The Social Costs of the "Arms Race" on American Roads: Evidence from Automobile Demand*

[Job Market Paper]

Shanjun Li †

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Abstract

The growing popularity of sport utility vehicles has been characterized as an "arms race" on American roads. Because SUVs can cause more damage to passenger cars in crashes, drivers may choose to buy SUVs preemptively for self-protection. Moreover, the incentive to buy SUVs may become stronger as more of them enter the road. This paper quantifies the spillover effect arising from safety concerns in vehicle demand and examines the social welfare consequences of the arms race. I estimate a market equilibrium model composed of a demand side and a supply side based on both market level data and a household survey. The estimation results provide evidence of the arms race in vehicle demand. I find that, in the long-run, the arms race accounted for at least 4.97% of SUV sales in 2005. The arms race caused a social welfare loss of $17.21 billion in 1999 dollars in 2005, implying a $243 loss imposed by each SUV on the road.

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†Department of Economics, Duke University, Durham, NC 27708. Email: SL39@econ.duke.edu.

1 Introduction

Americans have been running an "arms race" on the road by buying larger and larger vehicles such as sport utility vehicles (SUVs) and pickup trucks (White (2004)). The market share of new light trucks including SUVs, pickup trucks and passenger vans grew from 17 percent to 51 percent from the 1981 model year to the 2005 model year.[1] The most remarkable growth was in the SUV segment, whose market share increased from a mere 1.3 percent to 26.3 percent.

With more and more light trucks on the road, SUVs and pickups have received intensified scrutiny for their impacts on traffic safety. It is now well documented that in multiple-vehicle collisions, SUVs and pickups provide superior protection to their occupants while posing greater dangers to the occupants of passenger cars than cars do.[2] This is largely due to the mismatch between the design of SUVs and pickups and the design of passenger cars. SUVs and pickups are generally taller and have higher front-ends. When they collide with cars, they hit passenger compartments rather than the steel frames beneath, and cause greater injury to the heads and upper bodies of the occupants of the cars. Moreover, SUVs and pickups have stiffer and heavier body structures, which cause the opposing cars to absorb more of the crash energy in collisions.

The design mismatch and subsequent crash incompatibility problem produce spillovers in vehicle demand in that an individual's vehicle choice is affected by the choices made by others. The spillover effect from safety concerns can then lead to an "arms race", where consumers choose SUVs as a precautionary measure for self-protection in multiple-vehicle crashes. This preemptive incentive may become even stronger as more and more SUVs are on the road. Varian (2003) states that "the dynamics involved [in the demand for SUVs] is the same as that of an arms race: if other families buy bigger vehicles, then you will want to as well, if only in self-defense."

[1] Data source: the Environmental Protection Agency (EPA). A model year starts from the third quarter of the preceding calender year and ends after the second quarter of the current calender year.

[2] The Insurance Institute for Higher Safety (IIHS) offers the first serious study on how vehicle type and design affect crash compatibility using traffic accident data (See its Status Report on Feb. 14, 1998). Gayer (2004) and White (2004) offer more rigorous econometric analysis.

In this paper, I estimate spillover effects in vehicle demand and assess the welfare consequences of the arms race for both consumers and automakers. The importance of spillover effects in consumer demand has long been recognized. Since Leibenstein (1950) incorporated the interpersonal effects from psychological needs into the theory of consumer demand, a huge literature has been developed to study spillover effects both theoretically and empirically. Most recent empirical literature on spillover effects in demand has concerned consumer learning and network externalities.[3] This paper fits into this tradition. It contributes to the literature by studying spillover effects in vehicle demand. The focus of this paper is on the spillover effect that occurs through safety concerns arising from the crash incompatibility problem in collisions involving both cars and SUVs. This safety spillover effect has potentially important welfare implications for both consumers and the auto industry. To my knowledge, this is the first paper that analyzes the safety spillover effect of vehicle demand and examines its social welfare consequences.

While my focus in this paper is the spillover effect from safety concerns, I also incorporate another type of spillover effect that is attributed to psychological needs (e.g., conformity and status-seeking) and consumer learning in the demand for SUVs. Ignoring these effects can lead to biased estimates of the safety spillovers. The bias can potentially be significant. Many industry experts believe that the design of SUVs and the marketing efforts of automakers create a "fashion" motive, in which SUV drivers can show their adventurous image (Bradsher (2002)). Moreover, consumer learning can also contribute to the increasing share of SUVs in that potential SUV buyers take the increasing market share of SUVs as a signal of improved product quality. Although I control for the spillover effect that comes from both psychological need and learning, distinguishing them is difficult without making additional strong assumptions. [4]

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[3]To give a few examples, for the effect of learning on new product diffusion, see Foster and Rosenzweig (1995), Escarce (1996), Goolsbee and Klenow (2002), and Berndt, Pindyck, and Azoulay (2003). For studies on network effects, see Gandal (1994), Gandal (1995), Saloner and Shepard (1995), Brynjolfsson and Kemerer (1996), Gandal, Kende, and Rob (2000), Gowrisankaran and Stavins (2004), Rysman (2004), Ackerberg and Gowrisankaran (2006).

[4] Using a large household level data set in Finland, Grinblatt, Keloharju, and Ikaheimo (2004) try to separate emotional biases from information sharing in automobile demand and find that information sharing is a more reasonable explanation for the interpersonal influence in automobile consumption.

The arms race arising from the safety spillover effect can have important welfare implications for both consumers and automakers. As discussed above, the design of SUVs and pickups increases risks for the occupants of cars in multiple-vehicle crashes. However, current policies fail to internalize the safety hazard of SUVs and pickups so that SUV and pickup buyers do not bear the total social costs of their vehicles. Rather, the occupants of cars bear the higher accident costs.[5] Therefore, there may be too many SUVs and pickups from a standpoint of consumer welfare. Moreover, the arms race can have significant impacts on firm performance by tilting the market demand toward SUVs and pickups. Specifically, the major SUV and pickup producers benefit from the arms race while others suffer a loss from it. To investigate the welfare implications for both consumers and the auto industry, I estimate a market equilibrium model with both a demand and a supply side.

The demand side takes the random coefficient discrete choice approach advanced by Berry, Levinsohn, and Pakes (1995) (henceforth BLP). The approach enables the price endogeneity (due to unobserved product attributes) in a discrete choice model to be dealt with in a linear framework. In addition, the model allows for heterogenous preferences and produces plausible substitution patterns across products. To estimate the model, I use market level data from 20 Metropolitan Statistical Areas (MSA) from 1999 to 2005 augmented with the 2001 National Household Travel Survey (2001 NHTS). The household level data provide correlations between household demographics and vehicle choices. This information can significantly improve the estimation of heterogenous taste parameters in the model.

In the utility function, I explicitly incorporate the two types of spillover effects discussed above: the first from psychological needs or learning in the demand for SUVs, and the second from safety concerns. The former is specified as a function of the lagged fleet share of SUVs among all vehicles on the road. In several empirical studies of spillover effects in demand, a positive correlation between the number of a given product already in use (installed base) and the number of the same product being adopted (current adoption)

[5]In addition, SUVs and pickups consume more gasoline and pollute more. In this paper, I focus only on the safety externality of SUVs and pickups.

has been interpreted as evidence of spillover effects.[6] The safety spillover effect depends on both the probability of multiple-vehicle crashes and the fleet composition (e.g., the share of SUVs and pickups among all vehicles on the road). As more and more SUVs and pickups are on the road, a multilple-vehicle crash becomes more dangerous for the occupants of cars because the accident is more likely to involve SUVs and pickups. Moreover, in areas where multiple-vehicle accidents happen more often (e.g., due to road and weather conditions), SUVs and pickups present even larger safety hazards to the occupants of cars. Therefore, the identification of this type of spillover effect relies on variations in both the probability of multiple-vehicle crashes and the fleet composition.

A fundamental challenge in empirical studies of spillover effects is to control for unobserved regional or neighborhood heterogeneity which cause the agents in the same area to have similar tastes.[7] Without controlling for the unobserved geographic and temporal effects, we cannot interpret the positive correlation between the lagged fleet share of SUVs and current SUV demand as consumer learning or conformity. More importantly, these unobserved effects will bias the estimation of the safety spillover effect because of the endogeneity of the probability of multiple-vehicle crashes. For example, unobserved weather conditions (e.g., heavy snow) might make an area more prone to accidents, and these conditions might also make a certain type of vehicle (e.g., SUVs) more attractive. In this paper, I exploit the panel data structure to use fixed effects to control for unobserved heterogeneity in both geographic and temporal dimensions.

In order to assess the welfare consequences of the arms race, I conduct a counterfactual analysis. To that end, I set up a supply model where multiproduct firms engage in price competition. I recover marginal costs from the first-order conditions of firms' profit maximization problems. The implied marginal costs are essential for determining the new market equilibrium in a counterfactual scenario. With the estimates of taste parameters and marginal costs, I find the new market equilibrium in a world without

[6]For instance, see Gandal, Kende, and Rob (2000), Goolsbee and Klenow (2002), and Gowrisankaran and Stavins (2004).

[7]This problem has been studied in various contexts. See Manski (1993), Ellison and Glaeser (1997), Bayer and Timmins (2006), and Sweeting (2005).

the arms race where SUVs are designed (e.g., with lower bumper height and more flexible crush zones) such that they provide the same level of protection to their occupants as cars do in multiple-vehicle crashes. This scenario eliminates the safety spillover effect because an SUV or a pickup presents the same safety hazard to the occupants of a car as to the occupants of another SUV or pickup in multiple-vehicle crashes. I examine the changes in both consumer welfare and firms' profits under the new market equilibrium.

The demand analysis shows that consumers are willing to pay a premium for SUVs for their better protection in multiple-vehicle crashes. The tradeoff between the premium and the risk reduction implies that the value of a statistical life ranges from $6.44 million to $14.76 million in 1999 dollars. The estimation also confirms the dynamic aspect of the arms race in the demand for new vehicles by showing that the utility from a passenger car decreases with the share of SUVs on the road. The impact of the arms race on market demand in the long-run is significant, accounting for at least 4.97% of the sales of SUVs in 2005. I find that the arms race imposes significant welfare losses on both consumers and the auto industry, although the Big Three are better off with the arms race.[8] The social welfare loss is estimated at $17.21 billion in 1999 dollars in 2005, implying a $243 loss caused by each SUV on the road.

The remainder of this paper is organized as follows. Section 2 discusses recent trends in the U.S. auto industry and presents facts on the safety effects of SUVs. In Section 3, I describe the data. Section 4 outlines the empirical model. In Section 5, I discuss identification and estimation of the model. The estimation results are presented in Section 6. In Section 7, I conduct the counterfactual analysis. Section 8 concludes.

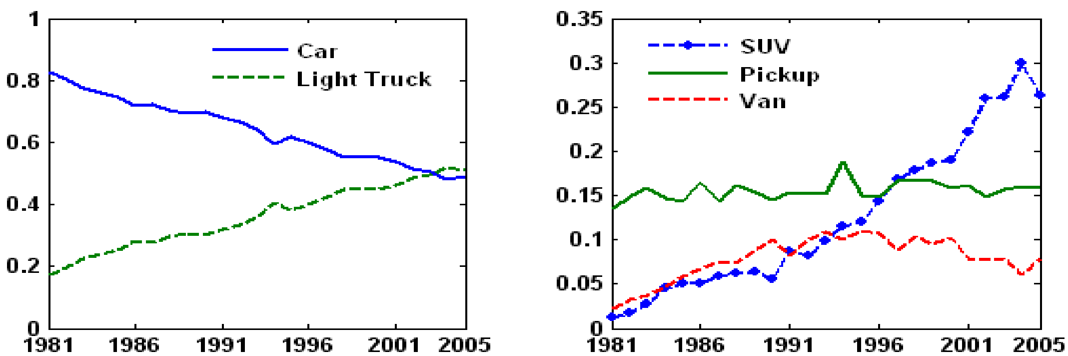
2 Industry Background

The U.S. auto industry witnessed dramatic structural changes during the past 25 years. The market share of new light trucks over total new light vehicles grew from 17 percent

[8] Several international mergers took place around year 2000. Chrysler merged with Mercedes-Benz. Saab joined GM while Jaguar and Volvo are now merged with Ford. In my analysis, the Big Three refers to the traditional Big Three prior to mergers.

to 51 percent from the 1981 to the 2005 model year as shown by the left panel of Figure 1.[9] Within the light-truck segment, the market share of vans increased from 2.3 percent to a peak of 11 percent in 1995 and then gradually decreased to 7.9 percent in 2005. The market share of pickups was fairly steady, ranging from 14 to 17 percent over the period. The majority of the increase in the light truck sales was accounted for by SUVs, whose share rose from 1.3 percent to 26.3 percent during the period.

Figure 1: Model year new vehicle market share by segment

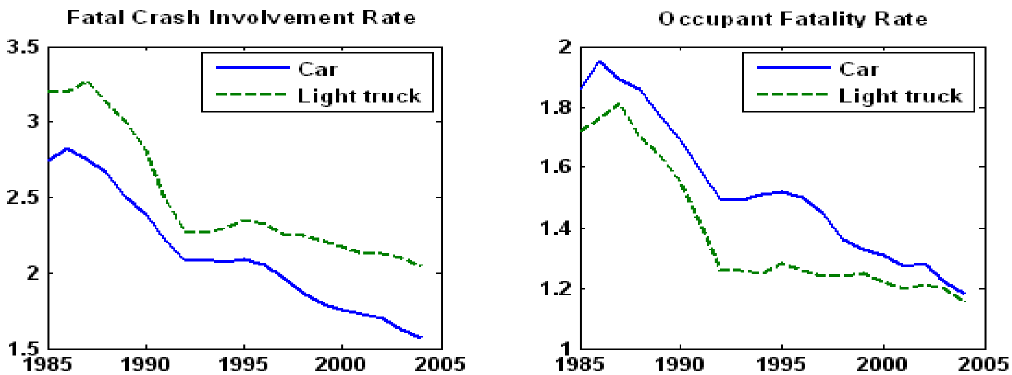


With more and more SUVs on the road, the negative safety effects imposed by SUVs on other motorists are subject to intensified scrutiny. It is now a well-established fact that SUVs and pickups protect their occupants at the cost of others in multiple-vehicle crashes. Figure 2 plots the fatal crash involvement rate and the occupant fatality rate per 100 million miles of travel for cars and light trucks from 1985 to 2004.[10] During this period, traffic safety has been improved dramatically – largely due to improvements in vehicle design, more safety equipment in new vehicles, and stricter enforcement of traffic rules. The left panel indicates that light trucks are more likely to be involved in fatal crashes than cars, while the right panel reveals that light trucks have a lower occupant fatality rate.

[9] Data source: EPA. Light vehicles, also called light-duty vehicles include passenger cars and light trucks. Light trucks include pickups, vans and SUVs. Vans include minivans and full-sized passenger vans with minivans being the majority.

[10] Source: *Traffic Safety Facts 2004* by the National Highway Traffic Safety Administration (NHTSA).

Figure 2: Fatal crash involvement and occupants fatality rates per 100 million miles



White (2004) analyzes the internal and external safety effects of light trucks based on a large sample of police-reported motor vehicle crashes from 1995 to 2001. She estimates the probability of fatalities and serious injuries in crashes involving different types of vehicles while controlling for a series of variables including driving conditions and driver demographics. Table 1, which is adapted from her study, is particularly interesting. If a car collides with another car, the predicted probability of having fatalities occur to the occupants of the first car is about 0.1 percent. If the second vehicle were instead a light truck, the predicted probability would increase to 0.16 percent. Comparing numbers across columns in both the fatality and injury cases, it is clear that light trucks pose greater dangers to the occupants of other colliding vehicles than cars do. Meanwhile, the comparison of numbers in the two rows indicates that light trucks protect their occupants better than cars in multiple-vehicle crashes.

It is worth noting that although vehicle weight is an important factor influencing crash outcomes, vehicle stiffness and geometric design are equally (if not more) important. SUVs and pickup trucks have higher front-ends and stiffer rail frames, both of which cause SUVs to inflict disproportional damage to cars in a collision. A study by the Insurance Institute for Highway Safety (IIHS Status Report, Feb. 14, 1998) showed that in collisions between an SUV and a car with similar weight, the fatality rate in cars is significantly higher.[11]

[11] Mayrose and Jehle (2002) provides a similar finding using a different data set.

Table 1: Probability of fatality and serious injuries in the first vehicle in 1000 crashes

	Fatalities		Serious injuries	
First vehicle	Second vehicle		Second vehicle	
	Car	Light truck	Car	Light truck
Car	0.997	1.610	22.8	28.2
Light truck	0.645	1.420	15.4	19.8

Based on the study, Brian O'Neil, then-president of the IIHS urged that making future SUVs and pickups more crash compatible, especially in crashes with cars, should be a priority for the auto industry. Many believe such redesigns can be done to make SUVs safer to others without sacrificing drivability (Bradsher (2002); Latin and Kasolas (2002)).

In addition to their adverse effects on traffic safety, SUVs are also criticized for America's stronger dependence on foreign oil and worsening air pollution.[12] However, many regulatory standards in place today were set in 1970's when the light-truck segment was mainly composed of pickup trucks and cargo vans. SUVs such as the Jeep were mainly used by small businesses and accounted for only a tiny share of the market. On the grounds that light trucks are mainly for business usage, standards were set to be more favorable for light trucks than for passenger cars: allowing light trucks to have a higher bumper, burn more fuel, and emit more pollution.[13] Despite the fact that the majority of SUVs are now serving as passenger vehicles (as cars do), they are still classified as light trucks and enjoy less stringent regulations.

[12] Bradsher (2002) asserts that "SUVs represent the biggest menace to public safety and the environment that the auto industry has produced since the bad old days of 1960s...."

[13] This was largely due to the lobbying efforts of automakers in the wake of the passage of Energy Policy Conservation by congress in 1975, which established the mandatory Corporate Average Fuel Economy Standard (CAFE). Bradsher (2002) offers detailed accounts on the events that lead to the classification of SUVs into light truck category.

3 Data

There are four data sets used in this paper: (1) new vehicle attribute data from 1999 to 2005, (2) the 2001 National Household Travel Survey (2001 NHTS), (3) vehicle sales and stock data from 20 Metropolitan Statistical Areas (MSAs), and (4) gasoline price and traffic fatality data.

Before I discuss each of the data sets, I provide information about the 20 selected MSAs.[14] The MSAs are chosen from different regions and exhibit large variations in terms of size and average household demographics. Table 2 shows the number of households and average household demographics in these 20 MSAs from the 2000 Census.[15] The largest MSA in the data in terms of the number of households is San Francisco, CA and the smallest is Lancaster, PA. The average household income is highest in San Francisco, CA and lowest in Syracuse, NY. Size is the average household size. Tenure is a dummy variable equal to one if the house is rented and zero if owned. Child is a dummy variable equal to one if there are children under 16 in the household. Age is the age of household head. Travel measures the average commute time to work in minutes.

3.1 New Vehicle Characteristics Data

This data set, collected from various issues of Automotive News Market Data Book, includes manufacturer's suggested listed prices (MSRP), total sales in the U.S., and product attributes for virtually all new vehicle models marketed in the U.S. from 1999 to 2005.[16] There are in total 1404 models, which include non-luxury models with total U.S. sales over 5,000 in quantity and luxury models with sales over 2,000 in quantity. Table 3 reports summary statistics for vehicle characteristics. Size, defined as the product of vehicle length

[14] The third data set is from a proprietary database maintained by R. L. Polk. Since the data are quite expensive, I was only able to purchase data for 20 MSAs.

[15] In the estimation of the random coefficient demand model, I sample those six observed household demographics shown in Table 2 for 500 households in each MSA, using the 5 percent public use microdata of Census 2000.

[16] Exotic models with tiny market shares are excluded. Although vehicle transaction prices are more desirable in the demand analysis, they are hard to obtain. MSRPs have been used in several previous studies (e.g., Feenstra and Levinsohn (1995); BLP; Petrin (2002)).

Table 2: Households and average household demographics in 2000

MSA	Households	Income	Size	Tenure	Child	Age	Travel
Albany, NY MSA	350,284	56,147	2.41	0.359	0.299	49.6	16.0
Atlanta, GA MSA	1,504,871	67,336	2.68	0.341	0.367	45.2	24.2
Cleveland, OH CMSA	1,166,799	55,233	2.47	0.317	0.308	50.0	16.8
Denver, CO CMSA	825,291	64,668	2.53	0.343	0.326	46.2	20.1
Des Moines, IA MSA	184,730	58,466	2.48	0.311	0.320	47.1	13.9
Hartford, CT MSA	457,407	65,939	2.49	0.387	0.312	50.3	15.1
Houston, TX CMSA	1,462,665	61,524	2.80	0.405	0.402	45.5	21.8
Lancaster, PA MSA	172,560	55,270	2.60	0.292	0.331	49.5	16.1
Las Vegas, NV-AZ MSA	512,253	57,318	2.62	0.409	0.332	47.9	17.3
Madison, WI MSA	173,484	61,575	2.37	0.422	0.278	45.4	15.3
Miami, FL CMSA	1,466,305	51,959	2.66	0.422	0.361	49.8	19.7
Milwaukee, WI MSA	587,657	58,457	2.51	0.390	0.313	48.6	15.9
Nashville, TN MSA	479,569	58,436	2.49	0.341	0.329	46.6	19.4
Phoenix, AZ MSA	1,071,522	59,456	2.67	0.325	0.339	47.9	18.6
St. Louis, MO-IL MSA	1,012,419	57,305	2.52	0.286	0.331	49.1	18.2
San Antonio, TX MSA	572,856	51,620	2.78	0.372	0.382	47.4	17.5
San Diego, CA MSA	994,677	63,231	2.73	0.445	0.349	47.8	18.5
San Francisco, CA CMSA	2,557,158	89,553	2.69	0.511	0.246	48.9	21.3
Seattle, WA CMSA	963,552	69,055	2.50	0.381	0.302	47.0	20.5
Syracuse, NY MSA	282,601	51,480	2.50	0.326	0.324	49.6	14.3

and width, measures the "footprint" of a vehicle. Miles per gallon (MPG) is the weighted harmonic mean of city MPG and highway MPG based on the formula provided by EPA to measure the fuel economy of the vehicle: $\text{MPG} = \frac{1}{0.55/\text{city MPG}+0.45/\text{highway MPG}}$. There are four types of vehicles in the data set: car, van, SUV, and pickup trucks. Automotive News further classifies different models into 15 segments based on product attributes and market orientations. Table 4 reports the number of products and average attributes for each segment. SUVs on average are the most expensive, have the largest horsepower, and the lowest fuel efficiency among the four types of vehicles.

Table 3: New vehicle attributes

Characteristics	Mean	Median	Std. Dev.	Min.	Max.
Quantity	80,949	46,573	105,737	2,090	939,511
Price ('000, in 1999 term)	25.001	21.951	12.023	8.514	81.695
Size ('0000 $inch^2$)	1.356	1.341	0.168	0.827	1.835
Horsepower (HP, '00)	1.925	1.900	0.571	0.550	4.050
Mile per gallon	22.270	21.923	5.142	13.187	64.746

Table 4: Mean vehicle attributes by segment

Class	No. of Models	U.S. Sales	Price	Size	HP	MPG
Small car	159	73,480	14.503	1.152	1.267	30.025
Compact car	162	110,350	16.482	1.260	1.462	26.215
Mid-size car	150	93,930	20.737	1.370	1.831	23.493
Full size car	57	84,602	22.565	1.487	2.032	22.986
Luxury car	272	24,022	40.506	1.368	2.422	21.287
Car Total	800	68,466	25.533	1.311	1.859	24.567
Minivan	99	79,375	21.396	1.455	1.868	20.084
Full size van	28	87,430	21.953	1.672	1.965	16.106
Van Total	127	81,151	21.519	1.502	1.889	19.207
Small SUV	44	56,513	16.010	1.1425	1.391	21.830
Mid-range SUV	109	94,086	24.977	1.325	2.046	18.004
Large SUV	48	100,752	30.410	1.651	2.648	15.685
Premium SUV	42	19,703	47.483	1.514	2.606	14.631
Small Crossover	89	70,196	19.632	1.285	1.696	23.056
Premium Crossover	48	42,825	32.316	1.400	2.362	18.618
SUV Total	380	70,373	26.885	1.366	2.070	18.997
Small pickup	51	112,772	13.852	1.321	1.464	23.444
Large pickup	46	357,592	21.650	1.704	2.488	16.260
Pickup Total	97	227,688	17.513	1.500	1.944	20.072
All Vehicles	1404	80,949	25.001	1.356	1.925	22.270

3.2 2001 National Household Travel Survey

The survey was conducted by agencies of the Department of Transportation from March 2002 through May 2003. This data set provides detailed household level data on vehicle stocks, travel behavior and household demographics at the time of survey. There are 69,817 households and 139,382 vehicles in the data, with 26,038 households from a random national sample and the remaining from nine add-on areas.[17] Among all the surveyed households, 45,984 are from Metropolitan Statistical Areas. Column 2 in Table 5 shows the means of several demographics for households living in Metropolitan Statistical Areas. Columns 3 to 7 present the means of household demographics for different groups based on household vehicle choice. These conditional means provide moment conditions in my estimation where I match the predicted moments from the empirical model to these observed moments. As household incomes are categorized and top-coded at $100,000, I provide the probability of new vehicle purchase for six income groups in Table 6. These conditional probabilities will be matched by their empirical counterparts in my estimation to identify the preference parameter on price, which is allowed to differ across income groups.

Table 5: Average household demographics

	All	Households who purchase				
		New	Car	Van	SUV	Pickup
Household size	2.55	2.88	2.67	3.81	3.02	2.84
House tenure (1 if rented)	0.364	0.211	0.266	0.090	0.147	0.163
Children (1 if children under 16)	0.336	0.402	0.328	0.696	0.499	0.352
Age of household head [a]	48.83	46.89	48.07	46.24	44.19	46.25
Travel time to work (minutes)	17.90	20.92	20.49	19.75	19.73	24.00

[a]Household head is not identified in the survey. We define household head as the oldest person among those who travel to work. If no one drives to work, the household head is the oldest person.

[17]The data from add-on areas include 3,804 households from Baltimore, Maryland; 1,310 from Des Moines, Iowa; 1,694 from Hawaii; 1,226 from Kentucky; 1,030 from Lancaster, Pennsylvania; 11,887 from New York; 1,751 from Oahu, Hawaii; 4,065 from Texas and 17,012 from Wisconsin.

Table 6: New vehicle purchase probability

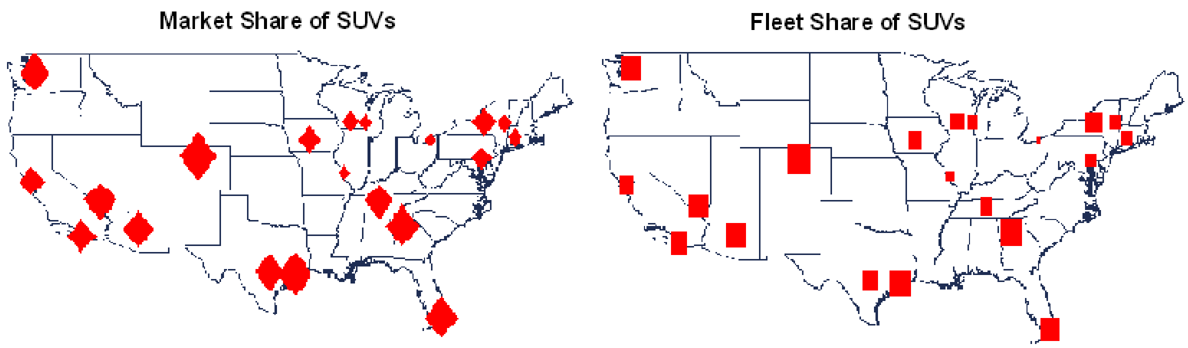
Income ('000)	Purchase probability
< 15	0.0020
[15, 25)	0.0440
[25, 50)	0.1125
[50, 75)	0.1728
[75, 100)	0.1972
≥ 100	0.2574
All households	0.1304

3.3 Vehicle Stock and Sales Data

The third data set includes two parts: 1) vehicle stock data by segment for the 20 selected MSAs from 1998 to 2004, and 2) new vehicle sales data by model for the same MSAs from 1999 to 2005. Vehicle stock data include the total number of registrations of both new and used vehicles at the segment level. Based on these data, I construct the fleet composition variables in each MSA: the fleet shares of each of the four types of the vehicles. The fleet composition variables are used as key regressors to capture spillover effects in vehicle demand. The second part of this data set is the new vehicle sales data for each of the 1404 models in each MSA.

The left panel of Figure 3 shows the market share of SUVs in 1999 in the 20 MSAs. The size of the diamonds corresponds to the magnitude of the market shares. The right panel plots the fleet share of SUVs (i.e., the proportion of SUVs in use among all vehicles) in 1998. Denver, CO has the highest market share of SUVs and the largest fleet share as well. Cleveland, OH has the lowest values for both of these variables. The empirical challenge in showing the existence of spillover effects is to control for unobserved heterogeneity in the MSAs, which could cause consumers in the same MSA to have similar preferences and make similar vehicle choices.

Figure 3: The market share of SUVs in 1999 and the fleet share of SUVs in 1998



3.4 Gasoline Price and Traffic Fatality Data

I collect annual gasoline prices from 1999 to 2005 from the Cost of Living Index Report by the American Chamber of Commerce Researchers Association (ACCRA). Table 7 presents summary statistics of annual gasoline prices in 1999 dollars from 1999 to 2005. Gasoline prices exhibit large variation across MSAs. The average gasoline price over the seven-year period is highest in San Francisco ($1.83 in 1999 dollars) and lowest in Atlanta ($1.33) among the 20 MSAs. Meanwhile, gasoline prices also exhibit significant fluctuations over time. For example, gasoline prices increase from $1.61 to $2.25 from 1999 to 2005 in San Francisco with the lowest point of $1.54 in 2001. Atlanta witnesses its highest gasoline price of $1.94 in 2005 and lowest gasoline price of $1.07 in 1999. The large variations in gasoline prices, particulary cross-MSA variations, are very important in estimating the preference parameter on operation cost of a vehicle measured by dollars per mile (DPM).

Table 7: Summary statistics of gasoline price and fatality rate

	Obs.	Mean	Std. Dev.	Min	Max
Gasoline price	140	1.486	0.265	1.067	2.247
Fatality (multiple-vehicle)	140	2.317	0.990	0.800	5.172
Fatality (single-vehicle)	140	1.926	0.744	0.845	4.018

I collect data on traffic fatalities occurring in multiple-vehicle crashes and single-vehicle crashes for each MSA from 1999 to 2005 from the Fatality Analysis Reporting System (FARS) database maintained by the NHTSA. These variables are used to construct proxies for the probabilities of multiple-vehicle crashes and single-vehicle crashes.[18] Traffic fatality rates are affected not only by the likelihood of traffic accidents due to weather and road conditions in the MSA, but also by the fleet composition. To construct the proxies for the probabilities of these two type of accidents, I estimate a traffic fatality model where the fleet composition variables are included as regressors. Based on the parameter estimates, I partial out the effects of the fleet composition from the actual traffic fatality data. I discuss the method in Appendix A.

Figure 4: Fatalities per 10,000 vehicles in vehicle crashes in 2005

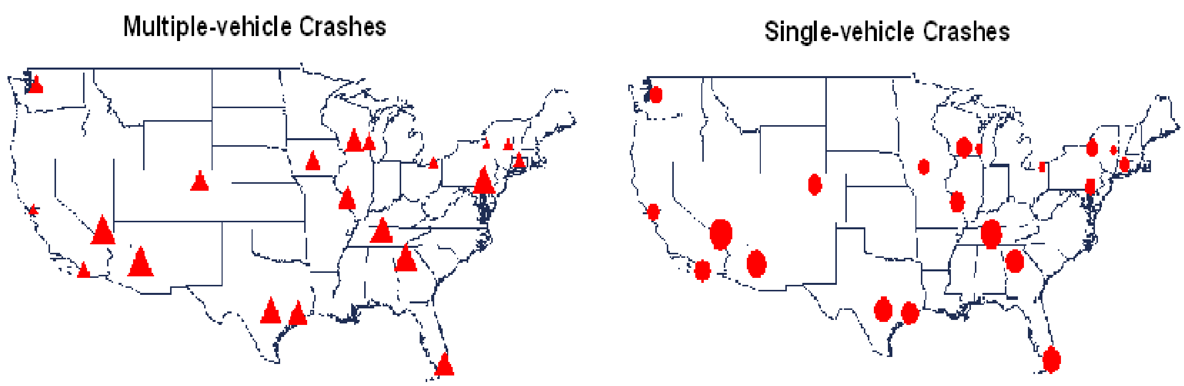


Table 7 also presents summary statistics for the fatality rate per 100,000 registered vehicles for each type of accident. Figure 4 plots fatality rates in multiple-vehicle crashes (shown in the left panel) and in single-vehicle crashes (in the right panel) in these 20 MSAs in 2005. The lowest fatality rate among multiple-vehicle crashes occurs in Cleveland, OH and the highest in Phoenix, AZ in 2005. In terms of single-vehicle crashes, Albany, NY has the lowest fatality rate while Las Vegas, NV has the highest. The correlation between the fatality rates of the two types of accidents is 0.824.

[18]Ideally, I would like to use the traffic accident data to construct the probabilities. The most comprehensive traffic accident database, General Estimates Systems (GES), also maintained by the NHTSA, only has data for some of the states. FARS, on the other hand, includes data of fatal crashes in all states.

4 Empirical Model

The empirical model includes both a demand side and a supply side. Vehicle demand is derived from a random coefficient discrete choice model in the tradition of BLP. A household makes a choice among all new models and an outside alternative to maximize household utility in each year. I use their revealed preference (in this case, the market share of each product) to recover the preference parameters. The supply side assumes that multiproduct firms engage in Betrand competition (taking the product mix decision as given) and that firms produce at constant marginal cost. The first-order conditions of firm profit maximization allows me to recover the marginal cost for each product. In policy analysis, I then use the recovered marginal cost and the oligopolistic supply curve to solve for new equilibrium prices.

4.1 Demand Side

The utility of a household from a choice is composed of two parts: the utility derived solely from the product attributes, that is, independent of the choices made by others, and the utility affected by the choices of others. I define the first part as the private utility and the second part as spillover effects. The private utility is specified over a bundle of product characteristics. In a market with many differentiated products, defining preferences over product characteristics has the advantage of generating a parsimonious demand system compared to a direct product demand system which specifies the demand of one product as a function of the prices of all products. The second part of utility is sometimes called the social utility in the literature, which reflects the utility from social interactions (Brock and Durlauf (2001)).

Let i denote a household and j denote a product. A household chooses one product from a total of J models of new vehicles or an outside alternative in a given year. To save notation, I suppress the market index m and time index t, bearing in mind the choice set can vary across markets and years. The utility of household i from product j is defined as

$$u_{ij} = v(p_j, X_j, \xi_j, y_i, Z_i) + w(FS, MCrash, j) + \epsilon_{ij}, \tag{1}$$

where $v(p_j, X_j, \xi_j, y_i, Z_i)$ is the private utility, p_j the price of product j, X_j a vector of observed product attributes, ξ_j the unobserved product attribute, y_i the income of household i, and Z_i is a vector of household demographics. To save notation, I allow Z_i to include demographics that are constant across households such as market level demographics. $w(FS, MCrash, j)$ is the spillover effect, where FS is a vector including the fleet shares of each of the four types of vehicles. These variables describe the fleet composition in each MSA. $MCrash$ is the probability of multiple-vehicle crashes in a market. ϵ_{ij} is the random taste shock that has type one extreme value distribution. Next I discuss the specifications of the private utility and the spillover effects in turn.

The private utility closely resembles that in BLP and Petrin (2002):

$$v_{ij} = \alpha_i log(y_i - p_j) + \sum_{k=1}^{K} x_{jk}\tilde{\beta}_{ik} + \xi_j, \tag{2}$$

where $\alpha_i log(y_i - p_j)$ is the utility from the composite good, i.e., all the other goods and services other than the purchased vehicle. I allow α to vary according to the income group of the household:

$$\alpha_i = \begin{cases} \alpha_1 & \text{if } y_i \leq \$25{,}000, \\ \alpha_2 & \text{if } \$25{,}001 < y_i \leq \$50{,}000, \\ \alpha_3 & \text{if } \$50{,}001 < y_i \leq \$100{,}000, \\ \alpha_4 & \text{if } y_i > \$100{,}000. \end{cases}$$

x_{jk} is the kth product attribute for product j. $\tilde{\beta}_{ik}$ is the random taste parameter of household i over product attribute k, which is a function of household demographics including those observed by econometrician (z_{ir}) and those that are unobserved (v_{ik}).

$$\tilde{\beta}_{ik} = \bar{\beta}_k + \sum_{r=1}^{R} z_{ir}\beta_{kr} + \nu_{ik}\beta_k^u.$$

The outside alternative ($j = 0$) captures the decision of not purchasing any new vehicle in the current year and therefore spending all the money on other goods and services. The outside alternative is a combination of the choices other than buying a new vehicle. These choices may include, but are not limited to, buying a second-hand vehicle, using the old vehicle owned by the household, and taking public transportation. The presence of the outside alternative allows the aggregate demand for new vehicles to be downward sloping:

overall demand for new vehicles decreases when the prices of all new vehicles increase. The utility of the outside alternative is specified as

$$v_{i0} = \alpha_i log(y_i) + Z_i \beta_0 + \nu_{i0} \beta_0^u + \epsilon_{i0}, \tag{3}$$

where ν_{i0}, the unobserved household demographics, captures different valuations of the outside alternative by different households due to the variations in vehicle holdings and transportation choices.

The overall spillover effects consist of two parts: one arising from consumer learning and psychological needs such as conformity in the demand for SUVs, and the other related to safety in multiple-vehicle crashes:

$$w(FS, MCrash, j) = w_{1j}(FS_{suv}) + w_{2j}(FS, MCrash). \tag{4}$$

In the above equation, w_{1j} represents the first part of the spillover effects and w_{2j} represent the second part. I specify the spillover effect from learning and conformity as a quadratic function of the fleet share of SUVs in a market.

$$w_{1j} = (\gamma_1 * FS_{suv} + \gamma_2 * FS_{suv}^2) * 1(j \in \mathcal{S}), \tag{5}$$

where $\mathcal{S}$ is the set of SUV models available on the market.

The safety spillover effect is specified as a function of the fleet composition, the likelihood of multiple-vehicle crashes, and the vehicle type. The fleet composition enters the utility function because, in a multiple-vehicle crash, the crash outcome is partly determined by the types of other vehicles involved. Table 8 parameterizes the damages that occur in multiple-vehicle crashes. These damages, from d'_1 to d'_6, are suffered by the occupants of the choice listed in the first column and differ according to the types of opposing vehicles.[19] Because cars and minivans perform similarly in crashes (IIHS Report Feb. 1998), I combine cars and vans (primarily minivans) together. SUVs and pickup trucks are combined together due to their similar design and safety effects in accidents. I normalize the damages occurred to the outside alternative, d'_5 and d'_6, to be zero because one of

[19] I focus on vehicle type only and abstract away from other vehicle characteristic such as weight. Vehicle type itself reflects many aspects of vehicle design that are important to crash compatibility.

Table 8: Damages incurred in multiple-vehicle crashes

	Car/van	SUV/pickup		Car/van	SUV/pickup
Car/van	d'_1	d'_2		d_1	d_2
SUV/pickup	d'_3	d'_4	$\Longrightarrow$	d_3	d_4
Outside alternative	d'_5	d'_6		0	0

the three damage parameters in the same column cannot be identified due to the ordinal property of utility functions. So in the table on the right, $d_1 = d'_1 - d'_5$ while $d_2 = d'_2 - d'_6$.[20] Because the two columns use different normalization, it is only meaningful to compare the damages in the same column. If $d_3 < d_1$ and $d_4 < d_2$, SUVs and pickups offer better protection to their occupants than cars and vans in multiple-vehicle crashes.

Based on Table 8, the spillover effects from safety concerns are specified as

$$\begin{aligned} w_{2j} &= \Big[(d_1 FS_{car+van} + d_2 FS_{suv+pick}) * 1(j \in \mathcal{C} \cup \mathcal{V}) \\ &\quad + (d_3 FS_{car+van} + d_4 FS_{suv+pick}) * 1(j \in \mathcal{S} \cup \mathcal{P})\Big] * MCrash * \lambda \\ &= \Big[d_3 FS_{car+van} + d_4 FS_{suv+pick} + (d_1 - d_3) FS_{car+van} * 1(j \in \mathcal{C} \cup \mathcal{V}) \\ &\quad + (d_2 - d_4) FS_{suv+pick} * 1(j \in \mathcal{C} \cup \mathcal{V})\Big] * MCrash * \lambda \\ &= \Big[d_3 FS_{car+van} + d_4 FS_{suv+pick} + (d_1 - d_3) * 1(j \in \mathcal{C} \cup \mathcal{V}) \\ &\quad + [(d_2 - d_4) - (d_1 - d_3)] FS_{suv+pick} * 1(j \in \mathcal{C} \cup \mathcal{V})\Big] * MCrash * \lambda, \end{aligned} \tag{6}$$

where $FS_{car+van}$ is the fleet share of cars and vans while $FS_{suv+pick}$ is the fleet share of SUVs and pickups. $\mathcal{C}$ denotes the set of new cars while $\mathcal{V}$, $\mathcal{S}$ and $\mathcal{P}$ indicate vans, SUVs and pickups, respectively. λ is the preference parameter for the damages and it transforms damages into utilities. I estimate normalized damage parameters, d_1 to d_4, jointly with λ. The first equality in equation (6) is straightforward and outlines the disutility from multiple-vehicle accidents associated with each type of vehicle. The second equality follows from $1(j \in \mathcal{C} \cup \mathcal{V}) = 1 - 1(j \in \mathcal{S} \cup \mathcal{P})$ while the third equality follows from

[20] The normalization is without loss of generality. We can allow the outside alternative to have different crash probabilities from new vehicles. In that case, d'_5 and d'_6 should be viewed as damages normalized by the ratio of the two crash probabilities. That is, d'_5 and d'_6 are the damages per new-vehicle-accident.

$FS_{car+van} = 1 - FS_{suv+pick}$. If $(d_2 - d_4) - (d_1 - d_3) > 0$, the disutility from a car or a van increases from its accident performance as there are more and more SUVs and pickups on the road. This reflects the self-defense argument by Varian (2003) quoted in the introduction.

In the estimation, I use the lagged fleet composition variables for FS in both parts of the spillover effects for the following reasons. First, the current fleet share of SUVs is determined simultaneously with individual household choices and therefore is endogenous. Second, with the current fleet share of SUVs entering into the utility function, the demand function is not guaranteed to be a one-to-one function. The multiplicity of demand levels for a given price vector not only imposes conceptual difficulties in firms' profit maximization problems, but also may induce either non-existence or multiplicity of the price equilibrium. These issues will be discussed further in subsection 4.3. The second reason also dictates the static modelling framework of the spillovers in this paper.[21]

Define θ as the vector of all preference parameters. With the above utility specification, the probability that the household i chooses choice $j \in \{0, 1, 2, ..., J\}$ is

$$Pr_{ij} = Pr_i(j|p, X, \xi, y_i, Z_i, \theta) = \int \frac{exp[v_{ij} + w_j]}{\sum_{h=0}^{J} exp[v_{ih} + w_h]} dF(\nu_i), \tag{7}$$

where p is the vector of prices of all products. w_j is defined in equation (4) for $j \neq 0$, while w_0, the spillover effects for the outside alternative, is zero. ν_i is a vector of unobserved demographics for household i. The market demand for choice j for a price vector p is then

$$q_j = q(j|p, X, \xi, \theta) = \sum_i Pr_{ij}. \tag{8}$$

4.2 Supply Side

The demand side parameters can be estimated without a supply side model. However, a supply side model is needed for the counterfactual analysis where I solve for the prices in a new equilibrium based on firms' price-setting rules derived from the profit maximization problem. Following the literature (e.g., BLP; Petrin (2002); Feenstra and Levinsohn

[21] See Ryan and Tucker (2006) for an estimation of a dynamic model of network-goods adoption by forward-looking agents based on data from a single market.

(1995) and Berry, Levinsohn, and Pakes (1999)), I assume firms engage in Betrand competition to maximize the profit in the current period while taking the product mix as given. The profit function does not explicitly take into account the dynamic consequences of current price decisions. However, dynamic considerations can be important given the demand side is about a durable good with spillover effects. It has been shown that introductory pricing (or penetration pricing) where the goods are priced low in the beginning is an equilibrium outcome in a network goods monopoly (Katz and Shapiro (1986); Cabral, Salant, and Woroch (1994); Mason (2000)). However, no paper to my knowledge has generalized this result to product differentiated oligopoly. To the extent that there are many firms and that firms are able to change their product mix relatively quickly, the incentive for dynamic pricing might be weak. On the other hand, Nair (2005) and Gowrisankaran and Rysman (2005) empirically investigate the pattern of falling prices of durable goods through firms' intertemporal price discrimination strategies (price skimming).

A serious model of dynamic pricing should incorporates firms' product choice decisions given the rapid product proliferation in the SUV segment: the number of SUVs grew from less than a dozen in early 1980's to about 80 in 2005. Moreover, the model must confront the oligopolistic structure of the auto industry: the industry consists of several big players that act strategically; each of them produces multiple differentiated products. With dramatic increases in computational power and significant headway in modelling dynamic games in recent years (Bajari, Benkard, and Levin (2004); Berry, Pakes, and Ostrovsky (2003); Pesendorfer and Schmidt-Dengler (2003); Ryan (2005)), such an analysis might eventually be possible.[22]

In this paper, I assume that a multiproduct firm f chooses prices to maximize its total profit in the current period. The total profit for firm f is

$$\pi^f = \sum_{j \in \mathcal{F}} \Big[(p_j - mc_j) q_j(p, \theta) \Big], \tag{9}$$

[22] There are dynamic pricing models that ignore product decisions. Copeland, Dunn, and Hall (2005) estimate a demand model with dynamic pricing to explain the pattern of falling prices within a model year. Esteban and Shum (2005) examine the effects of durability and secondary markets on equilibrium outcomes in the automobile market incorporating both forward looking consumers and firms.

where $\mathcal{F}$ is the set of products produced by firm f. mc_j is the constant marginal cost for product j. q_j is the aggregate demand for product j. Firm f's first-order condition is

$$\sum_{h \in \mathcal{F}} (p_h - mc_h) \frac{\partial q_h(p, \theta)}{\partial p_j} + q_j(p, \theta) = 0. \tag{10}$$

The equilibrium price vector is defined, in matrix notation, as

$$p = mc + \Delta^{-1} q(p, \theta), \tag{11}$$

where the element of Δ is

$$\Delta_{jr} = \begin{cases} -\frac{\partial q_r}{\partial p_j} & \text{if product } j \text{ and } r \text{ produced by same firm} \\ 0 & \text{otherwise.} \end{cases}$$

Equation (11) underlies the pricing rule in a multiproduct oligopoly: equilibrium prices are equal to marginal costs plus markups, $\Delta^{-1}q(p, \theta)$. The implied marginal costs can be computed following $mc = p - \Delta^{-1}q$, where p and q are the observed prices and sales. In a counterfactual analysis, the fixed point of equation (11) can be used to compute new price equilibrium corresponding to a change in the demand equation $q(p, \theta)$.

4.3 Equilibrium and Social Welfare

In the absence of spillover effects, Caplin and Nalebuff (1991) and Anderson, de Palma, and Thisse (1992) show the existence and uniqueness of price equilibrium for single-product firms under various utility function specifications. Sandor (2004) proves that there is a unique price equilibrium in multiproduct oligopoly with logit demand functions. However, the combination of a random coefficient utility function and a multiproduct oligopoly poses additional challenges to the theoretical properties of the price equilibrium, even when the spillover effects are absent. In empirical studies, the estimation of the demand side parameters assumes the existence of the price equilibrium. The uniqueness of price equilibrium can be checked in a policy analysis by empirically solving for a new price equilibrium through numerical procedures (Berry, Levinsohn, and Pakes (1999); Petrin (2002)).

When there exist contemporaneous spillovers where individual decisions are made simultaneously and interdependently, the assumption of a unique price equilibrium can be violated. It can be easily shown that the demand schedule is not necessarily a one-to-one function in a logit model with spillover effects, particularly under strong spillover effects.[23] The presence of multiple demand levels for a given price vector is analogous to the multiplicity of equilibrium in the models of social interactions (Brock and Durlauf (2001)) or strategic complementarities (Cooper and John (1988)). This complicates the analysis of firm behavior and market equilibrium: both non-existence and multiplicity of price equilibrium can arise. To avoid this problem, I assume individual decisions are affected by others' decisions made in previous periods. I use the installed base (i.e.,the lagged fleet composition) to capture the interdependence of individual decisions following the empirical literature on network effects (e.g., Gandal, Kende, and Rob (2000); Goolsbee and Klenow (2002); Gowrisankaran and Stavins (2004)).

Spillover effects can also have significant impacts on both consumer welfare and firms' profits. Because SUVs protect their occupants at the expenses of the occupants of other vehicles in multiple-vehicle accidents, the social cost of an SUV is higher than that faced by an individual SUV buyer. The external safety hazard of SUVs may exceed the risk reduction for SUV occupants by a large margin. White (2004) has confirmed that for each fatal crash that the occupants of light trucks avoid, at least 4.3 fatalities occur to the occupants of cars, pedestrians, bicyclists and motorcyclists. Latin and Kasolas (2002) declare that SUVs "are probably the most dangerous products (other than tobacco and alcohol) in widespread use in the United States." An additional equity issues is that, since SUVs drivers are richer on average than non-SUV drivers, the external cost of SUVs is borne largely by less affluent people. The spillover effects may also impact the auto industry by shifting market demands for cars and vans to SUVs and pickups. Since most of the automakers offer all four types of vehicles, whether an automaker benefits from the spillover effects depends on its profit loss from cars and vans and its gains from SUVs and pickups.

Despite the well-documented safety hazard of SUVs and pickups, current tort liability rules, insurance policies and traffic rules fail to internalize the negative externality posed

[23] I have constructed some examples where the multiplicity occurs in a simple logit model with only two products.

by SUVs (See White (2004) for a detailed discussion). Various policy suggestions have been proposed to solve the problem. Latin and Kasolas (2002) propose strict liability on SUV producers and urged tort lawyers to sue automakers on behalf of drivers killed or injured by SUVs. The "pay at the pump" insurance scheme links liability insurance to a gasoline tax so that those who uses more gasoline pay more in liability insurance. This idea dates back to Vickrey (1968) where he argues that lump-sum nature of an insurance premium fails to internalize accident costs associated with driving distance.[24] The owners of SUVs and light trucks will be charged more for liability insurance than passenger cars for the same distance travelled. Some policies used in Europe include higher registration fees, special excise taxes on SUVs, freeway tolls based on vehicle size and higher gasoline taxes (White (2004)).

Since the design of SUVs and pickups is the main cause of the safety hazard that they impose, an alternative policy is to induce redesigns that can reduce the negative safety externality of these vehicles without lowering their intrinsic utility. Under increasing pressure from both government and consumer groups, fifteen automakes reached a voluntary initiative in February 2003. They pledge to redesign their SUVs and pickups to address the crash incompatibility problem in order to improve protection for opposing car occupants of front and side crashes involving SUVs or pickups.[25] These redesigns are expected to phase in from 2007 to 2009.

The redesigns to be undertaken by the automakers provide a counterfactual scenario through which we can measure the social costs of SUVs and pickups. In section 7, I examine what would have been the market equilibrium and the resulting social welfare if all the SUVs and pickups in service had adopted the new designs. The new designs would reduce the extra risk that the occupants of cars and vans face (relative to the risk that the

[24]See Edlin (2003) for a analysis of more sophisticated per-mile premium system where insurance companies quote risk-classified per-mile rates.

[25]To reduce the likelihood of override and underride in front-to-front crashes between cars and SUVs or pickups, they agreed to redesign the primary energy-absorbing structures of new SUVs and pickup trucks to overlap at least 50 percent of the federally mandated bumper height zone for cars. Alternatively, automakers may elect to install a second energy-absorbing structure beneath the primary one, and the lower edge of the secondary structure cannot be higher than the bottom of the car bumper zone.

occupants of SUVs and pickups take) in multiple-vehicle crashes with SUVs and pickups. That is, the damages to the occupants of cars and vans, d_2, would become smaller and closer to d_4 when the opposing vehicles are SUVs or pickups. Moreover, the redesigns would make SUVs and pickups absorb more energy from crashes than before, increasing the risks to the occupants of SUVs and pickups in crashes with cars and vans. That is, d_3 should be closer to d_1. Therefore, in this counterfactual scenario, the drivers of SUVs and pickups would obtain less utility than before, while the drivers of cars and vans would obtain more due to the changes in crash outcomes. In terms of firms' profits, automakers would expect to make less money from the SUV and pickup segments but more from the car and van segments. I quantify the changes in both consumer welfare and firms' profits in the counterfactual analysis.

5 Identification and Estimation

As shown in the empirical model, $MCrash$, the probability of multiple-vehicle crashes, is a key variable that helps to separate two types of spillovers. Because comprehensive traffic accident data at the MSA level is not available, I construct a proxy for the probability of multiple-vehicle crashes based on traffic fatality data. Because traffic fatalities are affected by the type of vehicle being driven, vehicle fleet composition, and the likelihood of auto accidents, I estimate a model of traffic fatality in multiple-vehicle crashes with the fleet composition variables included in the regressors. The traffic fatalities that are not explained by the fleet composition are used as proxies for the probability of multiple-vehicle accidents. Similarly, I construct a proxy for the likelihood of single-vehicle crashes, $SCrash$, which serves as a control variable. The method and the results are presented in Appendix A. In this section I make use of these two variables and lay out an estimation strategy that addresses the endogeneity problem in the empirical model.

5.1 Endogeneity and Identification

The first identification problem arises from the correlation between the vehicle prices and unobserved product attributes, which is represented by a latent variable ξ. An automobile, like many other products, is a sophisticated product and has many attributes from which consumers draw utility. The econometrician only observes some of these attributes.

Since better product attributes often command a higher price, failure to take into account the unobserved product attributes often leads to an attentuation bias in the estimate of price coefficient, suggesting that consumers are less price sensitive than they really are. This bias also induces unreasonably high estimates of markups and price elasticities that are not consistent with firms' profit maximization objectives. This endogeneity problem has been documented extensively in the recent empirical industrial organization literature (Trajtenberg (1989); Berry, Levinsohn, and Pakes (1995); Petrin (2002); Goolsbee and Petrin (2004)).

An identification assumption that corrects the price endogeneity is that unobserved product attributes are mean independent of observed product attributes. Based on this assumption, valid instruments for the price of a given product are provided by the observed attributes of other products. These exclusion restrictions arise naturally in a differentiated-product market, where the level of product differentiation is an important factor in determining equilibrium prices. Therefore, the price of a given product depends not only on its own characteristics, but on the characteristics of all the other competing products. Moreover, the utility from a given product depends directly only on its own characteristics.

However, the large number of vehicles offered in the U.S. market yields more instruments than we can directly apply. I construct two "distance" measures for each product as parsimonious instruments for the price of the product. The distance measures reflect how differentiated a product is from other products (i) within the firm and (ii) outside the firm. The measures are based on distances between two products in a Euclidean space where different weights are applied to different dimensions of the product-characteristics space. The weights are the coefficients of the corresponding product attributes in a hedonic price regression.[26] The first measure is the distance between a product and all the other products offered by the same firm. The second is the distance between a product and all the other products produced by other firms.The method used to construct the distance measures is discussed in Appendix B.

[26]Stavins (1995) uses the coefficients in a hedonic price regression to collapse the multi-dimension product space into a single dimensional measure of quality. The distance between two products is used to measure product dispersion.

The second identification problem lies in the crash probability variable, $MCrash$, due to unobserved effects at the MSA level. These sources of unobserved heterogeneity (such as road and weather conditions) will affect the likelihood of traffic accidents in an MSA. Meanwhile, they can also make one type of vehicle more desirable, independent of the safety concern. For example, a vehicle with four-wheel-drive comes in handy in snow or when climbing slippery hills. On the other hand, accidents happen more often in these situations. If the unobserved effects are not controlled in the model, this correlation can cause overestimation of consumers' higher willingness-to-pay for an SUV or a pickup due to their better performance in multiple-vehicle crashes (relative to those provided by a car or a van). This is because the estimate will include consumers' higher willingness-to-pay for a four-wheel-drive system (which most SUVs and pickups have). The panel nature of my data allows me to use MSA fixed effects to overcome this identification problem.

The use of fixed effects in the model also eliminates the endogeneity problem in estimating the spillover effects from learning and conformity in the demand for SUVs. Controlling for unobserved neighborhood effects is a fundamental challenge in empirical studies of social interaction and network effects. A common strategy in cross-sectional studies is to use observed neighborhood and household level characteristics as instruments for the variable capturing the choices made by others. The maintained assumption is that these variables are mean independent of unobserved regional effects (see Goolsbee and Klenow (2002) for a reduced-form study, and Bayer and Timmins (2006) for a structural estimation). Panel data offer an advantage in such studies in that unobserved heterogeneity can be controlled for using fixed effects.

5.2 Estimation

To estimate the demand parameters, I employ a simulated nonlinear instrumental variable algorithm with a nested contraction mapping (BLP and Petrin (2002)) to account for the price endogeneity. This approach makes use of a contraction mapping technique proposed in Berry (1994) that recovers the unobservable product attributes as a simulated nonlinear function of the observables characteristics and model parameters. The recovered unobserved product attributes are then interacted with instruments to form moment conditions.

I separate the deterministic utility for a product j into the mean utility, δ_j, and the household specific utility, μ_{ij}.

$$u_{ij} \quad = \quad \delta_j + \mu_{ij} + \epsilon_{ij}, \tag{12}$$

where

$$\delta_j \quad = \quad \sum_k x_{jk}\bar{\beta}_k + \sum_{kn} x_{jk} z_n \beta_{kn} + \xi_j + w_j, \tag{13}$$

$$\mu_{ij} \quad = \quad \alpha_i log(y_i - p_j) + \sum_{kr} x_{jk} z^h_{ir} \beta^o_{kr} + \sum_k x_{jk}\nu_{ik}\beta^u_k. \tag{14}$$

The mean utility, δ_j, is constant for all households in the same MSA. z_n is the nth market level demographics and differs across MSAs. With the market index, m, suppressed, the last three terms in the mean utility can differ across MSAs. The mean utility from the outside alternative is normalized to zero. z^h_{ir} is the rth observed household specific demographics. The household specific utility for the outside alternative is defined by equation (3): $\mu_{i0} = \alpha_i log(y_i) + Z_i\beta_0 + \nu_{i0}\beta^u_0 + \epsilon_{i0}$. With this utility specification, p_j and ξ_j enter different parts of the utility function. Denote the parameters in the mean utility as $\theta_1 = \{\bar{\beta}_k, \beta_{kn}\}$, and the parameters in the household specific utility as $\theta_2 = \{\alpha, \beta^o_{kr}, \beta^u_k, \beta_0, \beta^u_0\}$. If we can recover δ_j, θ_1 can be estimated using OLS.

Berry (1994) shows that given a θ_2, there is a unique δ for each market that equates the observed market shares in a given market to the predicated market shares: $S(\delta, \theta_2) = S^o$ where S^o is the vector of observed shares of each vehicle model in the market.[27] Given a θ_2 and a sample of households with demographics Z and ν, the predicted market share of product j is computed using

$$S(j|p, X, Z, \nu, \delta, \theta_2) = \sum_{i=1}^{I} \frac{exp[\delta_j + \mu_{ij}(\theta_2)]}{\sum_{h=0}^{J} exp[\delta_h + \mu_{ih}(\theta_2)]}/I. \tag{15}$$

For a given θ_2, the unique δ for each market can be recovered using a fixed point iteration:

$$\delta^{n+1} = \delta^n + ln(S^o) - ln[S(\delta^n, \theta_2)], \tag{16}$$

[27]The sufficient condition for the uniqueness and existence of δ is that $\partial S_j/\partial\delta_j > 0$ and $\partial S_j/\partial\delta_k < 0$, for $k \neq j$. These conditions can be shown to hold in my model.

where n denotes the number of iterations. Convergence is achieved when the difference between δ^{n+1} and δ^n is smaller than a pre-specified tolerance level.

For a given θ_2 and $\delta(\theta_2)$, we can estimate θ_1 in the linear model defined by equation (13). The unobserved product attribute ξ_j is the error term of the equation. To estimate θ_1 and θ_2, we construct two sets of moment conditions. The first set of moments is based on the assumption that unobserved product attributes are mean independent of observed product attributes.

$$\mathrm{E}\Big[\xi_j(\theta_1, \theta_2)|X, D\Big] = 0, \tag{17}$$

D is a vector of instrumental variables that are constructed based on observed product attributes as shown in Appendix B.

I augment the above moment conditions with a set of micro-moments in the spirit of Petrin (2002) and Berry, Levinsohn, and Pakes (2004). These moments match the model predictions to the observed conditional means from the 2001 NHTS as shown in tables 5 and 6. For example, I match the predicted probability of new vehicle purchase among households with income less than \$15,000 to the observed probability in the data as shown in Table 6:

$$\mathrm{E}\Big[Pr_i(j \neq 0)|(y_i < 15,000; \delta(\theta_2), \theta_2,)\Big] = 0.0020.$$

We have six micro moments related to household income. Another four moments match the expected household size conditioning on the household choice of vehicle type. For example,

$$\mathrm{E}\Big[\text{Household Size}_i|j^*(i) \in \mathcal{C}\Big] = 2.67,$$

where $j^*(i)$ is the choice of household i. I also match the expected house tenure conditioning on the household buying one of the four types of vehicles. This provides four additional moment conditions. I then match the conditional probability of a household having children under age 16 given the fact that the household buys a new vehicle with the observed conditional probability. Similarly, I construct two other moment conditions based on household head age and travel time to work. In total, there are 17 micro-moment conditions.

To estimate $\theta = [\theta_1, \theta_2]$, I stack both sets of moment conditions to form the criterion function. The GMM estimator $\hat{\theta}$ minimizes:

$$\mathrm{J} = \mathrm{M}(\theta)'\mathrm{W}\mathrm{M}(\theta) = \begin{pmatrix} \mathrm{M}_1(\theta) \\ \mathrm{M}_2(\theta_2) \end{pmatrix}' \begin{pmatrix} \mathrm{W}_1 & 0 \\ 0 & \mathrm{W}_2 \end{pmatrix} \begin{pmatrix} \mathrm{M}_1(\theta) \\ \mathrm{M}_2(\theta_2) \end{pmatrix}, \tag{18}$$

where $\mathrm{M}_1(\theta)$ is the first set of moment conditions, and $\mathrm{M}_2(\theta_2)$ includes all 17 micro-moment conditions. Denote $\mathrm{G} = \mathrm{E}[\nabla_\theta \mathrm{M}(\theta)]$ and $\Omega = \mathrm{E}[\mathrm{M}(\theta)\mathrm{M}(\theta)')]$, the asymptotic variance of $\sqrt{n}(\hat{\theta} - \theta)$ is $(\mathrm{G}'\mathrm{W}\mathrm{G})^{-1}\mathrm{G}'\mathrm{W}\Omega\mathrm{W}\mathrm{G}(\mathrm{G}'\mathrm{W}\mathrm{G})^{-1}$. I estimate both θ and its asymptotic variance using a two-step procedure where the first step provides consistent estimates for θ and the optimal weighting matrix $\mathrm{W} = \Omega^{-1}$.

Using the demand side parameter estimates, I compute Δ and recover the marginal cost as $mc = p - \Delta^{-1}q$. The recovered marginal costs enable an estimation of a supply function. For example, with the assumption of a linear marginal cost function, the following equation can be taken to the estimation:

$$mc_j = \omega_j \rho + \zeta_j, \tag{19}$$

where ω_j is a vector of product characteristics. ζ_j is productivity shock or supply disturbance. The parameters in the demand side and the supply side could be estimated simultaneously as in Bresnahan (1987), BLP, Berry, Levinsohn, and Pakes (1999) and Petrin (2002). Simultaneous estimation of the demand and supply parameters improves efficiency at the cost of potential inconsistency induced by the specification of the supply side. I choose to estimate the demand side separately from the marginal cost function given that the supply side employs strong assumptions.

6 Estimation Results

In this section, I first report parameter estimates. I then present estimates of price elasticities and implied markups for several selected products. Based on the premium a household is willing to pay for the better protection provided by SUVs and pickups in multiple-vehicle crashes (relative to the protection provided by cars), I estimate the value of a statistical life.

6.1 Parameter Estimates

Tables 9 and 10 report the estimates of the parameters and their standard errors in the mean utility specified in equation (13). A large set of product attributes are used as control variables in the utility function. These include three continuous product attributes, four class dummies and eleven segment dummies. The three continuous product attributes are size, horsepower (HP) and dollars per mile (DPM). I also interact size and HP with class dummies to capture the fact that size and HP may be valued differently for different types of vehicles. DPM is defined as the gasoline price divided by miles per gallon. It measures the operating cost of a vehicle in terms of gasoline consumption using MSA-specific gasoline prices. A negative coefficient on DPM implies that a higher gasoline price not only reduces a household's tendency to buy a new vehicle, but also reduces the utility from a fuel-inefficient vehicle more than from a fuel-efficient vehicle.

The second and third columns of the table report the parameter estimates and their standard errors for a logit model where the price variable is instrumented using the constructed distance measures and their second-order polynomials. Berry (1994) shows that a logit demand can be transformed into a linear model that can be estimated by the 2SLS method using only market level data. The results in the second and third columns are for the following equation:

$$ln(\frac{S_j}{S_0}) = \alpha p_j + \sum_k x_k \bar{\beta}_k + \sum_{kn} x_{jk} z_n \beta_{kn} + w_{1j} + w_{2j} + \xi_j + \epsilon_j, \tag{20}$$

where z_n is market level demographics. w_{1j} and w_{2j} are specified in equations (5) and (6), respectively. The estimate of the price coefficient is -0.189 with a standard error of 0.006, implying all price elasticities are larger than one in absolute value. If the price variable is not instrumented for, the OLS estimation of equation (20) yields a price coefficient of -0.044 with standard error of 0.001. This implies that 799 out of 1404 price elasticities are less than one in absolute value, resulting in negative marginal cost estimates.

The fourth and fifth columns report the estimation results for a random coefficient model where the unobserved geographic and temporal effects are not controlled, while the last two columns report the results where the unobserved effects are controlled using fixed effects. In both cases, the price variable only appears in the household specific utility

Table 9: Parameter estimates in mean utility

Variable	Logit-IV		Unobserved effects		Final Model	
	Para.	Std. err.	Para.	Std. err.	Para.	Std. err.
Price	-0.189	0.006				
Car dummy	-10.619	0.308	-49.384	1.370	-69.304	2.136
Van dummy	-28.143	1.016	-195.996	21.055	-213.672	5.491
SUV dummy	-9.201	0.616	-73.368	1.764	-45.498	3.029
Pickup dummy	-17.112	1.279	-73.950	4.563	-41.708	5.267
log(size)	0.732	0.109	2.226	0.429	1.067	0.828
log(HP)	1.436	0.068	7.913	0.235	6.496	0.513
DPM	-2.074	0.112	-2.500	0.668	-1.164	0.753
Pickup dummy*log(size)	4.29	0.546	13.953	1.827	8.614	2.247
Van dummy*log(size)	7.372	0.353	-1.573	7.648	7.364	2.203
SUV dummy*log(size)	0.487	0.262	7.258	0.768	3.482	1.581
Pickup dummy*log(HP)	-1.441	0.152	-1.022	0.515	-4.536	0.899
Van dummy*log(HP)	-0.884	0.217	-12.199	3.426	-1.236	1.116
SUV dummy*log(HP)	-0.91	0.115	-2.424	0.335	-3.321	0.759
(Car + van)*SCrash	-0.106	0.348	-14.508	1.928	-4.965	0.879
(SUV + pickup)*SCrash	-0.051	0.502	10.585	1.672	-7.610	0.669
FS_{suv}	0.062	0.045	2.867	0.130	1.133	0.058
FS_{suv}^2	-0.002	0.002	-0.085	0.005	-0.041	0.002
Segment dummy(11)	Yes		Yes		Yes	
Year dummy*Class dummy(24)	Yes		No		Yes	
MSA dummy*Class dummy(76)	Yes		No		Yes	

function, μ_{ij}. In the model where the unobserved effects are not controlled, the coefficient on $(Car + van) * SCrash$ is underestimated while that on $(SUV + pickup) * SCrash$ is overestimated. This probably reflects the fact that in places where single-vehicle accidents occur more often, SUVs and pickups are also valued more due to reasons other than safety (e.g., four-wheel-drive in snow). The spillover effect from learning or conformity, captured by FS_{suv} and FS_{suv}^2, is overestimated due to the correlated taste problem.[28]

[28] FS_{suv}, ranging from 0 to 100, is defined as the lagged fleet share of SUVs multiplied by 100. The partial effect of FS_{suv} is positive if FS_{suv} is less than 27.6. FS_{suv} falls into the range of [7, 21] in the data.

Table 10: Multiple-vehicle crash damage parameters

	Car/van	SUV/pickup
Car/van	λd_1=-0.117	λd_2=0.183
	(0.015)	(0.026)
SUV/pickup	λd_3=-0.102	λd_4=0.270
	(0.011)	(0.027)
Difference	$\lambda d_3 - \lambda d_1$=0.015	$\lambda d_4 - \lambda d_2$=0.087
	(0.019)	(0.038)

I present the estimates of parameters in w_{2j} in Table 10. Because the preference parameter λ and the damage parameters, d_1 to d_4, cannot be separately identified, their joint estimates are presented in the table. The standard errors are in parentheses. The negative of these estimates can be interpreted as the damage disutilities from multiple-vehicle crashes. The estimates in this table clearly show that λd_1 is smaller than λd_3, i.e., the occupants of an SUV or a pickup suffer less damage than the occupants of a car or a van when the opposing vehicle is another car or van. Similarly, λd_4 is larger than λd_2. These results suggest that SUVs and pickups provide better protection than cars and vans in multiple-vehicle crashes no matter what the opposing vehicles are. Therefore, consumers will choose an SUV or a pickup over a car or a van for safety reasons pertaining to multiple-vehicle crashes.

Meanwhile, $\lambda[(d2 - d4) - (d1 - d3)]$ is equal to -0.072 with standard error of 0.042. This suggests that the premium a household puts on a SUV or a pickup increases with the fleet share of SUVs and pickups. The increasing premium implies that accidents become more dangerous for the occupants of cars and vans as more SUVs and pickups are on the road. Therefore, consumers are more likely to buy SUVs and pickups for self-protection as there are more SUVs and pickups in use. This confirms the dynamic aspect of the arms race in the demand for SUVs and pickups.

The parameter estimates and the standard errors for the household specific utility

Table 11: Parameter estimates in household specific utility

Variable	Para.	Std. err.
Log(y_i-p_j) if $y_i \leq$ 25,000	31.288	0.748
Log(y_i-p_j) if $y_i \leq$50,000 & y_i >25,000	28.076	0.633
Log(y_i-p_j) if $y_i \leq$ 100,000 & y_i >50,000	16.653	0.391
Log(y_i-p_j) if y_i > 100,000	12.009	0.647
Household size * car dummy	1.087	0.100
Household size * van dummy	12.014	0.619
Household size * SUV dummy	0.515	0.162
Household size * pickup dummy	0.600	0.195
Rented house * car dummy	-0.281	0.489
Rented house * van dummy	-34.372	1.289
Rented house * SUV dummy	-7.061	0.896
Rented house * pickup dummy	-5.214	1.319
Children dummy * outside alternative	-2.807	0.348
Household head age * outside alternative	0.112	0.011
Travel time * outside alternative	-0.070	0.022
Random Coefficients (std. error of consumer preference)		
Log(size)	1.311	0.079
Log(HP)	0.912	0.121
DPM	1.130	0.208
Car dummy	36.164	0.259
Van dummy	94.270	0.971
SUV dummy	13.844	0.324
Pickup dummy	2.348	0.361
Outside alternative	18.205	0.177

specified in equation (14) are presented in Table 11. All but one are estimated very precisely. The first four coefficients are the taste parameters on the composite good for each of the four income groups. The group with higher income has smaller coefficients. This implies richer households are less price sensitive. The second four parameters are for the interaction terms between household size and vehicle type dummies. These interaction terms allow families with different household size to have different tastes for a certain type of vehicle. All four coefficient estimates being positive means that the utility from a new vehicle increases with household size, *ceteris paribus*. I also interact house tenure with vehicle type dummies. All four coefficients being negative implies that a household in a rented house values a new vehicle less than those living in their own houses, holding other factors constant. The estimate of the term interacting the outside alternative with the children dummy suggests that households with children value a new vehicle more than those without. So do those households with a younger household head and those whose commuting time is longer.

The table then reports the estimates of eight random coefficients, which measure the dispersion of heterogeneous consumer preference. These coefficients are the standard errors of consumer preference for the corresponding product attributes while the means of consumer preference are presented in Table 9. For example, the preference parameter on DPM has a standard normal distribution with mean -1.164 and standard error 1.130. Therefore, 95 percent of the households have a preference parameter on DPM in the range of [-3.379, 1.051]. The random coefficients ultimately break the independence of irrelevant alternatives (IIA) property of standard logit models in that the introduction a new model into the choice set will draw disproportionally more consumers to switch to the new model from similar products than from others.

Based on the estimation of the demand side, I recover the implied marginal cost mc using equation (11). These implied marginal costs are needed to perform policy analysis in the next section. Using the implied marginal costs, I then estimate the marginal cost equation (19). All the parameter estimates, not reported here, have the expected signs.

6.2 Elasticities and Markups

We now look at implied elasticities and markups based on our demand and supply estimations. The markup for product j is defined as $\frac{p_j - mc_j}{p_j}$, where p_j and mc_j are the price and the marginal cost of product j, respectively. Table 12 reports own price elasticities and markups for selected products in 1999. One obvious pattern from this table is that within a vehicle class, demands for cheaper products are more price sensitive. Moreover, there appears to be a large variation in the estimates of both elasticities and markups.

Table 13 reports summary statistics of price elasticities and markups. The sales

Table 12: Price elasticities and markups

Products in 1999	Elasticities	Markups	Price
CARS			
Ford Escort	-19.934	0.055	11,920
Toyota Camry	-8.630	0.120	17,518
Nissan Maxima	-6.111	0.166	22,019
Lincoln Town car	-4.640	0.230	39,195
VANS			
Dodge Caravan	-15.753	0.063	18,585
GMC Savana	-5.606	0.239	23,659
PICKUPS			
Chevrolet S10	-8.485	0.163	12,658
Ford F Series	-3.457	0.299	17,840
SUVS			
Honda CR-V	-9.031	0.112	18,965
Jeep Grand Cherokee	-6.151	0.178	26,520
Cadillac Escalade	-4.638	0.242	46,525

weighted average elasticity is -9.398 while the average markup is 15.6 percent.[29] Price elasticities range from -56.499 (2000 GEO Metro) to -3.406 (2000 Ford F-series) while markups range from 1.9% (2000 GEO Metro) to 30.2% (2000 Ford F-series). Table 14 presents the estimates of variable profits for the whole automobile industry and seven large manufacturers. The variable profit is the total revenue minus the total variable cost, which is the product of the implied marginal cost and the quantity sold. The results show that the industry as a whole made the highest profits in 2000 while lowest in 2005. The profits from the Big Three were decreasing over the period while Japan's Big Three increased their profits largely due to their increasing shares in the U.S. market.

[29]The average markup is close to Petrin (2002)'s estimate of 16.7 percent based on vehicles sold from 1981 to 1993 including cars, vans and pickup trucks. Goldberg (1995) recovers a much larger estimate of 38 percent for cars from 1983 to 1987 while the average benchmark markup in BLP is estimated as 23.9 percent for cars sold between 1971 and 1990. I have 200 models each year on average while Petrin (2002) 185 models, Goldberg (1995) and BLP each have 110 models per year on average.

Table 13: Summary statistics of elasticities and markups (sales weighted)

	Mean	Median	Std. Dev.	Min	Max
Elasticities	-9.387	-7.124	5.968	-56.499	-3.406
Markups	0.156	0.1605	0.067	0.019	0.302
Price	20,361	18,906	7,459	8,514	81,695

Table 14: Variable profits in millions of 1999 dollars

Year	Industry	GM	Ford	Chrysler	Toyota	Honda	Nissan	VW
1999	59,076	18,845	14,927	9,195	4,409	2,617	1,701	1,017
2000	59,168	18,775	15,189	7,997	4,630	2,830	1,682	1,166
2001	57,186	18,845	14,039	6,955	5,074	2,925	1,391	1,180
2002	57,442	20,671	12,736	6,477	5,044	2,971	1,507	1,071
2003	55,822	19,409	11,732	6,290	5,331	3,253	1,880	1,008
2004	57,447	18,869	11,570	6,895	5,424	4,585	2,583	983
2005	54,508	16,698	11,093	6,837	6,178	3,806	2,725	894

6.3 Value of a Statistical Life

The value of a statistical life (VSL) is measured by economic agents' willingness-to-pay for a marginal change in mortality risk, scaled up to make that risk equal 1. It is often used to evaluate the life-saving benefits of a certain government regulation. There have been numerous estimates of VSL based on risk-compensating wage differences in the labor market, and consumer decisions in housing and product markets. Viscusi and Aldy (2003) survey many studies that are based on the labor market. These studies provide estimates from $0.5-20.8 million in 2000 dollars with the median estimate being about $7 million. Blomquist (2004) surveys several recent studies that are based on averting behavior in consumption and provides a range of $1.7-7.2 million.

The existence of various methods to reduce fatality risk in automobile driving has been exploited to obtain the estimates of VSL. Blomquist (1979) and Blomquist, Miller, and Levy (1996) estimate VSL based on the time cost and disutility of safety device usage. Atkinson and Halvorsen (1990), and Dreyfus and Viscusi (1995) use hedonic price techniques to estimate the premium for a safer vehicle. Ashenfelter and Greenstone (2004) measure VSL based on the tradeoff between increased fatality risk and time savings associated with increasing the speed limit on rural interstate roads.

Table 15: VSL in millions of 1999 dollars

	No. of serious injuries[a]		
	10	20	30
Lower bound	4.40	6.44	7.61
Upper bound	10.03	14.76	17.52

[a]These are the number of serious injuries whose value is assume to be equal to the value of one life.

Because SUVs provide better protection in multiple-vehicle crashes, consumers are willing to pay a premium for an SUV. I estimate the VSL based on the premium, and deaths and serious injuries (incapacitating injuries) averted for the occupants of SUVs. The premium, measured by compensating variation, is estimated at $2,895 on average in 1999. The number of deaths and serious injuries averted comes from White (2004). If 1 million SUVs were replaced by cars, 10.35-24.15 more deaths and 185.15-416.30 more serious injuries would occur to the occupants of these 1 million cars each year in multiple-vehicle crashes. Assuming a 10 year lifespan for a vehicle, Table 15 presents the estimates of VSL based on different ways to convert serious injures into deaths.[30] Based on the assumption that the value of a life is equal to that of 20 serious injuries, my estimate of VSL is between $6.44 million and $14.76 million in 1999 dollars. The National Safety Council (NSC) estimates that the average economic cost per death ($1,130,000) is 19.32 times of that per incapacitating injury ($58,500) from motor-vehicle crash. The average comprehensive cost per death ($3,760,000) is 20 times of that per incapacitating injury ($188,000).[31]

[30]The average lifespan of a vehicle is 13 years in the United States. This transforms into a 10 year discounted lifespan with a discount rate of 0.955.

[31]The economic cost only includes wage and productivity losses, medical expenses, administrative ex-

My estimate may overstate the true VSL for two reasons. First, the reduced risk for the occupants of an SUV or a pickup is measured only by the averted deaths and serious injuries. Non-incapacitating injuries are ignored. Therefore, the overall benefit of driving an SUV or a pickup in multiple-vehicle crashes may be underestimated. Second, the deaths and serious injuries averted are from White (2004), where vans are assumed to have the same safety effects as SUVs and pickups. To the extent that vans are less safe for their own occupants of multiple-vehicle crashes than SUVs and pickups, pooling them together causes the internal protection of SUVs and pickups to be underestimated.

7 Counterfactual Analysis

In this section, I first conduct a counterfactual analysis to estimate the social costs of the arms race in 2005. I then examine the effects of the arms race on SUV sales and the auto industry over a longer time span.

7.1 The Social Costs of the arms race

To estimate the social costs of the arms race, I examine the changes in both consumer welfare and firm profits in a counterfactual scenario where I eliminate the safety hazard of all SUVs and pickups already on the road. This counterfactual analysis is motivated by the voluntary agreement signed by 15 automakers in 2003. As discussed in Section 4.3, the automakers pledged to adopt new designs on their future SUVs and pickups in order to improve car occupants protection. The counterfactual scenario assumes that these new designs had been adopted before the introductions of all the SUVs and pickups that were in service in 2005. In particular, I assume that cars and vans are subject to the same risks as SUVs and pickups in accidents when the opposing vehicle is an SUV or a pickup. That is, d_2 is now equal to d_4. Moreover, the design changes would also make SUVs and pickups absorb more energy from crashes than before, so the occupants of these vehicles would be subject to more risks. I therefore assume that d_3 is now equal to d_1. These changes in

penses, motor vehicle damage, and employers' uninsured costs while the comprehensive cost also includes the value of a person's natural desire to live longer or to have a quality life.

damage parameters should be viewed as upper bounds for both the risk reduction for the occupants of cars and vans, and the risk increase for the occupants of SUVs and pickups.

Using the new damage parameters, I first solve for new equilibrium prices and simulate sales holding marginal costs and product mix in the market fixed in 2005. Table 16 reports the average changes in price (sales-weighted), sales, and profit by segment. Both the sales and the profits in the car and van segments increase while those in the SUV and pickup segments decrease. Interestingly, although the occupants of pickups are now subject to more risk in multiple-vehicle crashes, the prices of pickups on average increase. This counterintuitive result reflects the complex nature of profit maximization problems in the case of multiproduct firms. The complexity also underlies the difficulty in proving the existence and uniqueness of the price equilibrium.[32] Because SUVs and pickups are on average less fuel-efficient than cars, the average fuel economy of new vehicles sold in 2005 increases from 22.41 MPG to 22.72 MPG.[33]

Table 16: Changes in price, sales and profit

	Average price change		Total sales change		Total profit change	
Segment	$	%		%	$ million	%
Car	7.722	0.051	308,379	4.182	932	4.533
Van	26.14	0.124	82,605	7.313	91	2.708
SUV	-2.547	-0.010	-130,364	-3.015	-488	-2.895
Pickup	12.375	0.063	-140,453	-4.418	-547	-3.993

Table 17 lists the changes in variable profit for seven firms in 2005. The Big Three

[32]For example, in a single-product oligopoly with a logit demand, prices are strategic complements and Betrand competition is a supermodular game. The price equilibrium exists and is unique as shown in Milgrom and Roberts (1990). Prices of cars and vans should go up while prices of SUVs and pickups should decrease. However, in a multiproduct oligopoly, the game is not supermodular any more. Moreover, the direction of price change cannot be determined as in the case of single-product oligopoly.

[33]To achieve the same increase in average MPG of new vehicles, a $0.20 or so increase in gasoline prices (e.g., through an increment in gasoline taxes) is needed based on the estimates of Li, Timmins, and von Haefen (2006).

would have made less money under the counterfactual scenario while the other four firms would have made more. This is due to the fact that the Big Three capture 70 percent of the market share of light trucks, and only 43 percent of the market share of passenger cars. Therefore, the reduction in SUV and pickup sales hurts the Big Three more than other firms in a world without the arms race.

Table 17: Variable profit change (in 1999 dollars) in 2005

	$ million	%
GM	-129	-0.771
Ford	-167	-1.506
Chrysler	-43	-0.632
Toyota	50	0.810
Honda	82	2.146
Nissan	3	0.108
VW	34	3.775

Table 18 reports changes in consumer welfare and industry profit in 2005. Consumer welfare is measured by compensating variation. Compensating variation for a household is the extra money this household needs to be given (or have taken away) in the counterfactual scenario in order to reach the original utility level. To understand how consumers are affected by the first-order effects of the change in relative safety in the counterfactual scenario, we hold the equilibrium prices constant. Households can then be decomposed into three groups: those who originally bought a car or a van and would still buy a car or a van under the counterfactual scenario (Group A), those who bought an SUV or a pickup and would still do so (Group B), and those who would switch from an SUV or a pickup to a car or a van (Group C).[34] Group A would be better off from the elimination of the extra risk that the occupants of cars and vans had endured. However, Group B would be worse off from the elimination of the safety advantage that the occupants of

[34]Given prices do not change, no household would change from a car or a van to an SUV or a pickup because SUVs and pickups do not offer better protection than cars and vans anymore under the counterfactual.

SUVs and pickups had enjoyed. The direction of the welfare change for Group C is uncertain because it depends on the relative change in internal safety effects of cars and SUVs.[35]

The results show that the total benefits to consumers from the elimination of the arms race would have exceeded the total loss by $17.21 billion in constant 1999 dollars in 2005. However, the auto industry as a whole would have made $13 million less in profit. The small aggregate impact on industry profit masks large heterogeneity across firms. While the Big Three would have made $339 million less in profits (in 1999 dollars) in 2005, other firms would have made $326 more in profit. The total social welfare loss was $17.21 billion in 1999 dollars due to the arms race. Given that there were 70.6 million SUVs and pickup trucks on the road, the social welfare loss from each SUV or pickup was $243 in 2005.

Table 18: Impacts on social welfare

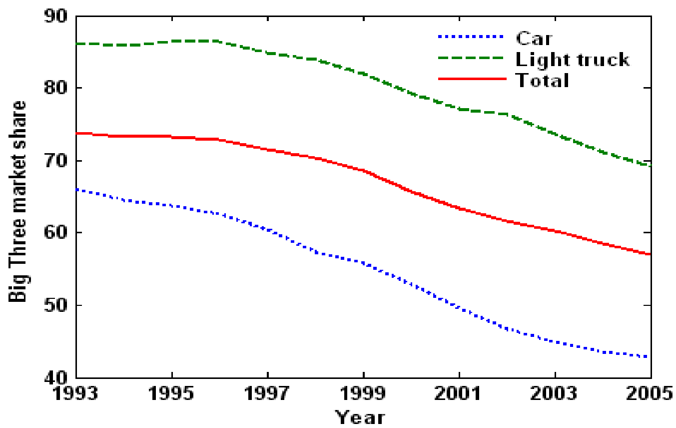
Consumer welfare	Profit	Social welfare	Number of SUVs and pickups	Loss per SUV or pickup
In 1999 $ million			In millions	In 1999 $
17,223	-13	17,210	70.60	243

7.2 Long-Run Impacts on Auto Industry

The U.S. auto industry has been undergoing significant structural changes. The Big Three have been losing their market dominance in the car segment to foreign competitors. Although the Big Three were also losing market share in the light-truck segment, they managed to retain 70 percent of the market in 2005 as shown in Table 5. In the market for all light vehicles, the Big Three were able to capture half of total sales during this period, thanks largely to the increasing popularity of SUVs, of which they were major producers.

[35]If we take price changes into account, there will be another group who switches from cars or vans to SUVs or pickups due to the increase in prices of some cars or vans, and the decrease in prices of some SUVs or pickups. In this case, we cannot even assign exact directions for Group A and Group B. However, we should expect that the price change would only have secondary effects on consumer welfare change.

Figure 5: The market share of the Big Three by segment



It is also interesting to examine the long-run impacts of the arms race on the auto industry, in terms of both sales and profits. To that end, I perform the same simulation as in the previous section except that the simulation starts from 1999. Assuming that SUVs and pickups provide the same level of protection as cars and vans do in multiple-vehicle crashes, I simulate the market shares and update the fleet composition in every year from 1999 forward. The SUV sales from 1999 to 2005 under this scenario are plotted on the bottom line in Figure 6. The top line plots the actual SUV sales during this period. The differences between the two lines are the SUVs sales explained by the arms race.

The reduction in SUV sales from the elimination of the arms race can be attributed to two factors: the contemporaneous effect and the multiplier effect. The contemporaneous effect occurs solely through the fact that SUVs and pickups do not provide better protection than cars and vans anymore in the counterfactual scenario. Therefore, some consumers switch from SUVs and pickups to other choices. The multiplier effect, on the other hand, captures the impact of a change in the fleet composition on SUV sales: the decrease in SUV sales in one period causes future SUV sales to decrease due to the two types of spillover effects. To look at how important each factor is in affecting SUV sales, I conduct another simulation where I hold the fleet composition as it is in the data. The simulated SUV sales are depicted by the middle line in Figure 6. In 2005, the sales of

SUVs decreased by 215,022 (4.97%). Among the total reduction in sales, 61% was due to the contemporaneous effect while 39% of the reduction was due to the multiplier effect.

Figure 6: SUV sales over time

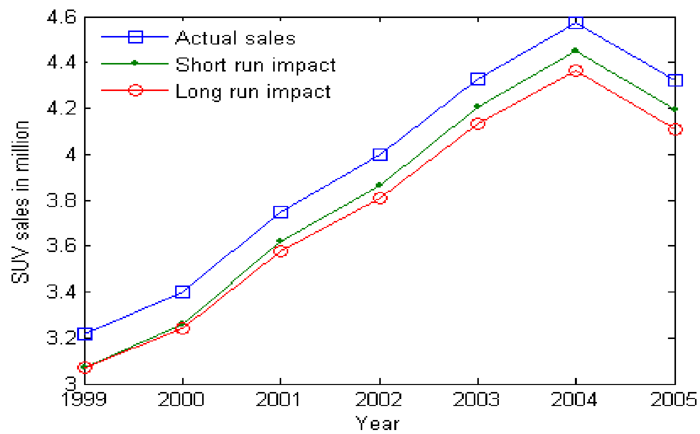


Table 19: Variable profit change in 1999 dollars

	Industry		Big Three		Other firms	
Year	$ million	%	$ million	%	$ million	%
1999	202	0.342	457	1.063	-255	-1.582
2000	319	0.540	531	1.266	-212	-1.231
2001	371	0.648	611	1.533	-240	-1.384
2002	421	0.734	688	1.726	-267	-1.520
2003	493	0.883	703	1.879	-211	-1.145
2004	544	0.947	725	1.942	-181	-0.898
2005	540	0.991	685	1.977	-144	-0.725
Total	2,891	0.721	4,400	1.605	-1,509	-1.192

Table 19 presents the changes in variable profits for the whole industry, the Big Three and other firms, respectively. The whole industry benefits from the arms race. The gains increase over time because of the stronger demand for SUVs and pickups induced by the arms race. The Big Three are the winners of the arms race, making $4.4 billion more in profit over the seven-year period than they would have made without the arms race. Other firms lose in the arms race, making $1.51 billion less in profit. Given that the simulation only starts from 1999, these results provide lower bounds for the long-run impacts of the arms race on both SUV sales and firms' profits.

8 Conclusion

The rise of SUVs is probably the most significant change in the U.S. auto industry during the last two decades. SUVs have been shown to protect their occupants better while inflicting disproportionate damage to cars in multiple-vehicle crashes, largely due to their higher front-ends and stiffer rail frames. In view of the increasing market share of SUVs, many have suggested that the aggressive design of SUVs induces an "arms race" on American roads where drivers are more likely to switch to SUVs as more of them are on the road.

This paper examines spillover effects in the demand for new vehicles and studies their welfare implications by estimating a flexible model of automobile demand. The empirical results confirm that consumers are willing to pay a premium for SUVs due to their better protection in multiple-vehicle crashes. Based on the tradeoff between the risk reduction and the premium, I estimate that the value of a statistical life ranges from $6.44 million to $14.76 million in 1999 dollars. Moreover, the paper presents evidence of the dynamic aspect of the arms race by showing that the utility from buying a car decreases with the number of SUVs on the road.

To investigate the welfare implications of the arms race, I conduct a counterfactual analysis where I eliminate the arms race in 2005 by assuming that SUVs and pickups are designed such that their occupants are subject to the same risks as the occupants of cars and vans in multiple-vehicle crashes. This scenario eliminates the self-protection incentive in buying SUVs and pickups. The simulation showed that the arms race resulted in $17.21 billion of consumer welfare losses in 2005 alone. While the auto industry as a whole gained only $13 million more in profit in the presence of the arms race, there were large profit redistributions among different automakers. Particularly, the Big Three made $399 million more in profit in 2005 while others made $336 million less due to the arms race. Based on the social welfare loss, I estimate the social cost that each SUV or pickup imposed in 2005 was $243.

To look at the long-run impact of the arm race on SUV sales and firm performance, I carry out another simulation where I eliminate the arms race from 1999. I find that the arms race has contributed to the increasing popularity of SUVs: while it only explains 3% of SUV sales in 1999, it accounts for almost 5% of SUV sales in 2005. From 1999 to 2005, the Big Three made at least $4.4 billion more in profit due to the arms race while other firms made $1.5 billion less. Since the simulation starts only from 1999, these results should be viewed as lower bounds on the long-run impacts of the arms race.

This research can be extended in several ways. One is to expand the discussion of VSL. First, I plan to obtain an improved measure of risk reduction for the occupants of SUVs in multiple-vehicle crashes. The measure used in this paper can be improved by controlling for the effects of driver demographics on accident outcomes. I will use a large traffic accident dataset from the NHTSA and estimate the risk reduction that is inherent to vehicle type and independent of driver demographics.

The second extension is to address the limitation in the modelling of the supply side. I have assumed that current price decisions have no dynamic consequences so that price equilibrium can be easily solved based on the first-order conditions of a static profit maximization problem. Given that I am studying a durable good with spillover effects, this assumption is strong and can induce biases in the estimates of both marginal costs and new equilibrium prices under the counterfactual scenarios. A natural future step is to study firms' pricing decision taking into account spillover effects. Given the rapid proliferation of new products in the SUV segment in the last two decades, another interesting and substantial extension is to study the product choice decision in the SUV segment when consumer demands are subject to spillover effects.

References

Ackerberg, D., and G. Gowrisankaran (2006): "Quantifying Equilibrium Network Externalities in the ACH Banking Industry," forthcoming, *Rand Journal of Economics*.

Anderson, S., A. de Palma, and J.-F. Thisse (1992): *Discrete Choice Theory of Product Differentiation*. MIT Press.

Ashenfelter, O., and M. Greenstone (2004): "Using Mandated Speed Limites to Measure the Value of a Statistical Life," *Journal of Political Economy*, 1(112), 226–267.

Atkinson, S., and R. Halvorsen (1990): "The Valuation of Risks to Life: Evidence from the Market for Automobiles," *Review of Economics and Statistics*, 72(1), 133–136.

Bajari, P., L. Benkard, and J. Levin (2004): "Estimating Dynamic Models of Imperfect Competition," forthcoming, *Econometrica*.

Bayer, P., and C. Timmins (2006): "Estimating Equilibrium Models of Sorting Across Locations," forthcoming, *Economic Journal*.

Berndt, E., R. Pindyck, and P. Azoulay (2003): "Consumption Externalities and Diffusion in Pharmaceutical Markets: Antiulcer Drugs," *Journal of Industrial Economics*, LI(2), 243–270.

Berry, S. (1994): "Estimating Discrete Choice Models of Product Differentiation," *RAND Journal of Economics*, 25(2), 242–262.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63, 841–890.

——— (1999): "Voluntary Export Restraints on Automobiles: Evaluating a Strategic Trade Policy," *American Economic Review*, 89(3), 400–430.

——— (2004): "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market," *Journal of Political Economy*, 112(1), 68–105.

Berry, S., A. Pakes, and M. Ostrovsky (2003): "Simple estimators for the parameters of dynamic games (with entry/exit examples)," Technical Report, Harvard University.

Blomquist, G. (1979): "Value of Life Saving: Implications of Consumption Activity," *Journal of Political Economy*, 87(3), 540–558.

Blomquist, G., T. Miller, and D. Levy (1996): "Values of Risk Reduction Implied by Motorist Use of Protection Equipment," *Journal of Transportation Economics and Policy*, 30(1), 55–66.

Bradsher, K. (2002): *High and Mighty:The Dangerous Rise of the Suv*. Public Affairs.

Bresnahan, T. (1987): "Competition and Collusion in the American Automobile Industry," *Journal of Industrial Economics*, 35, 457–482.

Brock, W., and S. Durlauf (2001): "Discrete Choice with Social Interactions," *Review of Economic Studies*, 68, 235–260.

Brynjolfsson, E., and C. Kemerer (1996): "Network Externalitiesin Microcomputer Software: An Econometric Analysis of the Spreadsheet Market," *Management Science*, 42(12), 1627–1647.

Cabral, L., D. Salant, and G. Woroch (1994): "Monopoly Pricing with Network Externalities," *International Journal of Industrial Organization*, 17(2), 199–214.

Caplin, A., and B. Nalebuff (1991): "Aggregation and Imperfect Competition: On the Existence of Equilibrium," *Econometrica*, 59, 25–59.

Cooper, R., and A. John (1988): "Coordinating Coordination Failures in Keynesian Models," *Quarterly Journal of Economics*, 103, 441–464.

Copeland, A., W. Dunn, and G. Hall (2005): "Prices, production, and inventories over the automotive model year," Board of Governors and Yale University.

Dreyfus, M., and W. Viscusi (1995): "Rates of Time Preference and Consumer Valuations of Automobile Safety and Fuel Efficiency," *Journal of Law and Economics*, 38(1), 79–105.

Edlin, A. S. (2003): "Per-Mile Premiums for Auto Insurance," in *Economics for an Imperfect World: Essays In Honor of Joseph Stiglitz*, ed. by R. Arnott, B. Greenwald, R. Kanbur, and J. Stiglitz. MIT Press.

Ellison, G., and E. Glaeser (1997): "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach," *Journal of Political Economy*, 105(5), 889–927.

Escarce, J. (1996): "Externalities in Hospitals and Physician Adoption of a New Surgical Technology: an Exploratory Analysis," *Journal of Health Economics*, 15(5), 715–734.

Esteban, S., and M. Shum (2005): "Durable-Goods Oligopoly with a Secondary Market," forthcoming, *Rand Journal of Economics*.

Feenstra, R., and J. Levinsohn (1995): "Estimating Markups and Market Conduct with Multidimensional Product Attributes," *Review of Economic Studies*, pp. 19–52.

Foster, A., and M. Rosenzweig (1995): "Learning by Doing and Learning from Others: Human Capital and Technological Change in Agriculture," *Journal of Policital Economy*, 103, 1176–1209.

Gandal, N. (1994): "Hedonic Price indexes for Spreadsheets and an Empirical Test for Network Externalities," *RAND Journal of Economics*, 25(1), 160–170.

——— (1995): "Competing Compatibility Standards and Network Externalities in the PC Software Market," *Review of Economics and Statistics*, LXXVII(4), 599–603.

Gandal, N., M. Kende, and R. Rob (2000): "The Dynamics of Technological Adoption in Hardware/Software Systems: The Case of Compact Disc Players," *RAND Journal of Economics*, 31, 43–61.

Gayer, T. (2004): "The Fatality Risks of Sport-Utility Vehicles, Vans, and Pickups Relative to Cars," *Journal of Risk and Uncertainty*, 28(2), 103–133.

Goldberg, P. (1995): "Product Differentiation and Oligopoly in International Markets: The Case of the US Automobile Industry," *Econometrica*, 63, 891–951.

Goolsbee, A., and P. Klenow (2002): "Evidence on Learning and Network Externalities in the Diffusion of Home Computers," *Journal of Law and Economics*, XLV(2), 317–344.

Goolsbee, A., and A. Petrin (2004): "The Consumer Gains from Direct Broadcast Satellites and the Competition with Cable TV," *Econometrica*, 72(2), 351–381.

Gowrisankaran, G., and M. Rysman (2005): "Dynamics of Consumer Demand for New Durable Consumer Goods," Working paper, Washington University and Boston University.

Gowrisankaran, G., and J. Stavins (2004): "Network Externalities and Technology Adoption: Lessons from Electronic Payments," *RAND Journal of Economics*, 35(2), 260–276.

Grinblatt, M., M. Keloharju, and S. Ikaheimo (2004): "Interpersonal Effects in Consumption: Evidence from the Automobile Purchases of Neighbors," NBER working paper.

Katz, M. L., and C. Shapiro (1986): "Technology adoption in the presence of network externalities," *Journal of Political Economy*, 94(4), 822–841.

Latin, H., and B. Kasolas (2002): "Bad Designs, Lethal Products: The Duty to Protect Other Motorists against SUV Collison Risks," *Boston University Law Review*, 82, 1161–1229.

Leibenstein, H. (1950): "Bandwagon, Snob, and Veblen Effects in the Theory of Consumers' Demand," *Quarterly Journal of Economics*, 64(2), 183–207.

LI, S., C. TIMMINS, AND R. VON HAEFEN (2006): “Do Gasoline Prices Affect Fleet Fuel Economy?,” Working paper.

MANSKI, C. (1993): “Identification of Endogenous Social Effects: The Reflection Problem,” *Review of Economic Studies*, 60(3), 531–42.

MASON, R. (2000): “Network externalities and the Coase conjecture,” *European Economic Review*, 44, 1981–1992.

MAYROSE, J., AND D. JEHLE (2002): “Vehicle Weight and Fatality Rish for Sport Utility Vehicle -Versus-Passenger Car Crashes,” *Journal of Trauma*, 53(4), 751–753.

MILGROM, P., AND J. ROBERTS (1990): “Rationalizability, Learning, and Equilibrium in Games with Strategic Complementarities,” *Econometrica*, 58(6), 1255–1277.

NAIR, H. (2005): “Dynamics of pricing in durable goods markets: Applications to 32- bit console video games,” Unpublished dissertation, University of Chicago Graduate School of Business.

PESENDORFER, M., AND P. SCHMIDT-DENGLER (2003): “Identification and Estimation of Dynamic Games,” NBER working paper No. w9726.

PETRIN, A. (2002): “Quantifying the benefit of new products: the case of minivan,” *Journal of Political Economy*, 110(4), 705–729.

RYAN, S. (2005): “The Costs of Environmental Regulation in a Concentrated Industry,” Working paper, MIT.

RYAN, S., AND C. TUCKER (2006): “Heterogeneity and the Dynamics of Technology Adoption,” Working paper, MIT.

RYSMAN, M. (2004): “Competition Between Networks: A Study of the Market for Yellow Pages,” *The Review of Economic Studies*, 71(2), 483–512.

SALONER, G., AND A. SHEPARD (1995): “Adoption of Technologies with Network Effects: An empirical examination of the adoption of automated teller machines,” *RAND Journal of Economics*, 20(3), 479–501.

SANDOR, Z. (2004): “On Price Equilibrium with Multi-Product Firms,” Working paper.

STAVINS, J. (1995): “Model Entry and Exit in a Differentiatied-Product Industry: The Personal Computer Market,” *Review of Economics and Statistics*, 77(4), 571–584.

SWEETING, A. (2005): “Coordination Games, Multiple Equilibria and The Timing of Radio Commercials,” Working Paper, Northwestern.

Trajtenberg, M. (1989): "The Welfare Analysis of Product Innovations, with an Application to Computed Tomography Scanners," *Journal of Political Economy*, 97, 444–479.

Varian, H. (2003): "The True Cost of S.U.V.," *The New York Times*, December 18th.

Vickrey, W. (1968): "Automobile Accidents, Tort Law, Externalities, and Insurance: an Economist's Critique"," *Law and Contemporary Problems*, 33, 464–487.

Viscusi, W., and J. Aldy (2003): "The value of a Statistical Life: A Critial Review of Market Estimates Throughout the World," *Journal of Law and Economics*, 27(1), 5–76.

White, M. (2004): "The 'arms race' on American Roads: The Effect of SUV's and Pickup Trucks on Traffic Safety," *Journal of Law and Economics*, XLVII(2), 333–356.

Appendix A: Crash Probability

Because of the lack of comprehensive traffic accident data at the MSA level, I construct proxies for the likelihood of traffic accidents based on traffic fatality data. Traffic fatalities in an area are determined not only by the likelihood of accidents due to road and weather conditions but also by the fleet composition in the area. In order to partial out the effects of the fleet composition on traffic fatality, I estimate a model of traffic fatality determination where the fleet composition variables are explanatory variables.

$$\begin{aligned} MFatal_{tc} &= FS_{tc}\tau_1 + CZ_{tc}\tau_2 + me_{tc} \\ SFatal_{tc} &= FS_{tc}\tau_3 + CZ_{tc}\tau_4 + se_{tc}, \end{aligned}$$

where $MFatal$ is the number of fatalities involved in multiple-vehicle crashes per 10,000 registered vehicles, and $SFatal$ is the number of fatalities involved in single-vehicle crashes. t, the time index, ranges from 1999 to 2005. c is the county index. The estimation is based on county level data.[36] CZ is a vector of county attributes including MSA dummies.

Because the current fleet composition variables, FS_{tc}, are simultaneously determined with the current traffic fatality rates, I use the lagged fleet composition, current gasoline prices and lagged gasoline prices as instruments for FS_{tc}. I perform 3SLS to deal with the possible correlation between the error terms in the two equations. The proxy for $MCrash$ is $MFatal_{tc} - FS_{tc}\hat{\tau}_1$ while that for $SCrash$ is $SFatal_{tc} - FS_{tc}\hat{\tau}_3$. The estimation results for 3SLS are shown in Table 20.

Appendix B: Price Regression and Distance Measures

The distance between two products is measured in analogously to Euclidean distance except that different weights are applied to different dimensions of product characteristics. The weights are the corresponding coefficients in a hedonic price regression. The hedonic price equation is

$$log(p_j) = X_j\beta + \epsilon_j, \tag{21}$$

[36]MSA level fatality data mask heterogeneity across counties within the same MSA. Moreover, the use of county level data increases the number of observations from 140 to 1126.

Table 20: 3SLS results of fatality rates

	SFatal		MFatal	
Variable	Para.	Std. err.	Para.	Std. err.
Contant	0.201	0.203	0.999	0.277
$FS_{suv+pick}$	-1.767	0.636	-1.015	0.868
$FS^2_{suv+pick}$	2.333	0.762	1.776	1.039
Pop in million	-0.079	0.021	-0.062	0.028
Median household income in \$10,000	-0.416	0.110	-0.754	0.151
Percent of rural household	0.296	0.050	0.059	0.069
Percent of farm household	-1.480	0.343	-0.333	0.468
Average household size	0.138	0.046	-0.035	0.063
Percent of rented house	-0.163	0.167	-0.831	0.228
Core county dummy	0.062	0.028	0.057	0.039
MSA dummies (19)	Yes		Yes	
Year dummies(6)	Yes		Yes	
No. of obs.	1126		1126	
Sargan Statistics	6.57		0.42	
P-value	0.167		0.981	

where p_j is the price of product j and X_j is the vector of K product attributes. Table 21 shows the coefficient estimates for the hedonic price regression. The distance between product j and h is defined as

$$d_{jh} = \sqrt{\sum_{k=1}^{K}[(x_{jk} - x_{hk})\hat{\beta}_k]^2},$$

where x_{jk} is the kth dimension of the attributes of product j. $\hat{\beta}_k$ is the estimate of β_k.

I take the sum of the distances between a product and all the other products offered by the same firm as the first distance measure, which reflects product differentiation within a firm. The second distance measure, reflecting the product differentiation across firms, is the sum of the distances between a product and all the other products by other firms. Table 22 presents summary statistics of the two distance measures. The results suggest that products in the car segment are least differentiated while those in the van segment are most differentiated both within a firm and cross firms.

Table 21: Hedonic price regression

Variable	Para.	Std. err.
Car dummy	3.169	0.067
Van dummy	2.982	0.176
SUV dummy	3.175	0.073
Pickup dummy	1.839	0.191
log(size)	-0.230	0.084
log(HP)	0.701	0.038
log(MPG)	-0.062	0.053
Pickup dummy * log(size)	1.208	0.425
Van dummy * log(size)	0.145	0.337
SUV dummy *log(size)	0.528	0.198
Pickup dummy * log(HP)	0.072	0.110
Van dummy * log(HP)	-0.440	0.150
SUV dummy *log(HP)	-0.413	0.079
segment dummies (11)	Yes	
No. of Obs.	1404	
R^2	0.837	

Table 22: Summary statistics of distance measures

Segment	Within-firm distance		Cross-firm distance	
	Mean	Std. Dev.	Mean	Std. Dev.
Car	4.47	4.32	18.07	5.46
Van	10.68	6.11	148.65	12.89
SUV	6.90	5.65	32.38	19.59
Pickup	10.05	5.34	147.60	7.71