	17	17	17	18	18	18	12
GM	Driver	0	1	1	1	3	10	7	2	0
	Dual	0	0	0	0	0	0	2	6	9
	Total	9	11	11	11	9	10	9	9	9
Mitsubishi	Driver	1	1	1	2	3	1	1	1	0
	Dual	0	0	0	0	3	5	5	5	6
	Total	9	7	9	8	8	7	6	6	6
Nissan	Driver	1	3	2	4	2	1	3	2	0
	Dual	0	0	0	0	2	6	5	6	8
	Total	8	8	8	9	8	9	8	8	8
Toyota	Driver	2	3	5	6	3	4	6	6	0
	Dual	0	0	0	1	5	7	7	7	12
	Total	9	10	12	12	12	13	13	13	12
VW	Driver	0	0	0	1	0	0	0	0	0
	Dual	0	0	0	0	3	4	4	4	5
	Total	7	7	6	7	5	4	4	4	5

Note: Only selected brands are reported. Data for all brands is available upon request.

2.3 Data

The dataset was constructed using data from Ward's Automotive Yearbook, an automobile magazine that publishes yearly statistics on new vehicles. I focus on the period between 1990 and 2002 as it covers the years during which the airbag adoption took place and several more years afterwards. The dataset offers the breakdown of the market offerings by year, make and model. An example of a single observation would be 2000 Ford F-150. The dataset omits certain exotic cars that were on the market but still covers over 95% of all cars sold in the US.

For each model I observe general characteristics (e.g. engine size, horsepower, miles-per-gallon etc.), manufacturer's suggested retail price (MSRP), unit sales and, most importantly, shares of cars with factory-installed equipment. Factory-installed equipment includes airbags, ABS, traction control, climate control, power windows,

Table 2.2: Descriptive statistics for years 1990-1998

Year	1990	1991	1992	1993	1994	1995	1996	1997	1998
MSRP	28.4	28.4	29.8	30.4	30.7	32.0	32.2	32.8	33.9
HP/Weight	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
MPG	2.4	2.4	2.3	2.3	2.3	2.3	2.3	2.3	2.3
Space	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.2	1.2
Airbag (Driver)	21.7	20.7	39.0	40.7	25.8	34.8	31.2	14.2	0.0
Airbag (Dual)	0.0	0.0	0.0	7.3	40.7	59.3	68.2	84.5	100.0
All-Wheel Drive	5.7	8.0	9.2	10.0	11.3	13.0	15.8	17.1	23.7
Power Brakes	74.9	66.3	56.0	50.6	31.9	31.5	29.7	27.1	22.6
Anti-Lock Brakes	25.1	33.8	44.0	49.4	68.1	68.5	70.3	72.9	77.4
Automatic AC	12.1	11.6	9.1	7.7	7.6	7.9	7.7	7.6	11.5
Automatic Lights	0.0	0.0	0.0	0.0	0.0	0.0	0.0	14.4	14.48
Adjust. Steering	75.9	74.6	77.4	77.4	79.3	82.8	82.0	84.6	89.8
Cruise Control	67.7	70.1	74.8	74.8	74.6	78.0	80.2	82.5	83.3
Keyless Entry	0.0	0.0	0.0	0.0	0.0	11.9	22.9	33.1	40.7
Rear Defogger	72.1	79.5	75.5	75.7	73.4	76.5	78.7	74.8	71.2
Power Equipment	45.2	40.1	46.8	51.0	54.6	59.1	61.0	63.2	67.1
Total Models	212	216	220	219	205	207	202	199	195
Total Sales (M.)	12.4	12.7	12.2	13.1	13.9	14.9	13.6	14.6M	14.7

Note: All variables except Total Models and Total Sales are sales-weighted averages. MSRP is given in 2017 dollars. Total Sales are given in million units. Full table for years 1990-2002 can be found in the Appendix.

rear defogger etc. Variables related to factory-installed equipment measure the share of cars of a given model that leave factory with a certain equipment pre-installed. However, in practice they almost always take values of 0 or 1 so I treat them as dummy variables[10].

There are two concerns about the data that could potentially make the analysis less precise. First, consumers could choose to fit their cars with certain features post purchase. This could cause our dataset to underestimate the number of cars with advanced safety equipment and thus underestimate demand for airbags. However, speaking to car dealers and manufacturer's representatives revealed that this is very unlikely to be the case for more advanced equipment such as airbags, ABS and power equipment. Dealers are reluctant to make major modifications to cars since this would void manufacturer's warranty and would rather offer a model that has the required equipment pre-installed. In that case it will be accounted for in my dataset. Third-party modifications were possible at a time, however they were significantly more expensive and much less common than factory-equipped cars[11].

[10]See Figure A.1 in Appendix.

[11]See Sperling et al. [2004].

Second, the data on factory-installed equipment and sales is available only on the model level and only general characteristics and prices are broken down by car trim (i.e. sub-model such as Ford Fiesta SE or Ford Fiesta ST). I aggregate general characteristics and prices to the model level by taking averages and use it to construct a model-level observation. If airbags appear more often in more expensive trims of a given model but prices are averaged across trims, it could make the results less precise. However, the data shows that for most models the share of airbag-equipped airbags takes values of either 0 or 1, which means that airbags are largely introduced for all variations of a given model at the same time[12].

The main advantage of this dataset is its exceptional coverage of car features. This information is required to precisely identify consumer preference for airbags. Airbags are very likely to appear first in luxury cars together with other desirable features. Without controlling for other characteristics we would be at risk of introducing omitted variable bias and overestimating the airbag-related preference and cost parameters. Furthermore, information on additional equipment helps with identification of other parameters. While BMW and Toyota may be similar in horsepower, size and fuel efficiency (variables commonly used in econometric analysis of car market), they may differ significantly in their luxury features. To my knowledge, this is one of the the most detailed datasets on car characteristics used in econometric analysis.

Aside from product characteristics, I use data on the number of households and consumer price index (CPI) to calculate the market size and translate all prices to 2017 dollars. Since consumer are likely to react to gasoline prices MPG is divided by the cost of gasoline to obtain miles-per-dollar (MPD). Finally, I use data on mean and variance of household income to account for consumer heterogeneity with respect to price sensitivity. All additional data comes from St. Louis FRED database.

2.4 Model

The model consists of two parts: the consumer problem where a consumer chooses what car to purchase, and the firm problem where a firm decides whether to adopt an airbag in a specific model line, and then how to price it. Since adoption of new features is driven by expected additional profits from having a more competitive product (beside regulation) understanding consumer valuation of safety equipment

[12]Some studies utilized datasets which distinguished between cars that had airbags provided as standard equipment and cars that had airbags offered as options. Their analysis found that controlling for cars that had optional airbags did not change the results significantly. See Mannering and Winston [1995] for more details.

is instrumental in understanding the firm decision to adopt. Broadly my model follows in footsteps of Berry et al. [1995] in estimating the demand and marginal cost parameters, and Bajari et al. [2007] in estimating dynamic parameters such as sunk costs of adoption.

2.4.1 Consumer Problem

Consumers are allowed to choose from the set of available cars in a given year plus the outside option of not buying a car, which includes having no car, buying a used one, or keeping an old one. They cannot choose a model and features separately - if they want a certain feature then they have to buy a car that comes with that particular feature.

Utility of a consumer i from purchasing a car j in year t:

$$U_{ijt} = \underbrace{\beta_A A_{jt} + \beta_X X_{jt} + \xi_{jt}}_{\delta_{jt}} - \alpha \log(y_{it} - P_{jt}) + \underbrace{\sigma_A A_{jt} \nu_{iA}}_{\mu_{ij}} + \varepsilon_{ijt}$$

A_{jt} represents the airbags in the model[13].X_j corresponds to all other car characteristics and features. Note that X_j also includes year fixed effects to account for demand fluctuations over time. ξ_{jt} is a characteristic that is observed to consumers but not the econometrician. It may be car's design or general appeal. The unobserved term ξ_{jt} is assumed to be uncorrelated with X_{jt}. Since it represents something that consumers may value, ξ_{jt} may be correlated with price P_{jt} thus leading to endogeneity problem due to omitted variable bias. I discuss instruments for this problem later in the next section. ξ_{jt} together with $X_{jt}\beta_X$ are often referred to as "mean utility" and are denoted δ_{jt}. It describes the part of the utility that is strictly product specific and does not vary across the consumers.

y_i describes consumer i's income. Its inclusion allows the consumers to be heterogeneous in their price sensitivity based on their income. Term μ_{ij} describes consumer-specific preferences for product characteristics just as in BLP, where σ_k is the standard deviation of the consumer preference for X_k and ν_{ik} is a consumer- and characteristics-specific taste shock from $N(0, 1)$. For computational simplicity I restrict the random coefficients to airbags only. The random shock ε_{ij} is assumed to capture all idiosyncratic disturbances. It is assumed to follow Extreme Value Type I distribution which allows me to calculate a closed-form expression for purchase probabilities.

[13] I experiment with several different specifications of how airbag enter demand. In the first one both driver and passenger airbags are restricted to have the same coefficient. In the other specifications they are allowed to have different coefficients.

Using the property of Extreme Value Type I shocks, namely, that their difference follows a logistic distribution, I calculate the probability of a consumer choosing a certain product j. It is (I suppress the t-subscript for better readability):

$$\Pr(i \text{ purchases } j|A, X, P) = \frac{\exp(\delta_i - \alpha \log(y_i - P_j) + \mu_{ij}(\nu_i))}{1 + \sum_{k=1}^{N} \exp(\delta_k - \alpha \log(y_i - P_k) + \mu_{ik}(\nu_i))}$$

where N is the total number of products offered for sale.

Note that a consumer has $N + 1$ choices: either buy one of the new N cars or not buy anything (i.e. choose outside option). For identification purposes we need to normalize the mean utility of the outside option to $\delta_0 = 0$. This results in the additional term of value 1 in the denominator.

Knowing the probability of purchase, I calculate the good j's market share $s_j(X, P)$ by aggregating over all the consumers:

$$s_j(A, X, P) = \int \frac{\exp(\delta_j - \alpha \log(y_i - P_j) + \mu_{ij}(\nu_i))}{1 + \sum_{k=1}^{N} \exp(\delta_k - \alpha \log(y_i - P_k) + \mu_{ik}(\nu_i))} f(\nu_i) d\nu_i$$

We can approximate this integral by calculating:

$$s_j(A, X, P) = \frac{1}{N_d} \sum_{i=1}^{N_d} \frac{\exp(\delta_j - \alpha \log(y_i - P_j) + \mu_{ij}(\nu_i))}{1 + \sum_{k=1}^{N} \exp(\delta_k - \alpha \log(y_i - P_k) + \mu_{ik}(\nu_i))}$$

where N_d is the number of consumers.

2.4.2 Firm Problem

In every period each firm faces two decisions: whether to adopt airbags and how to price their products. The adoption decision is a dynamic problem because it requires an initial investment and affects that characteristics of the product in the consecutive periods. The pricing decision is a static problem and prices affect only profits in the current period. While there may be a dynamic aspect to pricing (for example, if there is learning associated with higher output) I abstract away from this possibility for now.

Adopting airbags is costly to a firm in two ways. First, the firm has to pay a certain sunk cost to re-engineer a particular model, re-tool the production facilities, and train staff to handle the installation process. Second, airbags themselves are costly: their components need to be purchased from suppliers, and their installation requires additional labor. Thus, airbags affect the marginal cost of a car, which will be reflected in the final car price.

The sunk cost is payable only once for a given model for a given type of an airbag. Once it is paid, all cars in that model line will have that particular type of airbag unless the firm decides to upgrade to a different type of airbag or stop the production of the model. The two available types of airbags are driver and dual airbags. If a model has no airbags installed the firm can choose to install either driver or dual airbags. If the model already has a driver airbag installed, it can be upgraded to a dual airbag. I do not allow firms to downgrade their airbags[14]. This means that once a model has a driver airbag it can only either keep it or upgrade to a dual airbag. Adopting a dual airbag is a terminal state.

2.4.2.1 Assumptions

There are two assumptions that I have to make in order to reduce the complexity of firm dynamic problem. First, I assume that adoption decisions are made on the model level and not firm level. This means that the airbag adoption decision for Ford Mustang is independent of the airbag adoption in Ford Fiesta (although, I allow the pricing effects to be taken into account). I make this assumption only for the adoption decision and allow prices to be set on the firm level once the adoption decisions have been realized. While this could be viewed as a restrictive assumption, the descriptive evidence in section 2.2.2 suggests that there is not much "clumping" in adoption decisions within a firm (except for a couple of luxury brands). If there is little coordination in adoption decisions across model lines then viewing each model as a separate firm is not as restrictive[15].

The second assumption is that other product features and airbags costs are taken as given. Airbags are rather self-contained in the sense that they are no dependent on other features (e.g. central computer or other electronics), hence it is not a very restrictive assumption.

2.4.2.2 Timing

I impose the following assumptions on the timing of events in the model. Every period starts with a firm observing current costs of airbags, its current private cost shocks,

[14] This decision is motivated by firm behavior as observed in the data. There is only one model which experienced a decrease in the number of airbags over time.

[15] Of course, the absence of "clumping" in adoption decisions does not suggest the lack of coordination if the firm coordinates the adoption to be spread over time. However, if the firm coordination is of a sequential nature then it will be captured in my policy function specification which accounts for the number of airbag-equipped models in the firm's lineup.

and sunk costs of adoption. The firm also observes the features of competing models and features of other products of the same brand from the previous period. Given this information the firm decides whether it wants to adopt airbags in its product. Once all adoption decisions are made, all features of all products become public knowledge and firms compete in prices.

An important assumption in this setup is that the firms observe the features of other products from the previous period only. While it can be restrictive it is required in order to avoid solving for an equilibrium in adoption decisions which would be computationally impossible given that there are about 200 products in each year.

2.4.2.3 Adoption Decision

Model-level operating profits are given by:

$$\pi_{jt}(A_t, X_t, MC_t, \xi_t) = [P_{jt} - MC_{jt}] \cdot M_t \cdot s_{jt}(A_t, X_t, \xi_t)$$

where M_t is the market size in period t, and s_{jt} is the market share of the model. P_{jt} is the optimal price that is set on the firm level once all adoption decisions in a given period are realized. Since the adoption decision is made on the model-level we do not need to aggregate over all models within a firm.

Let a_{jt} denote a firm's decision to adopt an airbag in period t, and the sunk cost associated with adding one more airbag to a model be SC. Then the firm's goal is to maximize its present value of current and future profits:

$$V_{jt}(\cdot) = E\left[\sum_{\tau=t}^{T} \beta^{\tau-1}\left(\pi_{j\tau}(\cdot) - SC(a_{j\tau})\right)\middle| A_\tau, X_\tau, \xi_\tau\right]$$

Note that in practice the firm horizon is often not infinite. Many models exit at some point in time, which I assume happens exogenously. Furthermore, the mandate forces everyone to adopt in period T so the net present value of future profits past T is deterministic in the decision to adopt.

2.4.2.4 Pricing Decision

Prices are set on the firm level once all adoption decisions of the firm and its competitors are realized and outcomes become public information. The firm takes into account the effect of pricing decision for a model j on the sales of other models that belong to this firm. Its profits are:

$$\Pi_{ft} = \sum_{j \in F_f} (P_{jt} - MC_{jt}) \cdot M_t \cdot s_{jt}(A_t, X_t, P_t)$$

where F_f is the set of products of firm f, and M_t and s_{jt} are defined as above.

2.4.3 Evolution of Airbag Costs

I allow the marginal costs of cars to be separable in features following the approach outlined in BLP. However, I am also interested in the variation of airbag marginal costs over time in order to understand how it drives adoption. To do so I experiment with three different ways how airbag costs are specified in the model.

In the first specification the number of frontal airbags is interacted with year dummies:

$$\log(MC_{jt}) = \sum_{t=1990}^{1998+} \gamma_{A,y} \mathbb{I}_{\{year=t\}} A_{jt} + \gamma_X X_{jt} + \omega_{jt} \tag{2.1}$$

As before, A_{jt} stands for the number of airbags, and $\mathbb{I}_{\{year\}}$ are year dummies. Such specification allows to capture the variation in marginal costs of airbags over time in a very flexible form. Note that now the coefficients γ_A are subscripted by the year and capture the effect of adding one airbag to a car in a given year t on the logarithm of car marginal cost.

The second specification treats driver and passenger airbags separately and interacts them with a linear trend to capture the cost variation over time. I use A_1 to index variables related to driver airbags, and A_2 to index those related to passenger airbags. Variables T are the trend values for the respective airbags.

$$\log(MC_{jt}) = (\gamma_{A_1} + \gamma_{A_1,T} T_{1,t}) A_{jt,1} + (\gamma_{A_2} + \gamma_{A_2,T} T_{2,t}) A_{jt,2} + \gamma_X X_{jt} + \omega_{jt} \tag{2.2}$$

Finally, the third specification interacts the airbag dummies with the log of cars equipped with airbags of the corresponding type in the previous period as represented by variables V_1 and V_2. This is done in order to capture possible learning-by-doing and scale effects that might have occurred in the industry over time as suggested by Sperling et al. [2004].

$$\log(MC_{jt}) = (\gamma_{A_1} + \gamma_{A_1,V} V_{1,t-1}) A_1 + (\gamma_{A_2} + \gamma_{A_2,V} V_{2,t-1}) A_2 + \gamma_X X_{jt} + \omega_{jt} \tag{2.3}$$

The results of these regressions are reported in section 2.6.

2.5 Estimation

2.5.1 Static Parameters

2.5.1.1 Demand

The estimation procedure is identical to the one used in BLP. Our goal is to estimate $\theta = (\alpha, \beta, \sigma, \gamma)$. Recall that parameters β and γ enter the equations for δ and MC linearly and thus can be estimated using standard GMM estimator once δ and MC are known. Since α and σ enter the market share equation non-linearly I have to conduct a non-linear search over the objective function to find such (α, σ) that minimize it. The algorithm proceeds as follows.

For any starting value of (α, σ) I first to recover δ and MC. This can be done by using the BLP contraction mapping:

$$\delta' = \delta + \log(s) - \log(\hat{s}(X, P, \delta; \theta))$$

where s is a vector of market shares from the data and $\hat{s}$ is a vector of predicted market shares based on our parameter values and assumed δ. In every iteration δ is updated to a new value using the formula above and iterations stop once the difference between δ and δ' becomes smaller than $1.0e-14$[16]. Once the values of δ are recovered we can move onto estimation of preference parameters:

$$\delta_j = \beta X_j + \xi_j$$

and calculate the fitted values $\hat{\xi}_j$.

As mentioned before, ξ_j may be correlated with P_i leading to endogeneity. To deal with this problem I generate a set of instruments following BLP approach. The vector of instruments for a product j includes its own characteristics X_j, sum of characteristics of other products that belong to the same firm $\sum_{r \neq j, r \in F_f} X_r$, and, finally, sum of characteristics of products of other firms $\sum_{r \neq j, r \notin F_f} X_r$.

[16]Counterintuitively, I find that such tight tolerance decreases computational time (as opposed to the value of $1.0e-06$, for example). While solving for δ takes longer, the Nelder-Mead simplex algorithm converges faster and in less steps because the objective function is "smoother" near the solution due to the absence of noise that results from low tolerance values.

2.5.1.2 Marginal Cost

Given δ and θ I use the firm's first order conditions to estimate optimal markup and recover the marginal costs MC. I calculate MC using the following approach. Observe that a firm profit function is given by:

$$\Pi_f = \sum_{j \in F_f} (P_j - MC_j) \cdot M_t \cdot s_j$$

where F_f are all products of firm f, M is the market size and s_j is the product's market share. The firm then chooses price P_j to maximize its profit given its other products and competitor's products. The first order condition with respect to price for each product $j = 1, ..., J$ is:

$$s_j(P) + \sum_{r \in F_f} (P_r - MC_r) \frac{\partial s_r(P)}{\partial P_j} = 0$$

This yields J first order conditions that can be written jointly in a matrix form:

$$s(P) - \Delta(P)[P - MC] = 0$$

where

$$\Delta_{jr} = \begin{cases} -\frac{\partial s_r}{\partial P_j} & \text{if } r \text{ and } j \text{ are products of the same firm;} \\ 0 & \text{if } r \text{ and } j \text{ are NOT products of the same firm.} \end{cases}$$

Solve this system of linear equation for the vector of marginal costs MC:

$$MC = P - \Delta^{-1}(X, P) \cdot s(X, P)$$

Note that price P and market shares $s(X, P)$ are observed in the data, and $\Delta(X, P)$ can be calculated with the full knowledge of consumer preference parameters.

Having calculated the vector of marginal costs MC I estimate the effect of individual car features on marginal cost as specified in equation 2.1. Once both $\hat{\xi}$ and $\hat{\omega}$ are calculated, I construct the moment restrictions of the form $E[Z_1^T \xi]$ and $E[Z_2^T \omega]$ where Z_1 are demand-side instruments and Z_2 are supply-side instruments. Minimizing the objective function based on these moments allows me to recover (α, σ).

2.5.1.3 Computational Optimizations

At every step of the search algorithm I need to calculate $s_j(X, P; \theta)$ given the new set of parameters. This requires integrating over all the simulated consumers, which makes contraction mapping used to find δ rather computationally intensive. I find that there are several techniques that help reduce computational burden. The discussion of these techniques is below.

The first method is importance sampling as it is described in BLP. Importance sampling allows to reduce the number of simulations required for approximating the integral of market shares. I use 30,000 simulated consumers in the first stage of importance sampling to make sure that the market shares and resulting weights are calculated precisely, and then use 3,000 draws. The reason why I do not use a lower number of draws in the first stage is because it can introduce a simulation error in the market shares which can propagate further. I find that a minimum of 30,000 simulated consumers is required for the variance attributed to the simulation error to shrink down to a level when total market share has low enough variance. Moreover, reducing the number of simulated consumers helps a lot to speed up the computations while estimating dynamic parameters. Calculating value functions requires me to forward-simulate to form expected values over multiple possible future paths. Each of the simulated paths requires me to solve for a price equilibrium, which requires me to calculate market shares.

To speed up the algorithm I use several methods. The first one is to remove redundant calculations of exponents when calculating δ using the method proposed by Brunner et al. [2017]. Let $w_j = \exp(\delta_j)$. Then I iterate on the w_j instead of δ_j to avoid doing exponentiation which is computationally costly. Then the contraction mapping becomes:

$$\exp(\delta_j)' = \exp(\delta_j) \frac{s_j}{\frac{1}{N}\sum_{\mathrm{i}} \hat{p}_{ij}(w, \nu_i; \theta)}$$

where $\hat{p}_{ij}$ is an element from a $1 \times N$ vector of consumer purchasing probabilities $\hat{p}_j(w, \nu; \theta)$:

$$\hat{p}_j(w, \nu; \theta) = \frac{\exp(\delta_j \cdot \iota'_N + \mu_j(\nu; \sigma))}{1 + \sum_k \exp(\delta_k \cdot \iota'_N + \mu_k(\nu; \sigma))}$$

with ι being a vertical vector of ones. Then the former formula can be simplified as:

$$\begin{aligned} \exp(\delta_j)' &= \cancel{\exp(\delta_j)} \frac{s_j}{\frac{1}{N}\sum_r \frac{\cancel{\exp(\delta_j)} \cdot \exp(\mu_{jr}(\nu;\sigma))}{1 + \sum_k \exp(\delta_k) \cdot \exp(\mu_{kr}(\nu;\sigma))}} \\ &= \frac{s_j}{\frac{1}{N}\sum_r \frac{\exp(\mu_{jr}(\nu;\sigma))}{1 + \sum_k \exp(\delta_k + \mu_k(\nu;\sigma)}} \end{aligned}$$

This formula will need only $J + N$ divisions as opposed to $J + J \cdot N$ divisions in the original BLP contraction.

Another optimization trick is to use Modified Latin Hypercube Sampling for drawing random draws to simulate heterogeneity of consumer preferences. This technique spaces the draws from the normal distribution more evenly and allows better approximations and smaller variance of estimates by reducing simulation error[17].

2.5.2 Dynamic Parameters

The estimation of dynamic parameters follows the methodology developed in Bajari et al. [2007] and Blonigen et al. [2017]. I proceed in the following fashion. First, I estimate the policy functions which capture the probability of adopting airbags as a function of state variables. Then I use the estimates of policy functions to simulate the industry path multiple times and form expected payoffs in each period. Calculating the net present value allows me to construct the estimates of the value function. Finally, I permute the policy function to construct several alternative policy functions. Assuming that firms follow Markov perfect pure strategies when making the decisions these alternative policies should be sub-optimal and yield lower values of the value function than the ones we estimated. This will allow me to construct a set of inequalities. The final step is to find such estimates of sunk costs that rationalize these inequalities.

2.5.2.1 Policy Functions

The first step is to estimate the firm policy functions. Depending on the current number of airbags in the model, the firm can choose between installing none, only driver airbag, or dual airbags if none are already installed, or between keeping the driver airbag and upgrading to dual airbag. Having dual airbag is a terminal state. This gives us three outcome variables of the form a^{gh} where g denotes the number of airbags at the beginning of the period, and h denotes the number of airbags at the end of the period. For example, variable $a^{02}_{jt} = 1$ if model j had no airbags and decided to install dual airbags in period t.

I assume that the decisions to adopt and upgrade are based on the vector of five state variables: whether the brand in question is considered luxury LB_j, lagged average number of airbags in other models of the same firm OA_{jt-1}, lagged average number of airbags in models of competing firms CA_{jt-1}, current marginal costs of airbags MC^A_t, and years until mandate is in force YTM_t. Then the policy functions

[17] See Brunner et al. [2017] for more details.

Table 2.3: Probabilities of adopting and upgrading airbags

		to		
	# airbags	0	1	2
	0	$1-\Pr[a^{01}]-\Pr[a^{02}]$	$\Pr[a^{01}]$	$\Pr[a^{02}]$
from	1	0	$1-\Pr[a^{12}]$	$\Pr[a^{12}]$
	2	0	0	1

are estimated as follows:

$$a_{jt}^{type} = \psi_0 + \psi_1 LB_j + \psi_2 OA_{jt-1} + \psi_3 CA_{jt-1} + \psi_4 MC_t^A + \psi_5 YTM_t + \varepsilon_{jt}^{type}$$

The above regression is estimated twice. First, it is estimated using multinomial logit where the outcome variable is installation of 0, 1, or 2 airbags and only models with no airbags at the beginning of the period are used. Next, I use logit to estimate the above regression for observations where a model already has one airbag installed at the beginning of the period. This allows me to estimate how $\Pr[a^{01}]$, $\Pr[a^{02}]$, and $\Pr[a^{12}]$ vary in response to changes in state variables.

Note that the BBL method normally requires the assumption that the policy functions are stationary, that is, the policy function is independent of time t. This assumption is required to calculate the value functions by forward-simulation of the decisions, market outcomes, and profits. However, in my case the firms do not face an infinite horizon - they face a deadline to adopt, after which the adoption game ends. Even when considering a scenario without a deadline, as I do in the counterfactual, most of the models have a finite lifetime and exit after several years on the market. Assuming that the model exits are occurring exogenously and are known to the firm in advance, firms face a finite-horizon problem. Hence, approximating value functions does not require forward-simulation for a large number of periods, but only for the number of periods that the model is on the market. In that sense, the policy function is not required to be stationary in my estimation.

Nevertheless, it can be made stationary by including the time until the mandate directly into the policy function. Variable YTM_t captures that. Once we control for time left until mandate, adoption decisions are independent of t and depend exclusively on the state variables. I observe adoption in every year from 1990 until 1997. This gives me enough variation in the data to identify the coefficients on all parameters, especially when applied to a rather parsimonious regression specification.

2.5.2.2 Value Functions

I use the forward-simulation technique to approximate the value functions. The value function of a firm j is:

$$V_{jt}(\cdot) = E\left[\sum_{t=1}^{\infty}\beta^{t-1}\left(\pi_{jt}(\cdot) - SC(a_{jt})\right)\middle| A_t, X_t, \xi_t\right]$$

which is just the net present value of current and future profits and costs. Luckily, the value function can be made in linear in dynamic parameter SC and re-written as:

$$\begin{aligned} V_j(\cdot) = \underbrace{E[\sum_{t=1}^{\infty}\beta^{t-1}\cdot\pi_{jt}(\cdot)]}_{W_1} \quad &- \quad \underbrace{E[\sum_{t=1}^{\infty}\beta^{t-1}\cdot a_{jt}^{01}]}_{W_2}\cdot SC^{01} \\ &- \quad \underbrace{E[\sum_{t=1}^{\infty}\beta^{t-1}\cdot a_{jt}^{02}]}_{W_3}\cdot SC^{02} \\ &- \quad \underbrace{E[\sum_{t=1}^{\infty}\beta^{t-1}\cdot a_{jt}^{12}]}_{W_4}\cdot SC^{12} \end{aligned}$$

The three terms SC^{01}, SC^{02}, and SC^{12} represent sunk cost of adopting one airbag, two airbags, and upgrading from one to two respectively. The value function consists of four elements. W_1 is the discounted stream of profits. W_2, W_3, and W_4 are simply the counts of adoption actions undertaken by the firm[18].

This specification imposes a rigid structure on the form of sunk costs. It requires the sunk costs to be independent of the firm and the year, however, it allows sunk costs to vary by the number of airbags that the firm is adopting and whether the firm is upgrading or not.

I calculate the four terms $W_1 - W_4$ by forward-simulating the market 1,500 times. The simulation follow the timing scheme outlined earlier. First, I construct the state variables by using the current marginal costs of airbags, number of competing models with one airbag and two airbags, and time until mandate in a given period. Using the estimated policy functions I calculate the probabilities of adoption of one or two airbags (as well as upgrading from one to two) for each model, and simulate the adoption decision. Then I use the fixed point computation to find a Bertrand-Nash equilibrium in prices in a given period. This procedure generates the vector of profits

[18] An alternative way to specify the count of adoption actions would be by replacing $a_{jt}^{01} = \mathbb{I}_{\{A_{jt}=1\}} \cdot \mathbb{I}_{\{A_{jt-1}=0\}}$.

π_t, and adoptions decisions a_t^{01}, a_t^{02}, and a_t^{12}. Given the adoption decisions from period t I can construct the state variables OA_t and CA_t. Combined with marginal costs and years until mandate these yields the vector of state variables for period $t+1$. With that at hand, I repeat the simulation procedure. Note that it is necessary to do these calculations only for periods up until the year 1998 since the continuation values post-1998 are the same irrespective of adoption decisions. Finally, discounting and summing up the vectors π, a^{01}, a^{02}, and a^{12} allows us to calculate terms $W_1 - W_4$. To form the expectations of $W_1 - W_4$ I repeat the forward-simulation procedure and take an average.

2.5.2.3 Sunk Costs of Adoption

The next step is to construct the value functions for alternative, sub-optimal policy functions. The idea behind the identification of dynamic parameters is that the true values of parameters should rationalize the observed policy functions that the firms follow. I construct the alternative value functions by perturbing the estimated policy functions. Since our policy function is given by a vector of twelve parameters: four parameters for each state variable and three sets of parameters for each action a^{01}, a^{02}, and a^{12}, the number of possible permutations is very high. I restrict my attention to constructing 24 alternative policy functions where is each policy function has one parameter scaled up or down.

Given the alternative policy functions I repeat the calculation of value functions using the procedure outlined above. This generates a set of 24 inequalities that are used in the estimation. Denote the alternative policy functions as $\tilde{a}$. Then the objective function to be minimized is:

$$Q(SC) = \sum_j (\min[0, \hat{V}_j(a, \cdot; SC) - \hat{V}_j(\tilde{a}, \cdot; SC)])^2$$

Note that the only parameter to find at this stage of the estimation is the sunk cost of adoption SC. The demand and other cost parameters are all estimated in the static part of estimation.

2.6 Results

In order to better understand how the costs of airbag evolve over time I estimate them under three different specifications. In the first one, which is reported in the first column of all tables, I only use the number of frontal airbags in the regression.

This specification assumes that driver and passenger airbags are valued the same by the customers and cost the same to the manufacturers. Moreover, I allow the costs of airbags to be flexible over time by interacting them with year dummies. The second specification treats the driver and passenger airbags separately. I also interact both types of airbags with the trend variable on the cost side to capture the variation over time. The results are reported in the second column of all tables. Finally, the third and final specification is identical to the second one, except it interacts the airbags with the volumes produced in the regression of costs on characteristics. This is done in order to capture possible learning-by-doing and scale effects that might have driven the cost evolution of airbags.

Due to the large number of estimates I split the results into three tables: demand estimates, cost estimates except airbags, and cost estimates of airbags. However, all of these parameters are estimated jointly as was outlined in the previous sections.

2.6.1 Demand Parameters

Table 2.4 reports the estimates of mean preferences which are captured by β_k and a measure of consumers preference heterogeneity captured by σ_k. There are several variables that go into this regression.

The first one is the logarithm of manufacturer suggested retail price measured in 1,000 2017 USD. Next is horsepower-to-weight ratio (HP/Weight). I use their ratio to account for the fact that heavier cars are usually more powerful and taking these two variables separately into account would not be very informative. Miles-per-dollar (MPD) captures the fuel efficiency of the cars. It is more informative than miles-per-gallon as allows to implicitly control for variation in gas price over time. Space is a measure of physical size of a car and is calculated as a product of length and height of a car[19].

Number of airbags simply calculates the number of frontal airbags, which driver and passenger airbags enter as dummies. Number of comfort, driving, and safety features, as well as the number of power equipment are simply sums of dummies for each of the feature in the corresponding category. The detailed breakdown of how the features were categorized can be found in Table A.2 in Appendix. Aggregating the features in such a way helps avoid issues with collinearity, especially, when utilizing BLP instruments, and improve the precision of the estimates.

[19] I depart from the commonly used approach of calculating space as product of length and width. I observe much more variation in car height rather than width.

Table 2.4: Demand estimates

		I	II	III
Means (β_k)	log(MSRP)	-48.077***	-67.746***	-59.825***
		(3.243)	(4.961)	(4.144)
	HP/Weight	1.367***	1.468***	1.316***
		(0.302)	(0.309)	(0.296)
	MPD	0.370***	0.541**	0.286***
		(0.155)	(0.158)	(0.167)
	Space	2.552***	2.479***	2.439***
		(0.183)	(0.182)	(0.182)
	# Airbags	0.233***		
		(0.049)		
	Airbag (Driver)		0.328***	0.302***
			(0.101)	(0.109)
	Airbag (Passenger)		0.331***	0.289**
			(0.108)	(0.108)
	# Comfort Features	0.359***	0.298***	0.308****
		(0.029)	(0.027)	(0.027)
	# Driving Features	0.029	0.031	0.010
		(0.054)	(0.054)	(0.053)
	# Power Equipment	0.412***	0.395***	0.398***
		(0.046)	(0.046)	(0.046)
	# Safety Features	0.406***	0.217***	0.246***
		(0.080)	(0.072)	(0.071)
	Truck	0.468***	0.371***	0.311***
		(0.101)	(0.101)	(0.100)
	Luxury Brand	0.012	0.196***	0.129***
		(0.080)	(0.068)	(0.065)
	Constant	-8.021***	-6.465***	-6.594***
		(0.489)	(0.465)	(0.469)
Std. Deviations (σ_k)	# Airbags	1.789***		
		(0.144)		
	Airbag (Driver)		1.791***	1.674***
			(0.257)	(0.289)
	Constant	4.285***	1.528	3.123***
		(0.385)	(0.442)	(0.377)

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Truck and luxury brand variables control for the corresponding fixed effects. The exact list of brands that are considered luxury can be found in table B.1 in Appendix. While the extra controls help capture a lot of the appeal of luxury vehicles, one cannot discount the popular appeal of the brand itself.

It is worth pointing out that the estimates are robust to different specifications of airbag and its cost structure. Overall, the values are largely in line with general expectations. Price coefficient is negative and significant. HP/Weight and space enter the utility with a positive sign. The coefficient on MPD is positive. While it is in line with the expectations, that consumers prefer more fuel efficient cars, the negative coefficients on fuel efficiency occurred often in the literature[20]. Controlling for additional features seems to resolve this problem. Airbags enter the utility positively in all three specifications, although separating driver and passenger airbags into two separate variables reveals that consumers do not, in fact, value them in a significantly different fashion. Other features enter the utility with the positive sign as well.

The values of σ represent the consumer heterogeneity in their tastes for a particular characteristic. BLP estimates them for five variables, yet I restrict them to airbags (or only driver airbag in specifications II and III) and constant term in order to reduce computational burden. Remember that the estimation algorithm has to search over (α, σ) in a non-linear fashion and increasing the number of arguments leads to significant increases in computational time.

Since our demand-side dependent variable δ translates into market shares in a non-linear fashion and marginal costs enter the equation in logs, parameters are less straightforward to interpret. In order to understand what valuation the consumers assign to different features I do a simple exercise in calculating their willingness to pay. For every car in the dataset I calculate the utility that consumers assign to that car. Next I remove a feature from the car and calculate new utility levels resulting from a purchase of such car. Then I find corresponding change in the price of the product which would compensate the consumer for the loss of the feature and provide him with the same utility. Aggregating over the consumers allows me to capture the mean willingness to pay for a given feature. This calculations put the willingness to pay for an airbag in specification I at \$1,189, and for driver and passenger airbags at \$1,241 and \$1,187 respectively. The estimates of the willingness to pay for all the features can be found in table B.2 in Appendix.

[20]In particular, BLP estimate a negative coefficient on miles-per-dollar.

2.6.2 Airbag Cost

Table 2.5 presents the estimates of marginal costs of airbags, as well as the dollar equivalents of the parameters. Since it is the logarithm of marginal costs that is regressed on the features the interpretation of the coefficient may not be straightforward. The dollar equivalents are calculated in similar fashion to consumer willingness to pay, as described in the previous subsection.

The difference in the estimates between different specifications of airbag costs is more pronounced here. The first specification allows airbag costs to vary in each year independently by interacting the number of airbags with a year dummy. It is a very flexible specification, however, I cannot treat driver and passenger airbags separately[21] and have to to aggregate them into a total number of frontal airbags. The estimates show that the cost of airbags to manufacturers varies significantly with time. It starts at the high of almost \$4,200 in 1990 and drops down to \$1,700 in 1998 with largest decreases during 1992-1994 as the production and installation volumes have increased significantly. Note that these prices are reported in 2017 US dollars, and their values in 1990 US dollars are \$2,239 and \$906 respectively. While this numbers are high they are not too far away from the industry estimates. For example, price of airbags as options and according to other estimates was about \$750-1250 throughout the late 80's (as measured in 1980 USD)[22].

Specification II and III treat the driver and passenger airbags separately and interact them time trend and airbag installation volumes from the previous period respectively. In specification II variable Trend stands for a linear trend that that starts at 0 in 1990, then reaches a value of 9 in 1998, and stays constant afterwards. In specification III variable Volume captures the log of the number of cars equipped with the given type of airbag in the previous period. Notably the estimates for the base cost of driver and passenger airbags differ with the passenger airbags being cheaper by almost 25%. This is not surprising as there are a lot of synergies between two systems. For example, they could both use the same impact sensor for determining when a crash has occurred and whether they should inflate.

Figure 2.4 illustrates the dollar values of airbag costs over time according to the specifications I, II, and III. Overall, all estimates are sufficiently close to each other.

[21] Otherwise it leads to 16 dummies in the regression and the parameters cannot be estimated precisely enough.

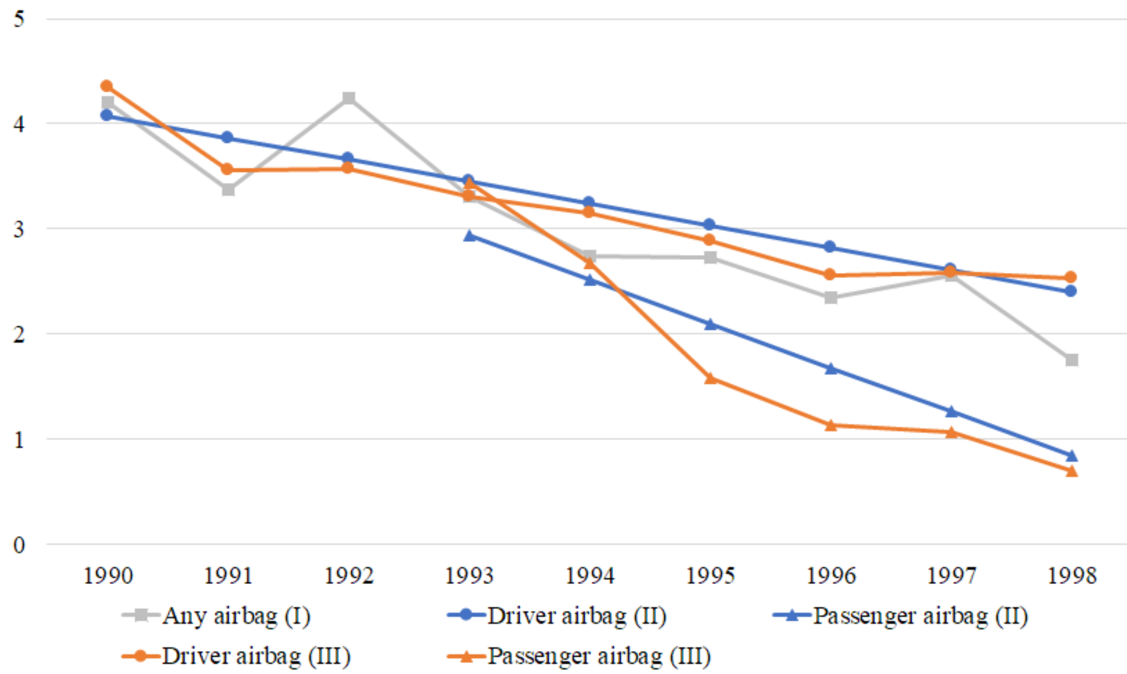
[22] See Sperling et al. [2004].

Table 2.5: Cost estimates of airbags and their dollar equivalents

	Parameter estimates	Cost ($1,000)
	I	
# Airbags $\times \mathbb{I}_{\{\text{year}=1990\}}$	0.146***	4.206
	(0.032)	
# Airbags $\times \mathbb{I}_{\{\text{year}=1991\}}$	0.115***	3.367
	(0.026)	
# Airbags $\times \mathbb{I}_{\{\text{year}=1992\}}$	0.148***	4.247
	(0.030)	
# Airbags $\times \mathbb{I}_{\{\text{year}=1993\}}$	0.113***	3.311
	(0.030)	
# Airbags $\times \mathbb{I}_{\{\text{year}=1994\}}$	0.093***	2.735
	(0.016)	
# Airbags $\times \mathbb{I}_{\{\text{year}=1995\}}$	0.092***	2.731
	(0.013)	
# Airbags $\times \mathbb{I}_{\{\text{year}=1996\}}$	0.079***	2.340
	(0.014)	
# Airbags $\times \mathbb{I}_{\{\text{year}=1997\}}$	0.086***	2.556
	(0.016)	
# Airbags $\times \mathbb{I}_{\{\text{year}=1998+\}}$	0.059***	1.758
	(0.017)	
	II	
Airbag (Driver)	0.141***	4.075
	(0.029)	
Airbag (Driver) × Trend	-0.007	-0.209
	(0.006)	
Airbag (Passenger)	0.100***	2.936
	(0.020)	
Airbag (Passenger) × Trend	-0.013**	-0.419
	(0.007)	
	III	
Airbag (Driver)	0.152***	4.347
	(0.034)	
Airbag (Driver) × Volume	-0.015*	-0.478
	(0.011)	
Airbag (Passenger)	0.118***	3.440
	(0.026)	
Airbag (Passenger) × Volume	-0.025***	-0.778
	(0.009)	

Note: Standard errors are given in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 2.4: Airbag cost over time under different specifications ($1,000)



2.6.3 Cost of Other Features

Table 2.6 presents the cost estimates of features other than airbags. It is almost the same set of variables that enter the demand equation with some minor changes. First, I replace HP/Weight, MPD and space with their log values and use miles-per-gallon instead of miles-per-dollar since this is the feature that the manufacturers set. I also add a trend variable which is supposed to capture general industry-related cost shifts over time.

All of the coefficients have positive signs as expected with exception of log(MPG) and log(Space). While somewhat counter-intuitive this result has been documented in the literature. BLP have negative coefficients on the same variables although they turn positive once they include the log of production volumes to control for scale effects. One possible explanation of the negative signs is that it is actually cheaper to produce fuel efficient and larger cars. Increases in fuel efficiency may rely on research and development which are fixed costs rather than on actual components or labor which are reflected in the marginal costs. While increasing car space may involve more materials it could also lead to cheaper labor.

In their dollar equivalents the costs are as follows. One comfort-related feature such as cruise control is estimated to cost about $161, and driving feature (e.g. all-

Table 2.6: Cost estimates of other features

		I	II	III
Means (γ_X)	log HP/Weight	0.53***	0.53***	0.53***
		(0.03)	(0.02)	(0.03)
	log MPG	-0.95***	-0.94***	-0.94***
		(0.05)	(0.04)	(0.05)
	log Space	-0.35***	-0.35***	-0.34***
		(0.04)	(0.03)	(0.04)
	# Comfort Features	0.01	0.01*	0.01*
		(0.01)	(0.01)	(0.01)
	# Driving Features	0.04***	0.03***	0.04***
		(0.01)	(0.01)	(0.01)
	# Power Equipment	0.01***	0.09***	0.01***
		(0.01)	(0.01)	(0.01)
	# Safety Features	0.15	0.15***	0.15***
		(0.02)	(0.02)	(0.01)
	Truck	-0.01	0.01	0.01
		(0.02)	(0.01)	(0.01)
	Luxury Brand	0.15***	0.15***	0.14***
		(0.01)	(0.01)	(0.01)
	Trend	-0.01***	-0.01***	-0.01***
		(<0.01)	(<0.01)	(<0.01)
	Constant	4.19***	4.18***	4.17***
		(0.05)	(0.05)	(0.05)

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

wheel drive or anti-lock brakes) is about $1,115. Powered equipment costs about $2,908 more, and a system of side airbags (as captured by safety equipment) is estimated to cost $4,494. It is not clear whether trucks are really more expensive to produce. Finally, cars produced by luxury brands have their cost increased by additional $4,288.

2.6.4 Policy Functions

The estimates of the policy functions are given in Table 2.7 below. The policy functions (and, later, sunk costs) are estimated using the results from the first specification reported in the above subsections. The probability of adopting driver or dual airbag when there are no airbags installed is estimated using multinomial logit, and the probability of upgrading from driver to dual is calculated using logit.

There are several variables that go in this regression. First, I account for the fact that luxury brands tend to adopt earlier. Then, I control for the average number

Table 2.7: Policy function estimates

No airbag → Driver airbag	
Luxury brand	2.889***
	(0.306)
# own models with airbags	0.016
	(0.011)
# competing models with airbags	-0.005**
	(0.015)
Airbag cost	-0.868***
	(0.171)
Years until mandate	-0.005**
	(0.002)
Constant	1.516**
	(0.592)
No airbag → Dual airbag	
Luxury brand	3.595***
	(0.552)
# own models with airbags	-0.018
	(0.014)
# competing models with airbags	-0.007***
	(0.002)
Airbag cost	-1.258**
	(0.511)
Years until mandate	-0.962***
	(0.234)
Constant	5.881***
	(0.784)
Driver airbag → Dual airbag	
Luxury brand	2.740***
	(0.489)
# own models with airbags	-0.018*
	(0.009)
# competing models with airbags	-0.034***
	(0.007)
Airbag cost	-3.813***
	(0.575)
Years until mandate	-1.063**
	(0.535)
Constant	16.275***
	(3.190)

Note: Standard errors are given in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

of airbags in other models of the same firm in order to capture possible cannibalization effects or synergies. I also include the average number of airbags in competing models to account for competitive pressure[23]. Airbag costs that were estimated in the previous subsections are included as well. I do not include the passenger airbag costs or future marginal costs in the regression since they are highly correlated with the current driver airbag costs as is evident in Figure 2.4. Finally, I add years until mandate in order to understand how the regulation affects the firm probability to adopt[24].

The signs on the policy function have the expected magnitude. Luxury brands are more likely to adopt any type of airbag. In general, the higher number of airbag-equipped cars of the same firm lowers the probability to adopt but the effects are often not statistically significant. A possible explanation for this could be cannibalization if the firm is concerned about cannibalizing the market share of its other products. The effects of the number of competitors on adoption probability is negative suggesting that the gains from airbag adoption are lower once multiple competitors have adopted. As more and more of their competitors adopt these firms become less able to recoup their investment in airbags and may adopt only at the deadline. Higher marginal costs decrease the probability of adopting either type of airbags. Finally, more time until mandate means the probability of adopting or upgrading is lower.

2.6.5 Sunk Cost

I report the estimates of sunk costs of adoption by type in table 2.8. The estimate of the sunk cost of adoption of one airbag for one model comes out at $704.8 million. To put this number in perspective, Ford revenues in 2019 were $160 billion, GM - $147 billion, Audi - $65 billion[25]. Furthermore, Blonigen et al. [2017] report that the redesign costs of a model were estimated to be around 1 billion USD.

The results suggest adoption of both airbag and passenger airbags at the same time was, in fact, slightly cheaper than adoption of driver airbags alone. However, this could be affected by the fact that adoptions of dual airbags occurred several years later than adoptions of driver airbags and could benefit from improved and cheaper

[23]Note that these two variables are lagged. The inclusion of lagged variables is required to avoid solving an equilibrium. See section 2.5.2 for more details.

[24]Since the firms are not aware of the regulation in 1990 and 1991 I assign a value of 100 to this variable in these years. Additionally, I tested the regression with values of 1,000, 10,000, and 100,000 of this variable for years 1990 and 1991. The results are robust to different values once accounted for scaling.

[25]See `https://www.macrotrends.net/`.

Table 2.8: Sunk costs of adoption estimates

	Cost ($ million)
No airbag → Driver airbag	704.8
No airbag → Dual airbag	652.8
Driver airbag → Dual airbag	596.4

technologies.

I do not report the standard errors at this stage due to high computational burden. Calculation of standard errors using bootstrapping approach requires calculating the parameter for multiple samples drawn from the dataset. Calculating the dynamic parameter requires solving for price equilibrium in each year from 1990 to 1998 for each simulated path of adoption (I use 1,500 simulated paths) and takes about several hours when fully parallelized to 24 cores on a server. While the standard errors are not reported at this stage, they will be reported in the future revisions of this paper.

2.7 Counterfactual

2.7.1 Welfare Calculations

The airbag mandate was announced in 1991 and was in force in 1998. In this counterfactual I explore what happens if the mandate has never happened, that is, it was never announced and never came into force. This exercise allows to clearly quantify the effects of the mandate on the market and understand what role it played in adoption of airbags by car industry.

The implementation is very close to that in Sweeting [2013] and Blonigen et al. [2017] as both papers utilize forward-simulation of firm decisions in their counterfactuals. One thing I do differently from Sweeting [2013] is that I use policy functions approximated by the first-stage multinomial logit regressions of firm behavior on the vector of state space variables. In contrast, he builds on these approximations to solve explicitly for value and policy functions in each state. In that regard, my implementation of counterfactual is closer to Blonigen et al. [2017] where they use policy functions from the first-stage as well.

My counterfactual is implemented as follows. Since time until mandate is a state variable and enters firm policy function I can shut it down and simulate the firm decisions without it[26]. To generate an industry adoption path I start in year 1991

[26]Implementation largely depends on how variable "time to mandate" is coded in the policy

with the industry state as observed in the data. Since the mandate regulation was announced only late in that year this represents a point in time when the industry was still unaffected by the mandate. Then I calculate the vector of state variables (with time until mandate shut down) and simulate adoption decisions for each firm. I also solve for the equilibrium in prices to calculate prices, shares, firm profits, and consumer surplus. Then I move onto the next period and repeat the process. Prices, shares, profits, and consumer surplus, averaged across simulations, are reported below.

Several assumptions are made for this analysis. First, I assume that the firm behavior before 1991 is unchanged as they could not anticipate the regulation being passed. This assumption allows me to use observations from 1990 in my dataset as the starting point in my simulations. Second, the firm costs remain unchanged, that is, both marginal and sunk cost are independent of firm behavior. This requires me to extrapolate the marginal costs of airbags beyond 1998 since I do not have estimates past this year[27]. Finally, I assume that entry and exit of models is not affected by the absence of regulation. This allows me to abstract away from modeling firm decision to enter and exit.

First, consider the adoption on the industry level. Figure 2.5 shows the averaged adoption path of the industry as observed in the data, as predicted by the model with the mandate, and as predicted by the model without the mandate. The model with the mandate provides the predictions that are reasonably close to the data. One noticeable difference is that the model predicts non-zero share of cars with dual airbags in year 1991 and 1992. However, this due to the non-zero probability of adoption any type of airbag in any year and occurs very rarely.

In the absence of mandate, adoption of airbags is significantly slower. In year 1998 only 58% of the models have an airbag, and only 31% have dual airbags. Adoption improves with time and 4 years later over a half of the models have dual airbags. This suggests the decreases in marginal costs of airbags are driving adoption but regulation is still an important factor.

Figure 2.6 reports the effect of the mandate on the market. The top-left graph reports the increase in the average sales-weighted prices. Across all years car prices were about 2.1% higher in the world with the mandate. The increase is particularly high between 1994 and 1998 as these were the years when the regulation had the

function regression. One way is to set it to some large value in 1990 and 1991 when no mandate is expected and then to number of years left until 1998 in consecutive years. Then, in counterfactual, it would have the same value as in 1990 in all years.

[27]All cars come equipped with dual airbags after 1997 so there is no variation in the data to identify the marginal cost of airbags in these years.

Figure 2.5: Number of models by airbag type

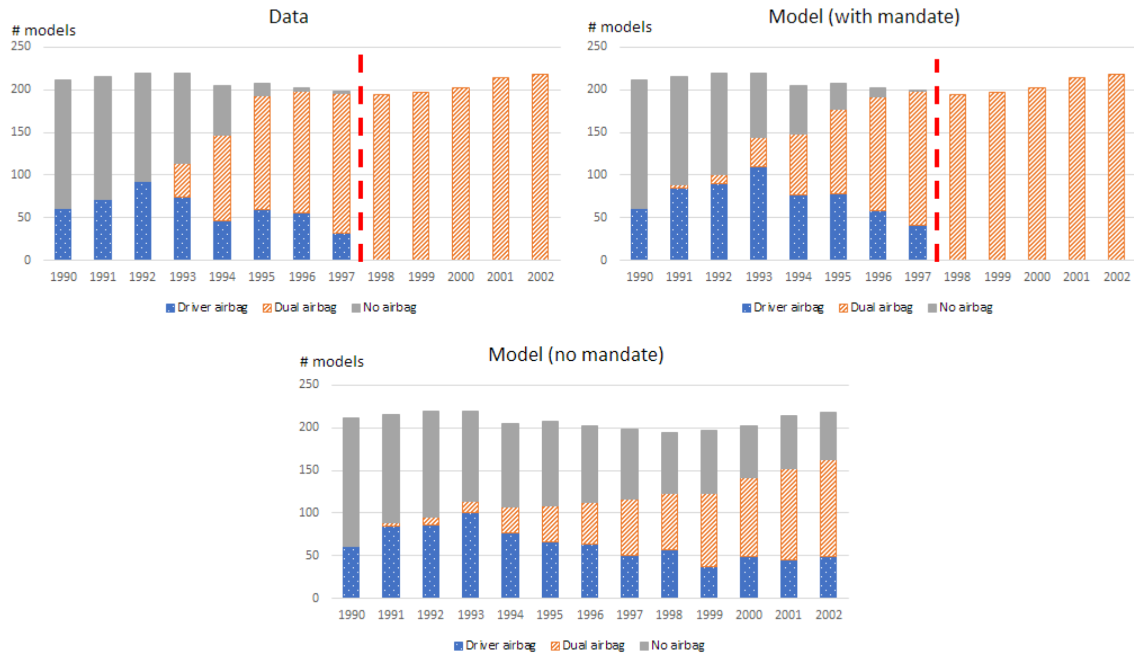
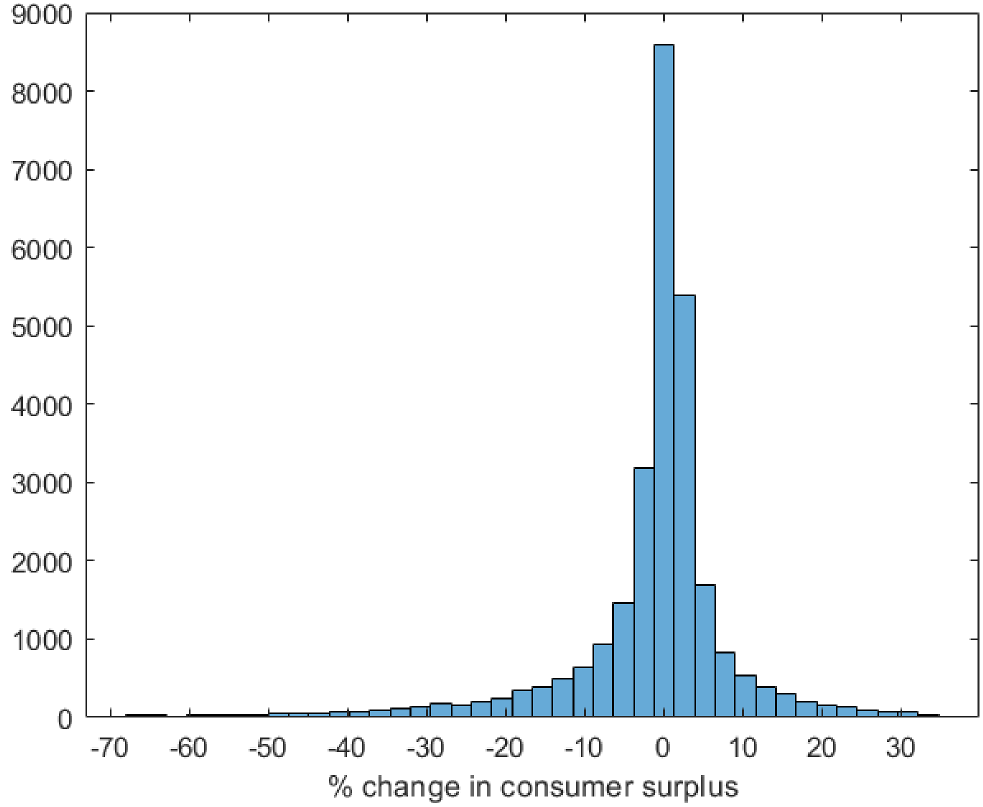


Figure 2.6: Effects of the mandate on prices, shares, profits, and consumer surplus

largest effect on adoption. The price effects are lower after 1998 as the marginal cost of airbags falls low enough by then, and most of the firms decide to adopt them anyway. The bottom-left graph illustrates the effect of the mandate on the total market share of new cars (in relative terms). 0.9% of the consumers who buy a new

Figure 2.7: Histogram of changes in consumer surplus due to mandate

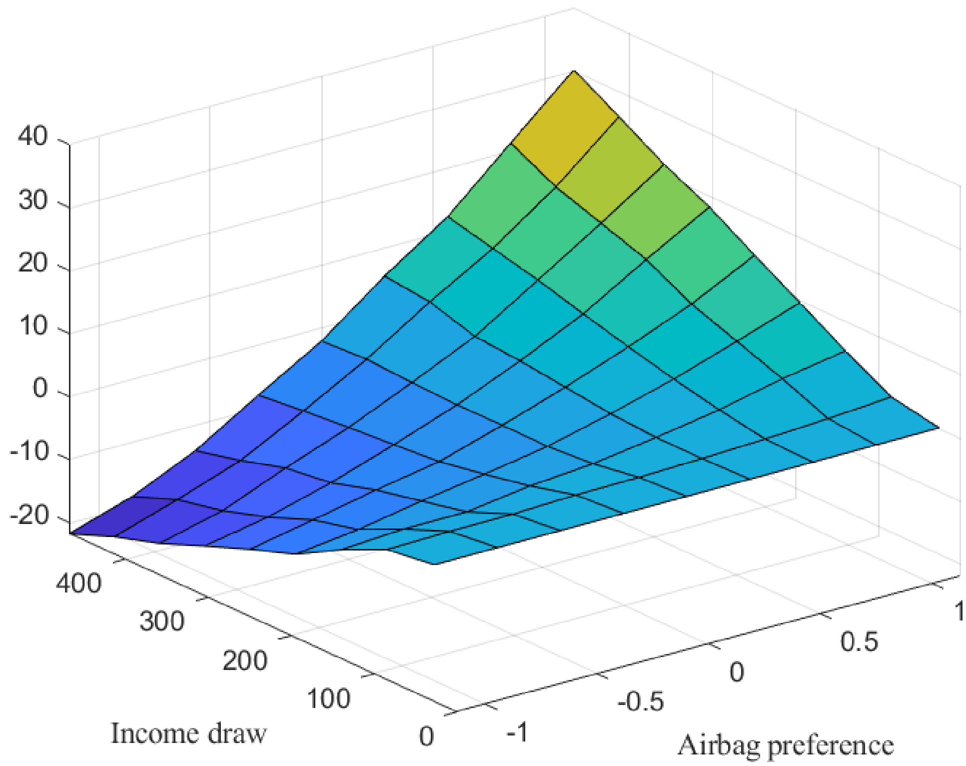


car in the world without a mandate are forced to switch to an outside option by the mandate. This is driven by the increase in prices. The right half of Figure 5 shows the changes in firm profits and consumer surplus. The profits are are affected negatively by the mandate and decrease by about 0.8% over the course of the 13 years as the markups are affected negatively by the regulation. Finally, consumer surplus increases by 1% despite higher prices. This due to the fact that some consumer get airbag-equipped cars cheaper and earlier in the world with the mandate, as opposed to their counterparts in the world with no regulation. However, some consumers, in particular those who switch to an outside option, experience decreased welfare.

Figure 2.7 shows the distribution of changes in consumer welfare over the continuum of all consumers over all years covered in the dataset. Total change in surplus is positive however only for 68% of the consumer base. The rest of the consumers which accounts for 32% of the consumer base experiences either no changes in welfare since they are very unlikely to buy any car or experience reduced welfare.

Finally, Figure 2.8 shows how compensating variation varies across consumer de-

Figure 2.8: Compensating variation by consumer income and preference for airbags in year 1995



Note: The values at the axis represent the values of random draws ν_i.

pending on their income and preference for airbag draws. The mandate mostly affects the consumers with the low preference for airbags most. Curiously, I find that low-income consumers do not feel the effects of the mandate as significantly. This is due to the fact that they are less likely to be in the market for a car and hence variations in their prices do not affect them as much. However, that does not mean that the low-income people were unaffected by the mandate. Since our estimation is based on the year-to-year variations in car sales the model captures short-run price elasticity. Furthermore, low-income people may be buying used cars rather than the brand new one and, hence, may feel the effect of the price increases later on once the airbag-equipped cars make it to the used car market.

2.7.2 Lives saved

The previous subsection examined the effect of mandate on consumer welfare treating airbags as a pure consumer good. However, the main purpose of airbags is to save lives. In that sense, considering how many lives were saved due to faster adoption of airbags is an important exercise. One could potentially make an argument that consumers are assessing the risk from driving and their valuation of airbags already reflects the increased safety that airbags grant. This paper does not try to answer this difficult questions, however there is evidence that suggest that consumers may under-estimate the risk that they are exposed to[28]. If this is the case then some people would under-value the airbags which would be reflected in their low willingness to pay. Hence, the number of lives saved is a useful alternative measure of the role of the mandate.

I conduct the calculations for lives saved by the mandate as follows. There were 14,219 car occupant fatalities resulting from frontal crashes and 157 million persons of working age in the US in 1989[29]. This gives an unconditional probability for a working-age person to be involved in a fatal frontal crash of about 0.009%. Note that this probability is calculated for year 1989 when airbags still had an extremely low market penetration. Hence, it can be interpreted as risk of being in a fatal frontal crash conditional on having no airbags in a car. Kahane [2015] estimates that the risk of death is reduced by 20.4% conditional on being in a frontal car crash if airbags are equipped for the given passenger. I assume that the probability of being involved in a frontal crash of a similar severity stays the same over time and different models. In that case, driving an airbag-equipped car should lower the risk of being in a fatal frontal crash to about 0.007%. Given these numbers I can calculate the expected number of fatal front crashes for occupants of cars with airbags and cars without airbags. One challenge is that it is unclear how often the right front passenger seat is occupied which is going to affect the calculations of passenger airbag effectiveness. Because of it, I will restrict my analysis to the lives saved by driver airbags only.

Assuming that every consumer kept his car until 2002 (the end of my sample) we can calculate what risk of fatal frontal crash he faced every year depending on whether airbags were present in his car. Aggregating the risk over all drivers gives the expected number of fatal frontal crashes in every year. Table 2.9 shows the estimates of how many fatal crashes would occur in a world with mandate and in a world without it. Note the numbers are reported only for cars that were sold in 1990 or

[28]See Greening and Chandler [1997]

[29]Source: Bean and Kahane [2009], `https://fred.stlouisfed.org`.

Table 2.9: Lives saved by the mandate

Year	Fatal frontal crashes in cars affected by mandate		Lives saved due to mandate
	mandate	no mandate	
1990	1,065	1,065	0
1991	2,118	2,136	18
1992	3,056	3,157	101
1993	4,019	4,246	227
1994	5,042	5,406	364
1995	6,174	6,719	545
1996	7,164	7,828	663
1997	8,288	9,060	772
1998	9,440	10,301	861
1999	10,709	11,620	911
2000	11,997	12,969	971
2001	13,533	14,659	1,125
2002	14,576	15,921	1,345
Total	97,182	105,086	7,904

Note: I assume that cars produced in 1991 and later are affected by the mandate.

later. I assume that the number of fatal frontal crashes involving cars sold before 1990 would not have been affected by the mandate and hence do not report them here.[30]. The number of crashes reported is increasing over time as cars produced in 1990 or later become a larger share of the fleet on the road. Overall, the estimates suggest that the mandate for airbags has saved 7,904 lives in the period from 1990 to 2002. NHTSA estimates that over the course of 30 years, from 1987 to 2017, airbags have saved 50,457 lives[31]. According to my estimates the mandate was responsible for a large share of these lives saved[32].

[30]This assumption greatly simplifies my analysis, however, the mandate may have an effect on crashes involving older cars. Since the mandate leads to higher prices some consumers may choose to have no car thus having a decreased risk of being involved in a crash. Alternatively, they may choose to keep their older, less safe car.

[31]See `https://www.nhtsa.gov/equipment/air-bags`.

[32]It should be noted, however, that there are several other factors that may affect these estimates which, unfortunately, are beyond the scope of my analysis. First, it assumes that the probability of a crash remains constant over time. Second, it does not account for lives saved by passenger airbags. And, finally, it restricts the analysis of lives saved to the period of 1990-2002. Undoubtedly, the effect of the mandate stretched far beyond these years.

2.8 Conclusion

This paper builds an empirical dynamic structural model of adoption of new features in the car industry in the presence of a deadline imposed exogenously. I estimate consumers valuation of airbags, marginal costs of airbags and sunk costs of airbag adoption. The results show that consumers are in fact willing to pay for airbags but their readiness to pay varies. Also, the paper documents that marginal costs of airbag fell significantly in the 1990's and were a major driver of adoption. Government regulation also plays a significant role, however comes at a cost to firm and some consumers. Most consumers benefit from the mandate but a significant share of them are made worse off.

The paper also provides several avenues for future research. One interesting question is the effect of government regulation on the cost structure of new technologies. It not uncommon for new technologies to be subject to scale effects or learning-by-doing. Such effects can occur on the industry or on the firm level. Since government regulation affects production and installation volumes, presence of such effects would make the cost structure of airbag endogenous. However, precise identification of such effects may be non-trivial and may require additional data.

Furthermore, adoption decisions for airbags can be made jointly with decisions to install other features, or with decisions to install airbags in other products of the same firm. Understanding how such decisions are made in multi-feature multi-product settings is another interesting question. The two directions above are the topics for future research.

Chapter 3

Concentration in Automobile Market

3.1 Introduction

It has been generally accepted by economists that competition between firms leads to more efficient market outcomes and higher welfare for consumers. However, several recent papers that studied the US industries have suggested that, in fact, markups have increased in the recent decades. For example, a widely-cited paper by De Loecker et al. [2020] finds that the aggregate markup of the US firms has tripled from 1980 to 2016[1]. Such findings could be worrisome as they may be an indicator of decreasing competition and thus could serve as a warning to policymakers[2]. In this paper I further investigate the markups and firm concentration in the US with a particular focus on the automobile industry using a distinct econometric approach that provides for more flexibility in estimating markups.

The method of De Loecker et al. [2020] was to use a so-called production approach to estimating markups. This approach obtained the markup by calculating the difference between an expenditure share of variable inputs in revenues and the output elasticity of inputs. In this paper, I utilize a different approach, that is based on demand estimation, to study the evolution of markups in the US car industry for the period of 24 years from 1990 to 2014. In order to do so I use a structural model of consumer demand for vehicles and firm pricing decisions similar to Berry et al. [1995] and estimate the consumer demand parameters, marginal costs of products, and other cost parameters. This approach allows me to not only calculate the markups but also

[1] An illustration of their findings can be found in Figure C.1 in Appendix.
[2] See Council of Economic Advisors [2016].

evaluate how consumer welfare changed over this period.

The dataset used for the estimation of markups covers the market for brand new cars sold in the US from 1990 to 2014, and covers product characteristics and features, prices, and sales volumes. The detailed nature of the dataset not only allows for estimation of markups but also controlling for the quality change in cars over time.

The findings show that the markups in the US automobile industry have, in fact, slightly decreased during the period observed in my data. My results are in line with other findings in the literature, which confirm that the markups in the car industry had no obvious increasing trend, despite steadily increasing prices. The growth in prices but not in markups is attributed to the growing quality of the products as measured by the number of features installed. Finally, my results indicate that consumer welfare has increased over the same period with the exception of the years right after the Great Recession.

This paper contributes to two areas of economic literature. First, it provides another look at the state of markups and firm concentration in the US, albeit limited to one industry. There were multiple papers that previously studied this question. Hall [1988] used firm's decisions with respect to cost minimization and choice of inputs in order to estimate markups using the aggregated data on several industries. De Loecker and Warzynski [2012] extend his approach further and apply it to firm-level data while also controlling for possible unobserved productivity. De Loecker et al. [2020] use this approach further to study the US industries. They find that the aggregate markups grow from 21% to 61% between 1980 and 2014, mostly due to further increases in markups of the firms with high markups. Gutiérrez and Philippon [2016] link the declining competition to corporate under-investment and Edmond et al. [2018] find that removing the distortions caused by high markups would increase the consumer welfare by as much as 7.5%. De Loecker and Scott [2016] provide a comparison of production-based and demand-based approaches to estimating markups and a discussion of results in application to US brewing industry.

Second, the paper contributes to the discussion of markups in context of the literature on car market. The seminal paper by Berry et al. [1995] suggested a method to estimation of markups jointly with the estimation of demand parameters. While the markups were not the main focus of the literature they were discussed in multiple papers such as Berry et al. [1999], Petrin [2002], Verboven [2002], Berry et al. [2004], Esteban and Shum [2007] to name a few.

3.1.1 Outline

The paper proceeds in the following fashion. The next section 3.2 describes the dataset used. Section 3.3 gives a brief overview of the model. Section 3.4 presents and discusses the results of the estimation. Section 3.5 concludes the paper.

3.2 Data

The dataset used in this paper consists of two parts. The first part that covers car sales, prices, and characteristics comes from the Ward's Automotive Yearbook. The second part of the dataset, which complements the first and consists of time series of the number of households used to construct the market shares, consumer price index used to normalize the prices over time, and mean and variance of household income, comes from the St. Louis FRED database.

The dataset covers the US market for light vehicles including cars, light trucks, vans, and SUVs in years from 1990 to 2014. It covers over 95% of all new cars that were sold in the US in these years[3]. The observations are reported on a model level. For example, one observation would be Ford Fiesta in 2013. For each observation, that is, a given model in a given year, the dataset reports the model price, number of units sold, and a list of characteristics. Possible characteristics include horsepower, weight, physical size, as well as, a list of features such as airbags, anti-lock brake system, keyless entry, and cruise control.

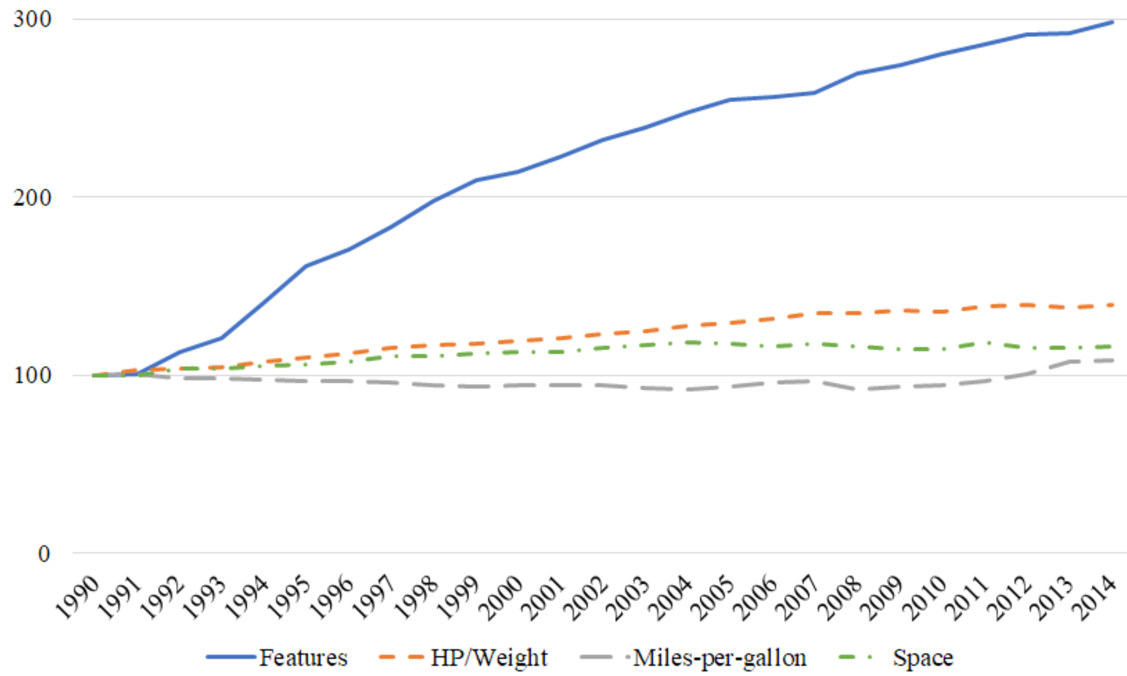
The unique feature of the dataset is the fact that it captures the characteristics of the products in great detail. Since the car industry has experienced a lot of innovation, simple analysis of markups is not sufficient to make a statement about consumer welfare. Figure 3.1 shows the evolution of several car characteristics over time. It shows an index of mean sales-weighted number of different features[4], ratio of horsepower to weight, fuel efficiency as measured by mile-per-gallon, and the physical size of the car. Notably there has been relatively little change in general characteristics of a car and most of the improvements came from additional features such as cruise control, automatic air conditioning, and airbags. The number of features in an average car has, at least, tripled over the course of the last 25 years[5].

[3]Some rare and exotic brands such as Ferrari and Lamborghini are not included.

[4]The full list of features can be found in Table A.2 in Appendix.

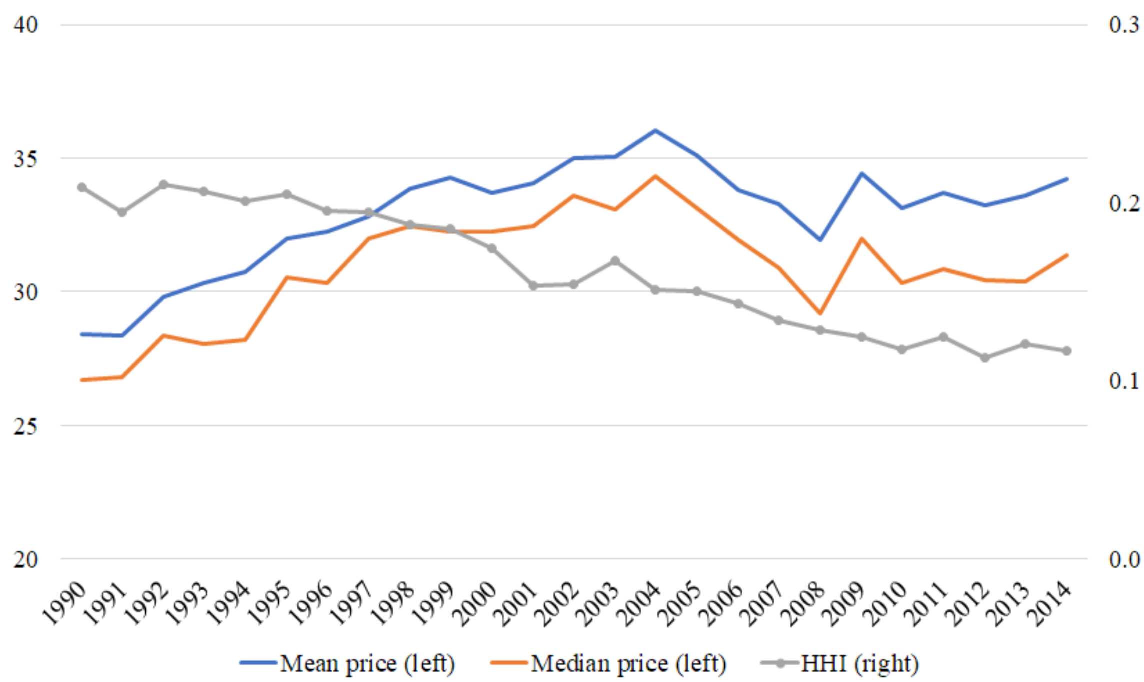
[5]Note that a lot of smaller or optional features are not captured in this dataset. For example, USB ports or sunroofs.

Figure 3.1: Index of car characteristics by year (1990=100)



Note: Variable "Features" is calculated as a sum of dummies for all non-continuous car features such as airbags, ABS, adjustable steering column etc.

Figure 3.2: Car prices and Herfindahl index by year



Note: Prices are reported in CPI-adjusted 2017 1,000 US dollars.

The prices of the new cars have increased over the same period as well. Figure 3.2 reports the mean and median sales-weighted prices of cars as measured in 2017 thousands of USD. Mean prices start out at the level of about 28 thousand USD in 1990 and increase by 21.3% by 2004. The mean prices are closely followed by the median prices as well suggesting that the increase in prices is not simply driven by a subset of market. However, such increase in prices cannot be interpreted as an increase in markups without further analysis. First, the price increases were associated with increases in the number of features that went into a car. Second, the government regulation imposed multiple standards on car manufacturers. These standard encompassed safety and environmental standards that could be associated with additional costs. For example, Sperling [2004] estimates that a third of the price increase of cars between 1967 and 2001 was due to environmental regulation. Nevertheless, despite the price increases the volumes of cars sold grew over time. Often they grew faster than the number of households. The graph illustrating the sales of cars over time can be found in Figure C.2 in Appendix.

Curiously, despite increasing prices Herfindahl index as reported in Figure 3.2 is decreasing over time. Herfindahl index, which is a common measure of industry concentration, has been falling steadily starting from 1990, in particular, due to stronger presence of Asian car makers in the US and declining share of the domestic car producers. For example, General Motors held 32% of the car market (although it was spread over its several brands) in 1990 but saw its share decline to 22% by 2010. While the number of independent firms has been fluctuating between 19 and 22 throughout the years the number of distinct models has increased from 212 at the beginning of the dataset to 251 in 2014.

3.3 Model and Estimation

My model follows in the footsteps of Berry et al. [1995] (further referred to as BLP). A reader who is well-familiar with it may want to skip directly to section 3.4 which talks about the results of the estimation. The description of the model is below.

In every period t each consumer i makes a decision whether to buy a new car out of the set of available cars $j = 1, ..., J_t$, or choose an outside option. The outside option encompasses all the decisions which involve abstaining from purchase: not having a car, keeping an old one etc. I define the market size to be equal to the number of households in the US in a given year, that is the consumer is a household. Furthermore, I allow a purchase of only one car per consumer. Customers view the offered products as given, that is, they cannot customize their characteristics. Under these assumptions the utility of a consumer i from a purchase of car j is given by the formula:

$$U_{ij} = \underbrace{\beta X_j + \xi_j}_{\delta_j} - \alpha \log(y_i - P_j) + \underbrace{\sigma \tilde{X}_j \nu_i}_{\mu_{ij}} + \varepsilon_{ij} \tag{3.1}$$

The time subscript t is suppressed for the clarity of the notation. Here X_j is the vector of all car characteristics and features, y_i is the consumer income, P_j is the car price. ν_i is the consumer's idiosyncratic taste for characteristics $\tilde{X}$ where $\tilde{X}$ denotes a subset of X[6]. ε_{ij} is the general taste shock[7].

The inclusion of y_i and μ_{ij} allows to capture the consumer heterogeneity in income and preferences. Furthermore, it is important as it allows to bypass the independence of irrelevant alternatives (IIA) issue that is endemic to the logit model without consumer heterogeneity. Because of it, the markups depend only on the market shares and price coefficient α which could lead to the unrealistic distribution of markups across products and firms.

Following the common property of the logit models the probability of a consumer i purchasing the model j is calculated as:

$$\Pr(i \text{ purchases } j|X, P) = \frac{\exp(\delta_i - \alpha \log(y_i - P_j) + \mu_{ij})}{1 + \sum_{k=1}^{N} \exp(\delta_k - \alpha \log(y_i - P_k) + \mu_{ik})}$$

Aggregating over all the consumers gives us the market share of model j:

$$s_j = \frac{1}{N_c} \sum_{i=1}^{N_c} \Pr(i \text{ purchases } j|X, P)$$

These market shares can be matched to the data to obtain an estimate of the mean utility δ_j. This can be done by doing the contraction mapping as suggested in BLP. Given the vector of non-linear parameters (α, σ) and for some value of δ calculate $\hat{s}(X, P, \delta; \alpha, \sigma)$. Then update the value of δ to a new value δ' which is calculated using the formula:

$$\delta' = \delta + \log(s) - \log(\hat{s}(X, P, \delta; \alpha, \sigma))$$

Repeat this process until convergence to a specified tolerance[8]. This approach allows

[6]Computational constraints and the number of car features observed in this dataset prevent me from estimating random coefficient for each feature.

[7]ν is drawn from the standard normal distribution and ε is assumed to follow Extreme Value Type I distribution.

[8]I use the tolerance value of $1.0e - 14$. While higher values allow the convergence to complete

to recover δ for any given values of (α, σ). Once δ is recovered it can be simply regressed on the observed car characteristics X and ξ as specified in Equation 3.1 where ξ is treated as an error term. This procedure will yield the vector of mean utility parameters β.

In order to recover the markups I also specify the firm problem. Here I assume that each firm faces the marginal costs that can be expressed as a function of product characteristics:

$$\log(MC_j) = \gamma X_j + \omega_j \tag{3.2}$$

Given these marginal costs the firm chooses its prices optimally so that they satisfy the first order condition:

$$s_j(P) + \sum_{r \in F_f} (P_r - MC_r) \frac{\partial s_r(P)}{\partial P_j} = 0$$

In case when a firm has multiple products the first order conditions generate multiple equations which can nevertheless be solved by solving the system of equation. Taking P as observed in the data and calculating $\frac{\partial s_r(P)}{\partial P_j}$ based on the parameter values from the demand regression allows to solve for the vector of marginal costs MC for all products. Once MC is recovered ω can be obtained from Equation 3.2.

The non-linear parameters α and σ are recovered using the non-linear optimization routine. The objective function for the optimization is constructed as:

$$J = G' W^{-1} G$$

where G is constructed using $E[Z_1^T \xi]$ and $E[Z_2^T \omega]$. W denotes the optimal weighting matrix. Here Z_1 are the instruments for the demand side regression, and Z_2 are the instruments for the supply side regression. Following BLP the instruments for a product j are calculated as the sum of characteristics of products that belong to the same firm as product j and the sum of features of all other competing products.

faster, they cause the objective function to be less smooth. Because of this, the minimization routine takes longer than under tighter tolerances.

3.4 Results

3.4.1 Parameter Estimates

The estimates of parameters are presented in Table 3.1. Estimates of β yield the mean utility levels from each of the car characteristics, and estimates of σ capture the consumer heterogeneity. The estimates of γ correspond to the results of the regression specified in Equation 3.2.

The demand estimates are largely in line with the parameters reported in the literature[9]. The coefficient on price, which measured in CPI-adjusted 2017 thousand of US dollars, is -56.011 and is statistically significant. The coefficients on car features, which are ratio of horsepower to weight (HP/Weight), miles-per-dollar (MPD), interior space, and number of features, are positive and statistically significant as well. This suggests that consumers do value more powerful, more fuel efficient, larger cars with more features. Curiously, the coefficient on truck dummy (which includes also vans and SUV's) is slightly negative, as well as, the coefficient on the luxury brand dummy.

The values of σ suggest that the consumer preferences are heterogeneous, although most of the heterogeneity is in their preference for cars in general rather than specifically for features.

I also include year fixed effects for years after the Great Recession of 2008 in order to account for a severe drop in car purchases. However, I do not include year fixed effects for other years since I find that saturation of the model with year fixed effects interferes with identification of the random coefficient on the constant term in particular, and to a lesser degree, of the random coefficient on other characteristics.

The cost estimates have largely the expected signs. More powerful cars are more expensive to manufacture. The number of cars also contributes positively to the cost. Two characteristics enter with a negative sign and these are fuel efficiency as captured by miles-per-gallon and space. One possible explanation for this is that manufacturing fuel efficient or larger cars is cheaper while it is the fixed costs (for example, research and development) that are higher for these cars. Finally, the results show a negative trend over time in the cost of the cars.

[9] For example, see Berry et al. [1995].

Table 3.1: Parameter estimates

Demand side

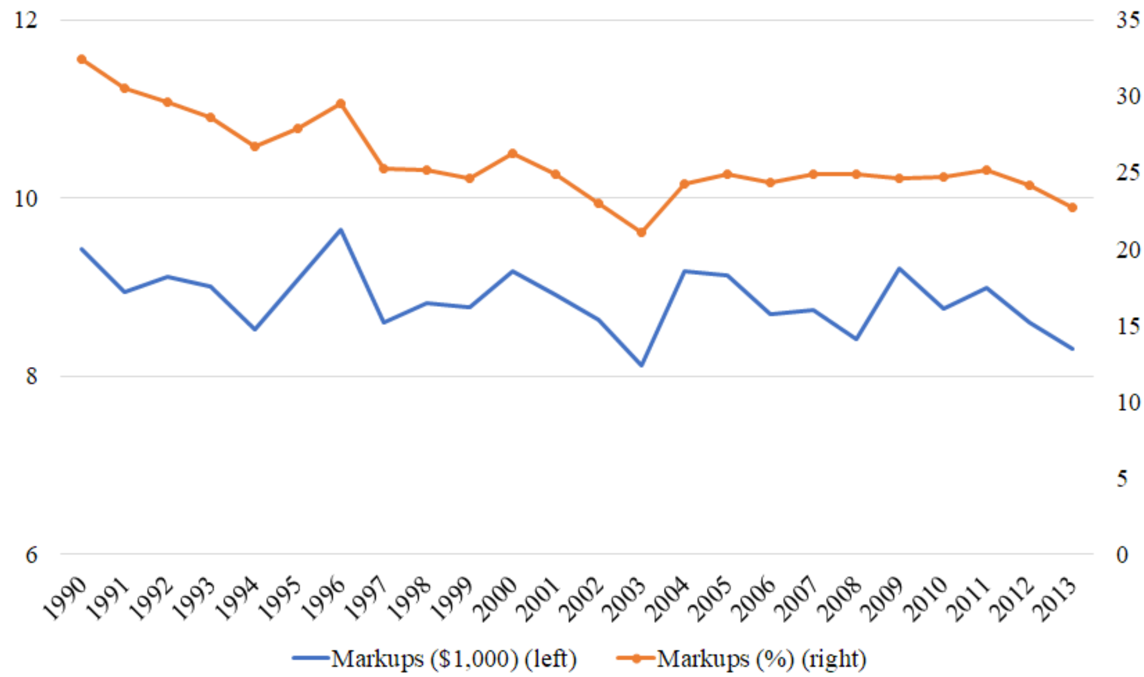
Means (β_k)	log(Price)	-56.011***
		(0.084)
	HP/Weight	3.138***
		(0.185)
	MPD	0.360***
		(0.124)
	Space	3.436***
		(0.140)
	# Features	0.029**
		(0.014)
	Truck	-0.307***
		(0.070)
	Luxury Brand	-0.146***
		(0.053)
	Year FE	yes
Std. Deviations (σ_k)	# Features	0.683***
		(0.021)
	Constant	5.203***
		(0.297)

Supply side

Means (γ_k)	log(HP/Weight)	0.484***
		(0.028)
	log(MPG)	-0.600***
		(0.039)
	log(Space)	-0.217***
		(0.038)
	# Features	0.077***
		(0.003)
	Truck	0.010
		(0.012)
	Luxury Brand	0.182***
		(0.009)
	Trend	-0.025***
		(0.001)
	Constant	3.569***
		(0.047)

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Year Fixed Effects capture only years 2009-2011. This is done in order to control for effects of the Great Recession on car sales. See Figure C.2 for more details. Inclusion of more years in fixed effects interferes with the identification of random coefficients and hence is avoided.

Figure 3.3: Sales-weighted markups



Note: Markups are reported in CPI-adjusted 2017 US dollars.

3.4.2 Markups

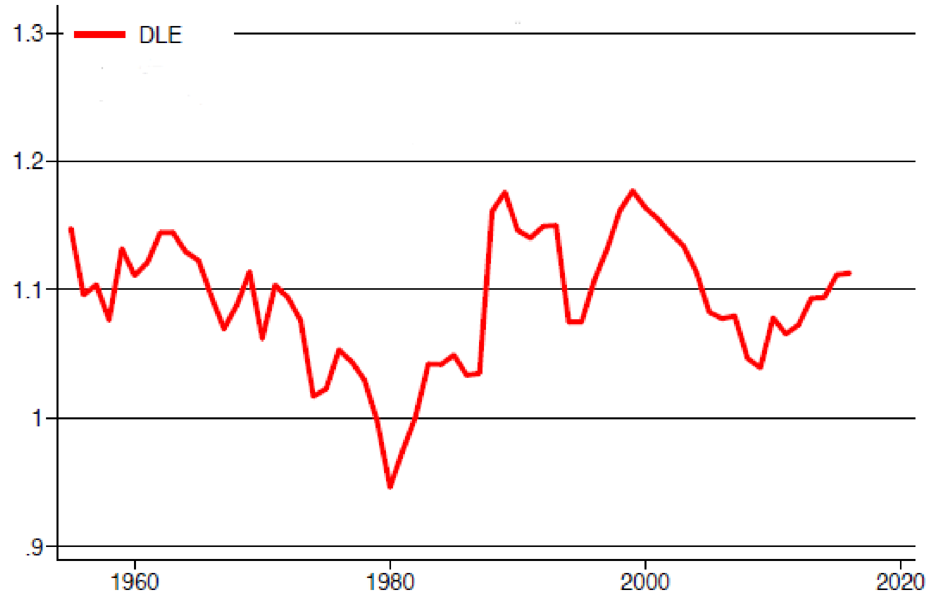
Figure 3.3shows the sales-weighted average markups by year as estimated in the regression discussed above. It shows that the absolute values of markups oscillated between $8,000 and $10,000 throughout the years 1990-2013. In percentage terms the markups are at 33% in the beginning of the period in 1990 and fall to about 25% by the end of the period. Their decrease over time is not surprising as the average prices have grown as was illustrated in Figure 3.2 but the markup has remained the same in absolute values.

Figure 3.4 shows the markups in the automobile industry as estimated in the paper by De Loecker et al. [2020] using the production approach. While they calculate their markups in a slightly different fashion[10] the graphs are comparable. While my estimated markups are slightly higher on average, they are close to those estimated using production approach.

The next section explores the changes in consumer welfare over the same time period.

[10]De Loecker et al. [2020] calculate markups as the ratio of price to cost while I calculated them as the ratio of the difference between price and cost to cost.

Figure 3.4: Sales-weighted markups for automobile industry as shown in De Loecker et al. [2020]



Source: De Loecker et al. [2020], Online Appendix, Appendix 7.
Note: De Loecker et al. [2020] calculate markups as the ratio of price to cost while I calculated them as the ratio of the difference between price and cost to cost.

3.4.3 Consumer Welfare

Consumer welfare may change not only due to availability of products and their prices but also due to their variety or inherent characteristics. Automobile industry industry has seen a lot of innovation over the course of the 1990's and 2000's as was shown by the change in the number of features in Figure 3.1. Ignoring the quality changes and focusing on prices only would lead to underestimation of the change in consumer welfare.

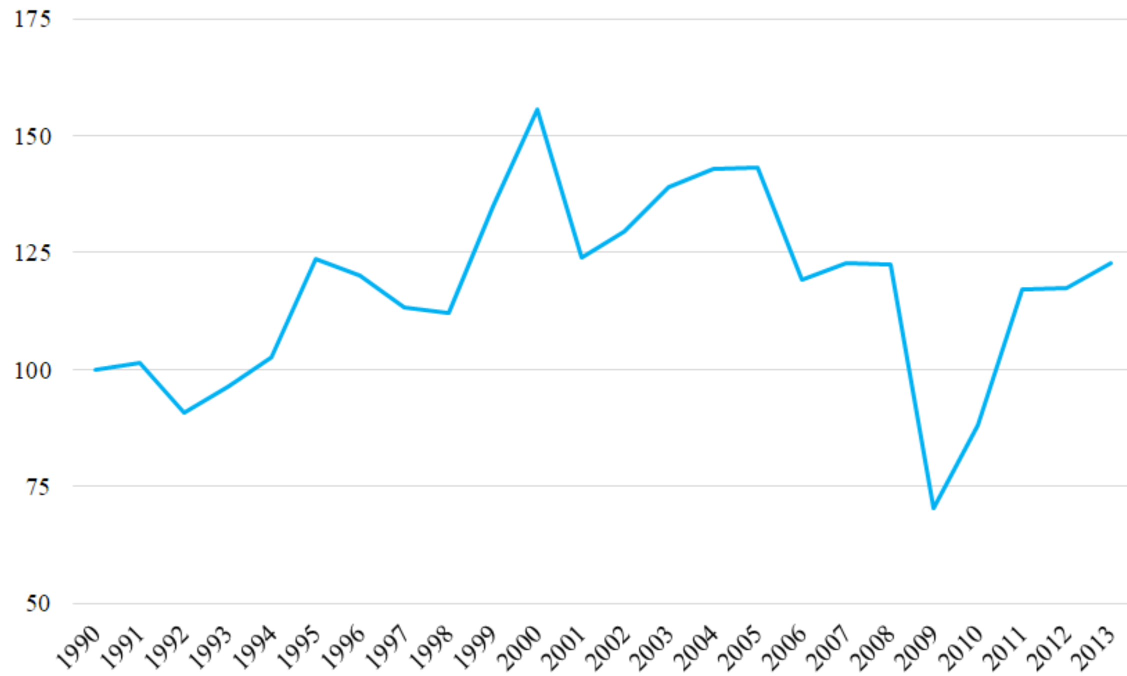
I use a simple formula to calculate the consumer surplus in year. The formula is:

$$CS_i = \frac{1}{\tau_i} \cdot \log\left(\sum_{j=1}^{J} \exp(\delta_{jt} - \alpha \log(y_{it} - P_{jt}) + \mu_{jt})\right)$$

where τ_i is the marginal utility of income of consumer i, and the rest of the notation is the same as given in Section 3.3.

Figure 3.5 shows the changes in consumer surplus over time. With the exception of the Great Recession in 2008 and after, the consumer surplus was increasing in most of the years despite the increasing prices. Such increases are most likely related to the improvements in car quality as captured by the number of features. This highlights

Figure 3.5: Index of consumer surplus by year (1990=100)



the importance of controlling for product quality changes over time when calculating consumer welfare.

3.5 Conclusion

In this paper I applied the econometric method based on the estimation of demand parameters to calculate the markups in the US automobile industry in 1990's and 2000's. While the prices of cars have grown by over 21.3% over this period, the relative markups have decreased slightly. While this finding differs from the general trend of markups in the economy as suggested by the previous literature, it matches the pattern of markups for the automobile industry that was calculated using production-based approach. This suggests that both demand- and production-based approaches are valid in estimating the structure of markups in an industry.

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Appendix A

Appendix to Chapter 1

Figure A.1: Distribution of values of factory-installed equipment variables

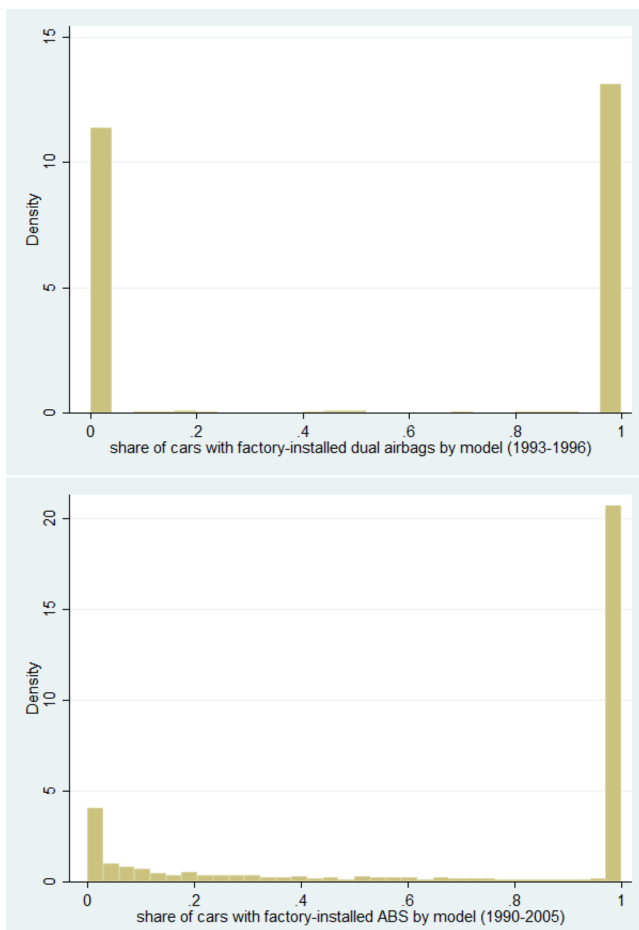


Table A.1: Descriptive statistics for years 1990-2002

Year	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
MSRP	28.4	28.4	29.8	30.4	30.7	32.0	32.2	32.8	33.9	34.3	33.7	34.1	35.0
HP/Weight	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6
MPG	2.4	2.4	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.2	2.3	2.3	2.3
Size	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.3
Airbag (Driver)	21.7	20.7	39.0	40.7	25.8	34.8	31.2	14.2	0.0	0.0	0.0	0.0	0.0
Airbag (Dual)	0.0	0.0	0.0	7.3	40.7	59.3	68.2	84.5	100.0	100.0	100.0	100.0	100.0
Airbag (Side)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.7	7.7	10.3	13.8	20.0	25.6
All-Wheel Drive	5.7	8.0	9.2	10.0	11.3	13.0	15.8	17.1	23.7	27.3	24.8	23.2	25.4
Power Brakes	74.9	66.3	56.0	50.6	31.9	31.5	29.7	27.1	22.6	22.3	21.1	20.9	36.1
Anti-Lock Brakes	25.1	33.8	44.0	49.4	68.1	68.5	70.3	72.9	77.4	77.7	78.9	79.1	76.5
Automatic AC	12.1	11.6	9.1	7.7	7.6	7.9	7.7	7.6	11.5	12.4	12.8	17.9	18.4
Automatic Lights	0.0	0.0	0.0	0.0	0.0	0.0	0.0	14.4	14.48	32.2	40.8	42.3	51.3
Adjustable Steering	75.9	74.6	77.4	77.4	79.3	82.8	82.0	84.6	89.8	90.9	94.8	94.2	98.1
Cruise Control	67.7	70.1	74.8	74.8	74.6	78.0	80.2	82.5	83.3	82.5	84.8	88.7	92.0
Keyless Entry	0.0	0.0	0.0	0.0	0.0	11.9	22.9	33.1	40.7	55.4	59.9	70.1	74.1
Rear Defogger	72.1	79.5	75.5	75.7	73.4	76.5	78.7	74.8	71.2	69.8	68.8	66.4	79.6
Power Equipment	45.2	40.1	46.8	51.0	54.6	59.1	61.0	63.2	67.1	70.7	70.2	74.9	75.0
Total Models	212	216	220	219	205	207	202	199	195	197	203	214	218
Total Sales	12.4M	12.7M	12.2M	13.1M	13.9M	14.9M	13.6M	14.6M	14.7M	16.3M	17.3M	15.8M	16.4M

Note: All variables except Total Models and Total Sales are sales-weighted averages. MSRP is given in 2017 dollars. Total Sales are given in million units. Power Equipment is a sum of Power Windows, Power Seats, and Power Locks.

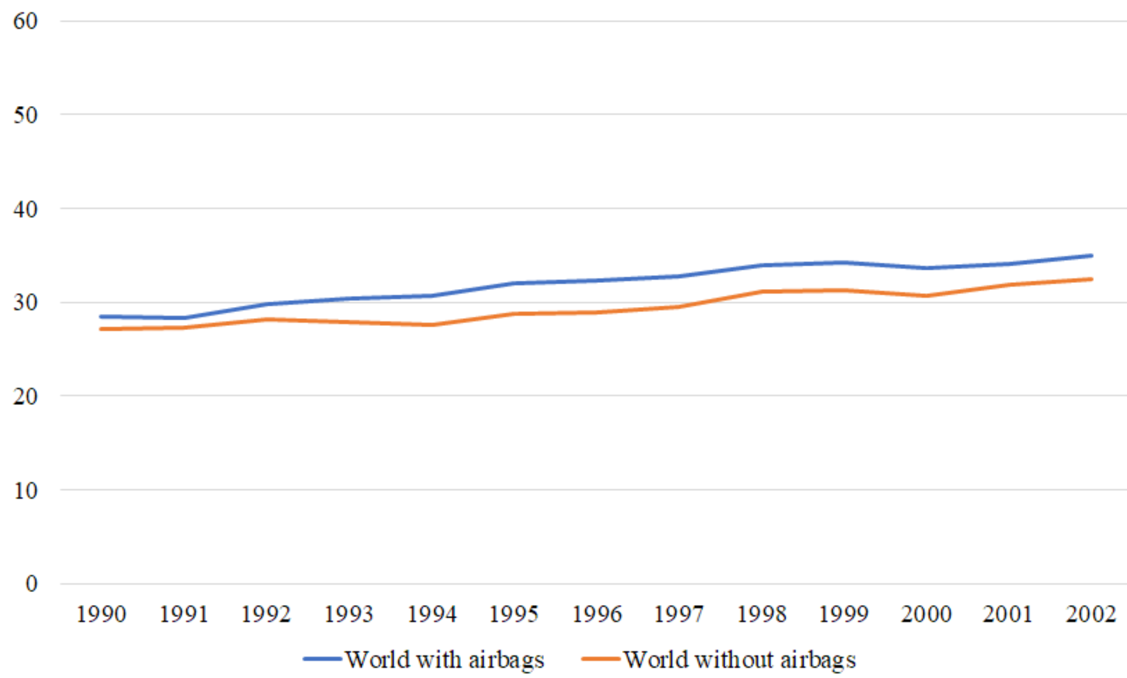
Table A.2: Classification of features

Frontal Airbags	Airbag (Driver)
	Airbag (Passenger)
Comfort Features	Auto AC
	Auto Headlights
	Adj. Steering
	Cruise Control
	Keyless Entry
	Rear Defogger
Power Equipment	Power Windows
	Power Locks
	Power Seats

Table A.3: Average feature contribution to marginal cost ($1,000)

	I	III
log(HP/Weight)	12.64	12.41
log(MPD)	-51.07	-46.78
log(Space)	-13.41	-12.63
# Airbags	3.12	4.30
Airbag (Driver)		
Airbag (Passenger)		
# Airbag × Trend		-0.32
# Comfort Features	0.07	0.16
# Driving Features	1.15	1.07
# Power Equipment	2.91	2.84
# Safety Features	4.16	4.05
Truck	-0.39	-0.05
Luxury Brand	4.41	4.28

Figure A.2: Mean equilibrium car prices in a world with and without airbags ($1,000)



Note: Prices are given in 2017 dollars.

Appendix B

Appendix to Chapter 2

Table B.1: List of luxury brands

Brand	Parent company
Acura	Honda
Audi	Volkswagen
BMW	
Cadillac	General Motors
Infiniti	Nissan
Jaguar	
Lexus	Toyota
Lincoln	Ford
Mercury	Ford
Porsche	
Volvo	

Note: The brands are classified as luxury based on a variety of sources which refer to them as such. For example, see `https://cars.usnews.com/cars-trucks/best-luxury-car-brands`.

Table B.2: Willingness-to-pay estimates ($)

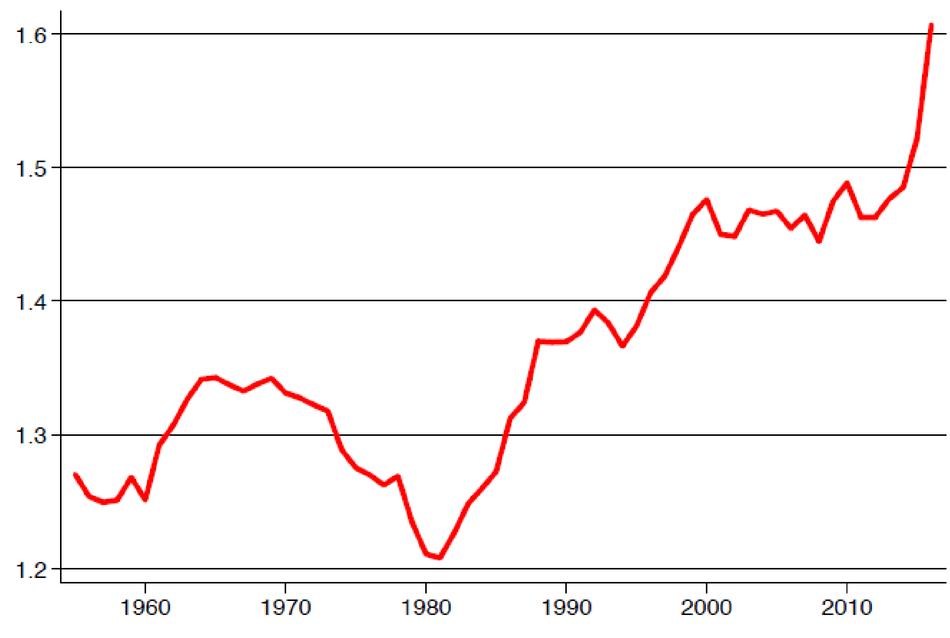
	I	II	III
# Airbags	1,189		
Airbag (Driver)		1,186	1,241
Airbag (Passenger)		1,196	1,187
# Comfort Features	1,834	1,079	1,264
# Driving Features	146	113	42
# Power Equipment	2,106	1,431	1,636
# Safety Features	2,074	785	1,012
Truck	2,390	1,344	1,277
Luxury Brand	61	710	530

Note: Three variables # Comfort Features, # Driving Features and # Power Features are sums of dummies for features related to driving (ABS, power brakes), comfort (auto headlights, adjustable steering wheel etc.) and power equipment (power windows, power locks etc.).

Appendix C

Appendix to Chapter 3

Figure C.1: Average markups for all industries as shown in De Loecker et al. [2020]



Source: De Loecker et al. [2020], Section 3.1, Figure 1.

Figure C.2: Sales of new cars by year (million units)