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Traffic Safety and Vehicle Choice

Quantifying the Effects of the "Arms Race" on American Roads

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RESOURCES FOR THE FUTURE

Traffic Safety and Vehicle Choice: Quantifying the Effects of the "Arms Race" on American Roads*

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Abstract

The increasing market share of light trucks in the U.S. in recent years has been characterized as an "arms race" where individual purchase of light trucks for better self-protection in collisions nevertheless leads to worse traffic safety for the society. This paper investigates the interrelation between traffic safety and vehicle choice by quantifying the effects of the arms race on vehicle demand, producer performance, and traffic safety. The empirical analysis shows that the accident externality of a light truck amounts to $2,444 in 2006 dollars during vehicle lifetime. Counterfactual simulations suggest that about 12% of new light trucks sold in 2006 and 204 traffic fatalities could be attributed to the arms race.

Key Words: Accident Externality, Automobile Demand, Random Coefficient Demand Model

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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 to about 50 percent from 1981 to 2006 with that of SUVs increasing from 1.3 to almost 30 percent.[1] The "arms race" provides an analogy for the proposition that although individuals may choose to purchase light trucks in part as a precautionary measure for self-protection in collisions, traffic safety for the society as a whole could become worse as more and more light trucks are on the road.

Several studies have documented that in multiple-vehicle collisions, light trucks provide superior protection to their occupants while posing greater dangers to the occupants of passenger cars (e.g., Gayer (2004), White (2004), and Anderson (2008)). This result is largely due to the design mismatch between light trucks and passenger cars. Light trucks, particularly 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, many light trucks have stiffer and heavier body structures, which cause the opposing cars to absorb more of the crash energy and inflict disproportionally more damage to cars in collisions. The design mismatch and subsequent crash incompatibility problem can lead to an arms race in vehicle demand where the individual incentive to secure better self-protection by driving light trucks results in a worsening of overall traffic safety.

The first objective of this paper is to investigate the interrelation between traffic safety and vehicle choice, focusing on the impact of the traffic safety effects of light trucks on vehicle demand. Although the safety effects of light trucks have been examined in several recent studies, their impact on vehicle demand has never been established in empirical studies. Therefore, the arms race on American roads has so far remained a conjecture. In this study, I investigate this missing link by estimating a structural demand model where vehicle safety

[1] After two decades of constant growth, the market share of light trucks started to stabilize from 2002 with slight decreases during 2005-2008 from the 2004 peak level largely due to high gasoline prices.

effects are explicitly incorporated. The demand analysis coupled with a stylized supply model allows me to further examine the effect of the arms race on the profitability of auto makers and the industry. The second objective of this paper is to quantify the accident externality of light trucks (in monetary terms) and to examine the impact of the arms race on overall traffic safety. Current tort liability rules, insurance policies, and traffic rules fail to internalize higher accident externality posed by light trucks.[2] Therefore, economic theory suggests that there may be too many light trucks compared to the socially optimal level from the standpoint of traffic safety. The empirical analysis in this paper provides an estimate for the accident externality of light trucks and thereby offers a basis for policy intervention such as a corrective tax on light trucks.

The empirical strategy includes two steps. The first step examines safety effects of passenger cars and light trucks in both single-vehicle and multiple-vehicle crashes using a rich data set of traffic accidents. Through tobit regressions controlling for driving conditions and driver demographics, I confirm that in multiple-vehicle crashes, light trucks offer better protection for their own occupants than passenger cars while posing greater risks to the colliding vehicles. However, occupants in light trucks are less safe in single-vehicle crashes. Taking into account crash severity as well as crash frequencies, I find that light trucks are on average safer for their occupants than passenger cars and that the safety advantage of light trucks increases as more of them are in service. Nevertheless, overall traffic safety would deteriorate as more people drive light trucks.

In the second step, I estimate a structural model of vehicle demand in the spirit of Berry, Levinsohn, and Pakes (1995) (henceforth BLP) and Petrin (2002) in order to investigate whether traffic safety concerns manifest themselves in consumer choices. The demand model is estimated based on new vehicle sales data in 20 MSAs augmented with the 2001 National Household Travel Survey (2001 NHTS). The household level data provide corre-

[2]For example, liability for damage in automobile accident is generally based only on the negligence rule, implying that drivers are not liable for the damage if the care level is above the negligence standard which is irrespective of vehicle type. Moreover, many U.S. states use no-fault system rather than the negligence rule and therefore do not penalize drivers of light trucks for causing larger damage. So in reality, insurance companies, following very different pricing practices for light trucks, may not charge higher premium for light trucks even for the same driver. See White (2004) for a detailed discussion.

lations between household demographics and vehicle choices and can significantly improve the estimation of heterogenous preference parameters in the model. In contrast to previous studies on vehicle demand, I observe the sales of the same model in 20 markets, which allows me to use product fixed effects to deal with price endogeneity due to unobserved product attributes. Therefore, my estimation method does not rely on the maintained exogeneity assumption of observed product attributes to unobserved product attributes in the literature.

The demand estimation shows that consumers are willing to pay a premium for the safety advantage of light trucks over passenger cars. The implied premium for the reduced fatality risk provides a natural way to estimate the value of a statistical life (VSL). The revealed preference from the demand analysis implies the VSL to be $10.14 million in 2006 dollars. Based on the estimates of vehicle safety effects and VSL, the accident externality posed by a light truck during vehicle lifetime is estimated at $2,444. Following this estimate, I conduct counterfactual analysis where the accident externality from light trucks are fully corrected for by a per-unit tax on light trucks (i.e., a special excise tax). The simulation results suggest that the arms race explained on average 13.87% of the market share of light trucks from 1999 to 2006. The increasing market share of light trucks due to the arms race resulted in worse traffic safety for the society. The simulation shows that should the accident externality be corrected for by the tax, the traffic fatalities would have been reduced by 204 in 2006. Moreover, the arms race benefited the auto industry as a whole, particularly the Big Three. This finding is consistent with the Big Three's continued lobbying efforts to prevent more government regulations on light trucks.

There exist several other policy suggestions that offer the potential of curbing the arms race in addition to a special excise tax on light trucks. The first suggestion calls for government regulations on the design of light trucks to alleviate the crash incompatibility problem (Bradsher (2002) and the Insurance Institute for Higher Safety (IIHS) Status Report, Feb. 14, 1998). One proposed regulation is to require light trucks to comply with a federally mandated bumper height zone as passenger cars do. Latin and Kasolas (2002) declare that SUVs are probably the most dangerous products (other than tobacco and alcohol) in widespread use in the U.S. and argue for stricter liability on SUV producers through the tort system. Edlin (2003) proposes a per-mile premium approach where insurance companies quote risk-classified per-mile rates and therefore owners of light trucks will be charged more for liability insurance than passenger cars for the same distance traveled. Some policies used in Europe include higher registration fees and freeway tolls based on vehicle size and high gasoline taxes.

The contribution of this paper is two fold. There is an ongoing debate within the academia as well as regulatory agencies (e.g., the National Highway Traffic Safety Administration) regarding the overall traffic safety effect of light trucks. The traditional view is that a heavier vehicle fleet is safer (Crandall and Graham (1989)), which implies that a vehicle fleet with more light trucks would be safer. However, several recent studies (White (2004), Gayer (2004), Anderson (2008)) show that light trucks have a negative effect on the overall traffic safety. This finding underlies that although vehicle weight is an important factor influencing crash outcomes, vehicle stiffness and geometric design can be equally if not more important. This paper adds to these recent evidence based on a different empirical framework. More importantly, this paper contributes to the literature by examining the link between traffic safety and vehicle choice. Together with the results on the safety effects of passenger cars and light trucks, the demand estimation provides the first evidence of the arms race in vehicle demand. Moreover, this paper is the first in quantifying the effects of the arms race on vehicle demand, industry performance, and traffic safety as well.

The remainder of this paper is organized as follows. Section 2 discusses data. Section 3 pays a close look at the safety effects of passenger cars and light trucks. Section 4 presents the demand model and the estimation results. Section 5 is the post-estimation analysis including counterfactual simulations. Section 6 concludes.

2 Data

Several data sets are employed to study vehicle safety and its effect on vehicle demand. The safety effects of vehicles are examined based on a large sample of police reported traffic accidents from 1998 to 2006. This data set is from the General Estimate System (GES) database maintained by the National Highway Traffic Safety Administration (NHTSA). Data are sampled from accident reports in about 400 police agencies across the United States. They provide detailed information regarding the accident, vehicles, and persons involved in each accident. In the empirical estimation, I examine safety effects of different type of vehicles to their own occupants and to the occupants in colliding vehicles while controlling for a rich set of traffic conditions and driver demographics. To be able to tie these results to vehicle demand which utilizes sales data in recent years, I focus on single-vehicle and two-vehicle accidents involving passenger cars and/or light trucks with model year after 1997. There are 76,586 passenger cars involved in two-vehicle collisions, 418 of them with occupants sustaining fatalities and 6,037 of them with occupants suffering incapacitating injuries. 59,733 light trucks are involved in two-vehicle collisions, 171 of them with occupants sustaining fatalities and 3,268 of them with occupants suffering incapacitating injuries. There are in total 48,813 single-vehicle accidents, with 27,911 involving cars and 20,902 involving light trucks. For those passenger cars, 616 accidents prove to be fatal and 4,118 accidents result in incapacitating injuries for their occupants. For those light trucks, 561 accidents prove to be fatal and 3,248 accidents result in incapacitating injuries.

The effect of traffic safety on vehicle demand is investigated based on vehicle sales data in 20 selected MSAs. These MSAs are chosen from different regions and exhibit large variations in MSA size, household demographics, and geographic features. In terms of average household demographics and vehicle fleet characteristics, they are well representative of the national data.[3] Table 1 lists these 20 MSAs with several MSA level variables in 2000. 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 median household income was highest in San Francisco and lowest in Syracuse, NY in 2000. Atlanta, GA saw the lowest gasoline price while San Francisco the highest based on the data collected by the American Chamber of

[3]Vehicle sales data are from a proprietary database maintained by R. L. Polk & Co. The expensive nature of the data set limits the number of MSAs I can select. The correlation coefficient between model sales in the 20 MSAs and the national total is 0.941. More details on the representativeness of these MSAs are given in Li, Timmins, and von Haefen (2009).

Commerce Researchers Association (ACCRA). Based on total fatal crashes in each MSA from the Fatality Analysis Reporting System (FARS) database by the NHTSA as well as vehicle stock data provided by R. L. Polk & Co., I calculate the fatality crash rate per 1,000 vehicles. As shown in the table, Las Vegas and Phoenix have the highest fatal crash rate while San Francisco and Cleveland have the lowest among these 20 MSAs. The last column shows the share of light trucks among all light vehicles (i.e., passenger cars and light trucks) on the road.

Table 1: MSA Characteristics in 2000

MSA	Total Households	Median House Income	Gasoline Price	Fatal Crash Per 1,000 Vehicles	Share of Light Trucks
Albany, NY	350,284	44,761	1.68	0.085	0.293
Atlanta, GA	1,504,871	50,237	1.33	0.159	0.369
Cleveland, OH	1,166,799	40,426	1.56	0.073	0.298
Denver, CO	825,291	50,997	1.59	0.120	0.407
Des Moines, IA	184,730	44,088	1.52	0.111	0.346
Hartford,CT	457,407	50,481	1.66	0.098	0.291
Houston, TX	1,462,665	42,372	1.50	0.145	0.408
Lancaster, PA	172,560	43,425	1.58	0.116	0.342
Las Vegas, NV-AZ	512,253	42,822	1.80	0.177	0.382
Madison, WI	173,484	46,774	1.60	0.124	0.348
Miami, FL	1,466,305	37,500	1.52	0.080	0.273
Milwaukee, WI	587,657	45,602	1.60	0.080	0.299
Nashville, TN	479,569	42,271	1.49	0.230	0.368
Phoenix, AZ	1,071,522	42,760	1.58	0.164	0.406
St. Louis, MO-IL	1,012,419	42,775	1.42	0.128	0.335
San Antonio,TX	572,856	38,172	1.48	0.147	0.413
San Diego, CA	994,677	47,236	1.77	0.077	0.372
San Francisco, CA	2,557,158	62,746	1.93	0.060	0.339
Seattle, WA	963,552	52,575	1.68	0.095	0.367
Syracuse, NY	282,601	39,869	1.68	0.102	0.327

Three data sets are used to study vehicle demand: (1) new vehicle attribute data from 1999 to 2006, (2) vehicle sales data at the model level, and (3) the 2001 National Household Travel Survey (2001 NHTS). The first data set shows the choices that consumers face while the second data set tells what choices consumers make at the aggregate level. The third data set provides links between household demographics and vehicle choices. New vehicle attribute data are collected for 1608 models of light vehicles marketed in the U.S. from 1999 to 2006 from annual issues of Automotive News Market Data Book.[4] Table 2 reports summary statistics of several important vehicle attributes. Price is the manufacturer suggested retail prices (MSRP).[5] Size 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: MPG $= \frac{1}{0.55/\text{city MPG}+0.45/\text{highway MPG}}$. These models are further classified into four vehicle types: cars, vans (minivans and full-size vans), SUVs, and pickup trucks, the last three of which are collectively called light trucks.

Table 2: New Vehicle Attributes

	Mean	Median	Std. Dev.	Min	Max
Price (in 1,000 $)	30.1	26.4	14.2	10.3	98.9
Size(in 1,000 inch^2)	13.5	13.4	1.6	8.3	18.9
Horsepower	195	190	59	55	405
MPG	22.4	22.0	5.2	13.2	64.7

Table 3: Summary Statistics from the 2001 NHTS

	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 dummy	0.336	0.402	0.328	0.696	0.499	0.352
Time to work (minutes)	17.90	20.92	20.49	19.75	19.73	24.00

Income ('000)	Vehicle 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

The second data set, new vehicle sales, provides total number of vehicles sold for each of the models in the first data set in each MSA. In total, we have 32,160 observations of

[4]These are virtually all the model sold in the market. Exotic models with tiny market shares such as Farrari are excluded.

[5]Although vehicle transaction prices are more desirable in the demand analysis, they are not easy to obtain. MSRPs have been used in several previous vehicle demand studies (e.g., Feenstra and Levinsohn (1995); BLP; Petrin (2002)).

vehicle sales. The third data set, the 2001 NHTS, provides detailed household level data on vehicle stocks, travel behavior, and household demographics at the time of survey during 2001 and 2002. Among total 69,817 surveyed households, 45,984 are from Metropolitan Statistical Areas. Column 2 in Table 3 shows the means of several demographics for these households. Columns 3 to 7 present the conditional means of household demographics for different groups based on household vehicle choice. As household incomes are categorized and top-coded at $100,000, I provide the probability of new vehicle purchase for six income groups. These summary statistics provide additional moment conditions in my estimation where they will be matched by their empirical counterparts.

3 Vehicle Safety

In this section, I investigate the safety effects of passenger cars and light trucks, both internally (i.e., on the occupants in the vehicle) and externally (i.e, on the occupants in the colliding vehicles). The purpose of this section is two fold. First, it shows that the two types of vehicles offer different safety properties, which then gives rise to the possibility of the arms race in the demand for automobiles. Second, some of the results are used to construct the measure of vehicle safety that is the key variable of interest in the vehicle demand model to be estimated. In this section, I first examine the crash outcomes for passenger cars and light trucks in both single-vehicle and multiple-vehicle crashes. To derive the overall/unconditional safety of the two types of vehicles, I then look at the issue of crash frequencies.

3.1 Crash Outcomes

I examine the factors that determine outcomes in vehicle crashes, with a particular interest in the effect of vehicle type. The police-reported accident data in the GES database define crash severity for *each* occupant in a vehicle into several mutually exclusive categories including fatal, incapacitating injuries, non-incapacitating injuries, possible injuries, and others. To ease exposition and to avoid high multicollinearity in the demand analysis in the next section, I derive a single comparable measure across different crash outcomes based on the concept of an equivalent fatality. An equivalent fatality corresponds to 1 fatality or a certain number of incapacitating injuries (or other injuries). This concept has been used by regulatory agencies such as National Highway Traffic Safety Administration (NHTSA) in cost-benefit analysis. Based on the comprehensive cost estimates of traffic accidents by the National Safety Council (NSC), I convert 20 incapacitating injuries into 1 fatality (baseline definition).[6] To check the sensitivity of the results to different conversion scale, I also conduct analysis for two alternative conversions (10 and 30) from incapacitating injuries to fatalities. In this paper, the crash severity for a vehicle in a crash is defined as the rate of equivalent fatality per occupant. This measure ranges from 0 (no fatality and incapacitating injury in the vehicle) to 1 (all the occupants are killed).

To examine both internal and external safety effects of a vehicle, I estimate a tobit model with two-sided censoring for three types of accidents: two-vehicle accidents involving at least a passenger car, two-vehicle accidents involving at least a light truck, and single-vehicle accidents. In the case of two-vehicle accidents involving a passenger car, the dependent variable is the crash outcome for the passenger car (i.e., the first vehicle). If the accident involves two cars, one of the two is randomly selected as the first vehicle. The dependent variable is similarly defined for two-vehicle accidents involving a light truck. For single-vehicle accidents, the dependent variable is the crash outcome for the vehicle involved. All the vehicles in the dependent variable are models after 1997 in order to be consistent with the demand analysis in the next section. Regressions on all vehicles are also performed and the results are presented in Table 6. Three tobit models are estimated and weights are used to produce nationally representative results.[7]

[6]The NSC estimates that the average comprehensive cost per death is about 20 times of that per incapacitating injury in motor-vehicle crashes. Comprehensive costs include economic costs such as wage and productivity losses, medical expenses, administrative expenses, motor vehicle damage, and employers uninsured costs, as well as valuation for reduced quality of life through empirical willingness-to-pay studies. I focus on fatal and incapacitating injuries and ignore non-serious injuries in measuring vehicle safety. Given that crash outcomes are defined by the individual police officer at the scene, non-serious outcomes can be subject to inconsistency to a larger extent than serious outcomes.

[7]White (2004) and Anderson (2008) perform separate logit regressions for fatal crashes and for crashes that result in fatalities or serious injuries for each type of accidents. I define a single measure of crash outcome in order to facilitate the demand estimation in the following section. Moreover, I focus on crash outcomes for vehicles produced in recent years to be consistent with the demand estimation. Several robustness checks are performed and results are reported below.

Table 4: Regression Results of Tobit Models

	v1=passenger car		v1=light truck		Single vehicle	
	Para	Std Err	Para	Std Err	Para	Std Err
	(1)	(2)	(3)	(4)	(5)	(6)
v2 = light truck	0.031	0.006	0.028	0.006		
Single= light truck					0.060	0.008
Small city	-0.064	0.008	-0.056	0.009	-0.098	0.012
Medium city	-0.067	0.009	-0.073	0.011	-0.119	0.015
Large city	-0.081	0.007	-0.067	0.008	-0.101	0.010
Seat belt	-0.012	0.007	-0.031	0.008	-0.126	0.011
Rain	-0.016	0.008	-0.007	0.010	0.007	0.011
Snow	-0.049	0.021	-0.048	0.024	-0.234	0.023
Dark	0.019	0.006	0.028	0.007	-0.046	0.008
Weekday	-0.014	0.006	-0.013	0.007	-0.020	0.008
Interstate highway	-0.048	0.010	-0.002	0.010	0.079	0.012
Divided highway	0.057	0.006	0.036	0.006	0.098	0.011
Alcohol (v1)	0.062	0.014	0.068	0.017	0.183	0.012
Drugs (v1)	0.027	0.010	-0.006	0.010	0.057	0.012
Age <21 (v1)	0.017	0.011	-0.005	0.014	0.075	0.015
Age > 60 (v1)	0.052	0.008	0.063	0.011	0.076	0.016
Male driver (v1)	-0.037	0.006	-0.033	0.006	-0.027	0.009
Young male (v1)	-0.040	0.015	-0.009	0.019	-0.037	0.019
Occupants (v1)	0.037	0.004	0.023	0.003	0.052	0.004
Speeding (v1)	0.260	0.026	0.206	0.042	0.307	0.018
Alcohol (v2)	0.074	0.013	0.091	0.014		
Drugs (v2)	-0.025	0.009	0.010	0.009		
Age < 21 (v2)	-0.004	0.010	0.008	0.011		
Age > 60 (v2)	0.032	0.008	0.029	0.009		
Male driver (v2)	0.018	0.006	0.004	0.006		
Young male (v2)	0.012	0.013	0.004	0.014		
Speeding (v2)	0.187	0.031	0.093	0.026		
Occupants (v2)	0.007	0.003	0.010	0.004		
Intercept	-0.706	0.033	-0.601	0.042	-0.780	0.029
σ	0.304	0.014	0.260	0.018	0.452	0.015
Observation	76,586		59,733		48,813	

Similar explanatory variables are used in White (2004). Year dummies (8) are included in all regressions. The omitted category for vehicle type is passenger car. The base group for city size is rural area. Alcohol is 1 if the driver is found under the influence of alcohol. Young male is 1 if the driver is male and younger than 21. Speeding is 1 if the travel speed is 10 miles per hour above than the speed limit. Occupants is the number of occupants in the vehicle.

The parameter estimates for the three tobit models are presented in table 4 for the baseline definition of an equivalent fatality. v1 and v2 represent the first and second vehicles in a two-vehicle collision, respectively. The first 2 columns report the results for two-vehicle accidents where the first vehicle is a passenger car. Columns 3 and 4 present the results for two-vehicle accidents where the first vehicle is a light truck. The last two columns are for single-vehicle crashes. The parameter estimates generally have the expected signs. The positive coefficient estimates on v2 being a light truck in the first two regressions suggest that compared to passenger cars, light trucks pose greater danger to occupants in the first vehicle no matter what the type of the first vehicle is. In single-vehicle crashes, the positive coefficient for the vehicle being a light truck tells that occupants in light trucks sustain more server outcome. Among other variables, the results show that accidents are more dangerous in rural areas. Seat belt usage reduces crash severity while alcohol involvement and speeding result in the opposite. Moreover, alcohol involvement and speeding by the driver in the second vehicle also expose the occupants in the first vehicle to greater risks in two-vehicle accidents.

Table 5: Equivalent Fatalities Per Occupant in 1,000 Crashes

	Two-Vehicle Crash		Single-Vehicle Crash
First Vehicle	Second Vehicle		
	Car	Light Truck	
Car	D_{cc}=1.622	D_{ct}=2.130	D_c=7.364
	(0.077)	(0.101)	(0.285)
Light Truck	D_{tc}=0.902	D_{tt}=1.216	D_t=9.589
	(0.072)	(0.099)	(0.422)
Difference	D_{cc}-D_{tc}=0.720	D_{ct}-D_{tt}=0.915	D_c-D_t=-2.225
	(0.104)	(0.136)	(0.374)

Based on the regression results, I now evaluate the relative safety of two types of vehicles in accidents as well as the effect of vehicle type on crash outcomes in two-vehicle crashes. To do so, I calculate the predicted equivalent fatality rate per occupant for each observation of all two-vehicle crashes based on tobit regression results. Similarly, I obtain the predicted equivalent fatality rate per occupant for all single-vehicle crashes. The sample means of these fatality rates are reported in Table 5 with bootstrap standard errors presented in parenthesis. D_{ct} is the total number of equivalent fatalities (per occupant) in a passenger car in 1,000 crashes involving a passenger car and a light truck. Comparing number across rows, occupants in light trucks face smaller risks than those in passenger cars no matter what the colliding vehicle is in two-vehicle crashes. However, the comparison across columns in two-vehicle crashes suggests that the better protection provided by light trucks to their own occupants comes at the cost of the colliding vehicles. In single-vehicle accidents, the evidence shows that light trucks are less safe for their occupants than passenger cars. This is likely due to the fact that light trucks, particularly SUVs and pickups, have higher center of gravity and therefore have a larger tendency to rollover in accidents.

Table 6: Robustness Check for Crash Severity

Severity	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Multinomial logit	
								Fatal	Injury
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D_{cc}	1.622	2.079	1.486	2.067	2.617	1.888	0.487	0.303	11.633
D_{tc}	0.902	1.205	0.807	1.315	1.678	1.273	0.284	0.121	7.712
D_{ct}	2.130	2.723	1.963	2.877	3.625	2.61	0.975	0.632	13.292
D_{tt}	1.216	1.621	1.090	2.000	2.54	2.005	0.460	0.192	9.693
D_c	7.364	8.423	7.021	9.104	10.435	8.468	3.592	1.806	22.968
D_t	9.589	10.900	9.094	11.156	12.775	10.332	5.333	2.763	29.414
D_{cc}-D_{tc}	0.720	0.874	0.679	0.752	0.939	0.615	0.203	0.182	3.921
D_{ct}-D_{tt}	0.914	1.101	0.873	0.877	1.085	0.605	0.515	0.440	3.599
D_c-D_t	-2.225	-2.478	-2.073	-2.052	-2.34	-1.864	-1.741	-0.957	-6.446

Seven robustness checks are performed based on alternative definitions of the dependent variable or different assumptions on the distribution of the error term. All robustness checks point to qualitatively the same findings. The first column of Table 6 repeats the results presented in Table 5 for the baseline definition of an equivalent fatality. The results in the second and third columns are based on the assumption that 10 and 30 incapacitating injuries are equivalent to 1 fatality, respectively. The results in the first three columns are all based on tobit regressions that focus on crash outcomes for vehicles after model year 1997. To check whether the findings apply to vehicles produced earlier, I estimate tobit models where the dependent variable is the crash severity for models of all vintages for three different conversions from incapacitating injuries to fatalities. Columns 4 to 6 present the predicted rate of equivalent fatalities per occupant based on vehicles of all vintages for the three cases. The comparison between columns 1 and 4 suggests that vehicles produced after model year 1997 are safer than older vehicles in collisions. The sixth robustness check (column 7) focuses on most serious outcomes: fatal crashes. I estimate a tobit model with the dependent variable being the fatality rate per occupant (treating all non-fatal outcomes the same)for each of the three types of accidents as shown in Table 4. Based on the estimation results, column 7 reports the predicted fatality rate per occupant in a vehicle. In the last robustness check, I define the crash outcome for a vehicle to be three categories: fatal, incapacitating injury, and others. I then estimate a multinomial logit model for each of three types of accidents. Columns 8 and 9 present the predicted probability of the occupants in a vehicle suffering fatalities or incapacitating injuries. A benefit of the tobit model is that it allows straightforward calculation of the number of equivalent fatalities averted by driving a light truck, which can then be measured against consumers' willingness-to-pay to be estimated from the demand model.

3.2 Crash Frequencies

The preceding section analyzes vehicle safety in an accident. The empirical evidence shows that in a two-vehicle accident, light trucks protect their occupants better at the cost of occupants in colliding vehicles. Nevertheless, light trucks are less safe to their occupants in a single-vehicle crash. To obtain the overall safety of a vehicle, I now examine the issue of crash frequencies.

Table 7: Crash Frequencies by Accident and Vehicle Type

	Multiple-vehicle Crashes		Single-vehicle Crashes	
Year	Passenger car	Light truck	Passenger car	Light truck
1998	0.0506	0.0409	0.0087	0.0077
1999	0.0464	0.0422	0.0082	0.0081
2000	0.0454	0.0420	0.0085	0.0085
2001	0.0437	0.0410	0.0084	0.0087
2002	0.0423	0.0408	0.0084	0.0080
2003	0.0413	0.0394	0.0082	0.0083
2004	0.0391	0.0383	0.0077	0.0079
2005	0.0376	0.0362	0.0075	0.0075
2006	0.0358	0.0351	0.0071	0.0072
Average	0.0432	0.0399	0.0082	0.0081

Table 7 presents the probability of being involved in the two types of accidents separately for passenger cars and light trucks from 1998 to 2006. They are calculated based on national vehicle stock data and the total number of vehicles involved in the two types of crashes from annual issues of Highway Statistics by the NHTSA. Crash frequencies decrease over the period for both type of vehicles, reflecting improved vehicle design as well as improved traffic regulations. The numbers for multiple-vehicle crashes suggest that passenger cars are slightly more likely to be involved in multiple-vehicle crashes than light trucks, with the difference becoming smaller over time. Similar pattern also exhibits among single-vehicle crashes.

To the extent that drivers of these two type of passengers may have systematic difference in their risk type or risk preference, these numbers may mask possible selection problems. On one hand, risky drivers may be more likely to choose light trucks for the purpose of self protection. This adverse selection problem would cause the overestimation of the crash frequencies of light trucks. On the other hand, drivers who are more risk averse may be more likely to choose light trucks. If these drivers are also less risky drivers, there arises a problem analogous to the advantageous selection in the insurance literature. This selection problem could result in the underestimation of the crash frequencies of light trucks.[8]

In addition to these selection problems, there may exist a moral hazard problem in that drivers in light trucks may have tendency to engage in riskier behavior.[9] This would result in the overestimation of the crash frequency of light trucks. Quantifying the net effect of these problems, although interesting, necessitates rich data on drivers' risk level/safety performance as well as detailed demographic variables (see e.g., Chiappori and Salani (2000) for a study on testing the presence of asymmetric information in the automobile insurance market). Due to the lack of adequate data sets to address this issue, I assume that the two types of vehicles have the same probability of being involved in vehicle accidents.This amounts to assuming that the crash frequencies of light trucks are slightly underestimated by the numbers in Table 7. Although light trucks are in general taller and larger than passenger cars, it is reasonable to argue that drivers can quickly learn how to handle these

[8]The advantageous selection can be due to other factors such as income or age. For example, since light trucks are more expensive than passenger cars on average, the users of light truck have higher income than those of passenger cars. If drivers with high income are less risky, the crash frequencies of light trucks would be underestimated without controlling for drivers' income.

[9]This is in the spirit of the Peltzman effect which is the hypothesized tendency of people to react to a safety regulation by increasing other risky behavior. For example, seat belt law may induce people to drive less safely.

vehicles differently, e.g., making slower turns when driving an SUV than driving a car.

The data in Table 7 also show that a vehicle is about 5 times as likely to be involved in multiple-vehicle crashes as in single-vehicle crashes. Although the GES data used in the previous section to analyze crashes outcomes do not contain all accidents and hence prevent a direct inference of crash frequencies, the comparison of crash frequencies across the two types of accident can be carried out because the sample is based on the same underlying vehicle population. The result suggests that a vehicle is 5.53 times as likely to be involved in multiple-vehicle accidents as in single-vehicle accidents.[10] This is consistent with the national level data. Interestingly, the GES data show that the ratio varies across areas with different population size (which may reflect the level of road congestion). The ratio is 7.1l in areas with a population large than 100,000 and is only 3.36 in rural areas.

3.3 Vehicle and Traffic Safety

With crash frequencies examined, I now compare internal vehicle safety between passenger cars and light trucks. The internal safety of a vehicle can be measured by the annual rate of equivalent fatalities per occupant. To derive this measure, I utilize the following relationship:

$$EF_j \equiv (D_{jc}S_c + D_{jt}S_t)P_j^{MV} + D_j P_j^{SV},\ j = \{c, t\}, \tag{1}$$

where EF_j is the internal safety of vehicle type j. j can be a passenger car denoted by c, or a light truck denoted by t. D_{jk} is the probability of an occupant in a vehicle of type j suffering an equivalent fatality when colliding with a vehicle of type k. These measures of crash severity are estimated based on tobit regressions and presented in Table 5. P_j^{MV} is the probability of being involved in a multiple-vehicle crash for the vehicle type j.[11] S_j, the probability of colliding with a type j vehicle in a two-vehicle accident, is measured by

[10] Under-reporting of less serious accidents is likely to more frequent for single-vehicle crashes. This may partly explain the empirical finding in Table 5 that single-vehicle crashes are more deadly than multiple-vehicle crashes. However, this under-reporting problem is unlikely to bias the overall/unconditional safety measure, which is a function of both the crash outcome and the crash frequency.

[11] Since D_{tk} is the measure of crash severity for two-vehicle crashes, P_j^{MV} should be considered as the equivalence of the probability of two-vehicle crashes for any multiple-vehicle crash involving at least two vehicles (e.g., three-vehicle crashes are converted to two-vehicle crashes according to some implicit metric).

the share of type j vehicles among all the vehicles on the road. P_j^{SV} is the probability of a single-vehicle crash for the vehicle type j.

To compare the overall internal vehicle safety, assuming that $S_t = 0.35$, $P^{MV} = 0.04$, and $P^{SV} = 0.008$, the annual rate of equivalent fatality per occupant in passenger cars, EF_c, is estimated at 0.1309 per 1,000 vehicles while that in light trucks, EF_t is estimated at 0.1172. The difference in vehicle safety, $EF_c - EF_t$, is 0.0137 per 1,000 vehicles with a standard error of 0.0042. This suggests that light trucks are overall safer to their occupants than passenger cars. The number implies that replacing 10 million passenger cars with light trucks will result in 192 more equivalent fatalities among the occupants in these passenger cars assuming 1.4 occupants per vehicle.[12]

According to Equation (1), the difference in vehicle safety is:

$$\begin{aligned} EF_c - EF_t &\equiv \Big[(D_{cc} - D_{tc})S_c + (D_{ct} - D_{tt})S_t\Big]P^{MV} + (D_c - D_t)P^{SV} \\ &= \Big[(D_{cc} - D_{tc}) + [(D_{ct} - D_{tt}) - (D_{cc} - D_{tc})]S_t\Big]P^{MV} + (D_c - D_t)P^{SV}. \end{aligned} \tag{2}$$

$D_{cc} - D_{tc}$ defines the safety advantage of a light truck over a passenger car in collisions with other passenger cars. It is easy to see as long as the safety advantage depends on the type of the colliding vehicle, that is, $D_{ct} - D_{tt} \neq D_{cc} - D_{tc}$, the difference in vehicle internal safety will be affected by the fleet composition, S_t. Based on the estimation results of tobit models in the previous section, $(D_{ct} - D_{tt}) - (D_{cc} - D_{tc}) = 0.915 - 0.720 = 0.195$ with a bootstrap standard error of 0.099. The result implies that the safety advantage of a light truck becomes even stronger as more of them are in use. To understand the effect of vehicle composition on the relative safety of two types of vehicles, I increase the share of light trucks from 35 to 45 percent in the previous numerical example. The difference in equivalent fatalities among 10 million vehicles rises from 192 to 203. Moreover, the safety advantage of light trucks also increases with the probability of multiple-vehicle crashes and decreases with the probability of single-vehicle crashes.

[12] The GES data shows that the average number of occupants in a vehicle is about 1.4. While the data show that the average number of occupant is 1.44 in a light truck versus 1.37 in a passenger car, I assume they are the same to easy exposition. The share of light trucks in the U.S. has reached 40% in recent years.

With the internal safety of the two types of vehicles examined, it is interesting to further look at the relationship between the overall traffic safety and the fleet composition. The total number of equivalent fatalities in a year among all users of light vehicles (including both passenger cars and light trucks) is defined by the following equation:

$$\begin{aligned} TEF &\equiv OCC\ (EF_c\ S_c + EF_t\ S_t) \\ &= OCC\Big\{P^{MV}\Big[D_{cc} + (D_{ct} + D_{tc} - 2D_{cc})S_t \\ &- \big[(D_{ct} - D_{tt}) - (D_{cc} - D_{tc})\big]S_t^2\Big] +\ P^{SV}\big[D_c + (D_t - D_c)S_t\big]\Big\}, \end{aligned}$$

where OCC is the total number of occupants/users of light vehicles. The second equality follows directly from Equation (1). The relationship between total equivalent fatalities, TEF, and the fleet composition, S_t, hinges on the magnitude of the D's.

Figure 1: Traffic Safety and Fleet Composition

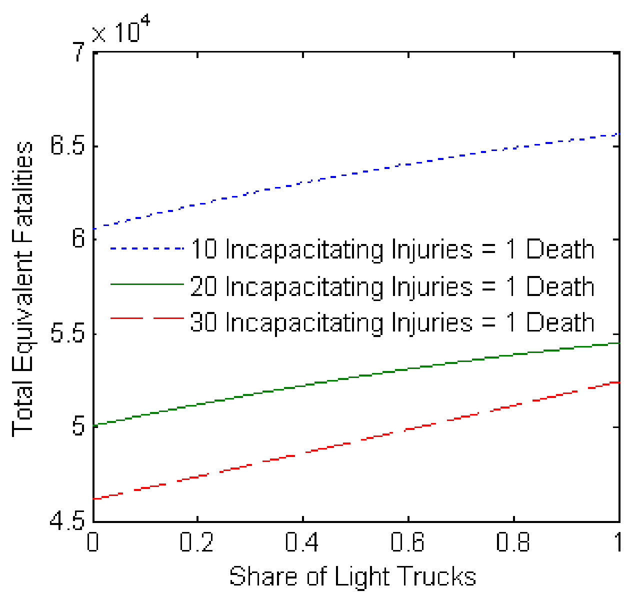

Figure 1 shows the relationship between overall traffic safety and the fleet composition for all three different definitions of an equivalent fatality. The total equivalent fatalities are calculated based on the estimated D's from the tobit models for vehicles of all vintages (as presented in columns 4 to 6 of Table 6) and the assumptions that $P^{MV} = 0.04$, $P^{SV} =$

0.008, and total number of occupants $OCC = 322$ millions (230 million light vehicles in use multiplied by the average number of occupants of 1.4 per vehicle.) The figure shows a monotonically increasing relationship between the fleet share of light trucks and total equivalent fatalities for all three definitions. Under the baseline definition of 20 incapacitating injuries being equivalent to 1 fatality, a vehicle fleet composed of only passenger cars is the safest, resulting in 50,075 equivalent fatalities. However, a vehicle fleet with only light trucks would cause 4,423 more equivalent fatalities. Together with the result that light trucks are safety to their own occupants, the figure makes clear that the traffic safety consequence of the conjectured arms race among drivers is analogous to the welfare consequence of the Prisoner's Dilemma game: although the overall traffic safety would be at its best when people drive only passenger cars, the incentive to obtain better self-protection by driving light trucks would result in worse overall traffic safety.

4 Vehicle Demand

The previous section establishes that light trucks are on average safer to their own occupants than passenger cars. Since safety is often cited as one of the top concerns in vehicle purchase decisions, this finding can have important implication on vehicle demand.[13] My goal in this section is to examine whether the finding about vehicle safety manifest themselves in vehicle demand and the extent to which the safety concern explains the increasing popularity of light trucks in recent years.

To that end, I estimate a flexible model of vehicle demand in the spirit of BLP and Petrin (2002), taking advantage of new vehicle sales data at the model level in 20 MSAs from 1999 to 2006. I augment the sales data with the household survey data from the 2001 NHTS to improve the estimation of consumer heterogeneity. In order to carry out counterfactual analysis, I also set up a simple supply side model where profit maximizing auto makers compete in prices. The first order conditions of the profit maximization problem give rise to new equilibrium prices and sales under a counterfactual scenario. I now discuss the

[13] A consumer survey by the J. D. Power and Associates (J.D. Power and Associates Report Oct. 20, 2000) shows that keeping the family safe is a top priority among consumers, especially among SUV drivers.

empirical model, the estimation strategy, and the estimation results in turn.

4.1 Empirical Model

The demand side starts from a random coefficient utility model. A household makes a choice among all new models and an outside alternative to maximize household utility in each year. Let i denote a household and j denote a vehicle model. A household chooses one model from a total of J models of new vehicles or an outside alternative in a given year. To save notation, I suppress both the market and year indices, bearing in mind the choice set vary across years. The utility of household i from model j is defined as

$$u_{ij} = v(p_j, X_j, \xi_j, y_i, Z_i) + \lambda_i EF_j + \epsilon_{ij}, \tag{3}$$

where p_j the price of model j, X_j a vector of observed model attributes, ξ_j the unobserved model attribute, y_i the income of household i, and Z_i a vector of household demographics. To save notation, I allow Z_i to include MSA level variables such as MSA dummies. EF_j is the internal safety of vehicle j measured in equivalent fatalities per occupant in a year. The variable is constructed following Equation (1) with details provided in the appendix. As shown in the previous section, the safety measure varies across the two types of vehicles and differs across MSAs even for the same type of vehicle due to the variations in crashes frequencies as well as the fleet composition. λ_i, the key parameter of interest, captures consumers' willingness-to-pay for vehicle safety. ϵ_{ij} is the random taste shock that has type one extreme value distribution. The first part of the utility function is specified as:

$$v_{ij} = \alpha_i log(y_i - p_j) + \sum_{k=1}^{K} x_{jk}\tilde{\beta}_{ik} + \xi_j, \tag{4}$$

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.[14] I allow α to vary according to the income group of the household. x_{jk} is the kth model attribute for model j. $\tilde{\beta}_{ik}$ is the random taste param-

[14]This functional form is used in Berry, Levinsohn, and Pakes (1995) and is derived from a Cobb-Douglas utility function in expenditures on other goods and services and characteristics of the vehicle purchased.

eter of household i over model 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. The outside alternative is a combination of the choices other than buying a new vehicle. The presence of the outside alternative allows the aggregate demand for new vehicles to be downward sloping. The utility of the outside alternative is specified as

$$v_{i0} = \alpha_i log(y_i) + Z_i\beta_0 + \lambda_i EF_0 + \nu_{i0}\beta_0^u + \epsilon_{i0}, \tag{5}$$

where EF_0 the safety measure for the outside alternative and will be normalized to be zero in the empirical estimation. The normalization will change the vehicle safety EF_j in Equation (3) into relative measures. 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.

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

$$Pr_{ij} = Pr_i(j|p, X, \xi, y_i, Z_i, \theta) = \int \frac{exp[v_{ij} + \lambda_i EF_j]}{\sum_{h=0}^{J} exp[v_{ih} + \lambda_i EF_h]} dF(\nu_i), \tag{6}$$

where p is the vector of prices of all products. ν_i is a vector of unobserved demographics for household i. The market demand for choice j for a price vector p is the following.

$$q_j = q(j|p, X, \xi, \theta) = \sum_i Pr_{ij}. \tag{7}$$

Following the literature (Bresnahan (1987), Goldberg (1995), and BLP), the supply side assumes that a multiproduct firm f chooses prices to maximize its total profit in the current period. The total profit for firm f is

$$\pi^f = \sum_{j \in \mathcal{F}} \Big[(p_j - mc_j) q_j(p, \theta) \Big], \tag{8}$$

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. The equilibrium price vector derived from the first-order conditions is defined as

$$p = mc + \Delta^{-1} q(p, \theta), \tag{9}$$

where the element of Δ is

$$\Delta_{jr} = \begin{cases} -\frac{\partial q_r}{\partial p_j} & \text{if product } j \text{ and } r \text{ produced by same firm} \\ 0 & \text{otherwise.} \end{cases} \tag{10}$$

Equation (9) 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 (9) can be used to compute new price equilibrium corresponding to a change in the demand equation $q(p, \theta)$.

4.2 Estimation

The above random coefficient demand model is estimated via simulated Generalized Methods of Moments (GMM) with a nested contraction mapping algorithm developed by BLP. A key identification problem arises from the correlation between vehicle prices and unobserved model attributes, which are represented by a latent variable ξ_j. Since better product attributes often command a higher price, failure to take into account the unobserved product attribute often leads to omitted variable bias in the estimate of price coefficient, suggesting that consumers are less price sensitive than they really are. A common, although strong, identification assumption is that the unobserved product attribute is uncorrelated with observed product attributes. Similar to Nevo (2001), I avoid invoking this assumption by exploiting the fact that we observe sales for each product (i.e., a model in a given year) in 20 MSAs and using product dummies to absorb unobserved product attributes.

To illustrate our estimation strategy, I bring the market index m into the utility function. With year index t still suppressed, the utility function can be written as

$$u_{mij} = \delta_{mj} + \mu_{mij} + \epsilon_{mij}, \tag{11}$$

where δ_{mj}, the mean utility of model j in market m, is the same for all the households in market m. The mean utility from the outside alternative is normalized to zero. μ_{mij} is the household specific utility. Following notations in equations (4) and (5), the household specific utility is

$$\mu_{mij} = \alpha_i log(y_i - p_j) + \sum_{kr} x_{mjk} z^h_{ir} \beta^o_{kr} + \sum_k x_{mjk} \nu_{ik} \beta^u_k. \tag{12}$$

All the unobserved household demographics, ν_{ik} and ν_i, are drawn from the standard normal distribution. The mean utility is specified as follows

$$\delta_{mj} = \delta_j + X_{mj}\gamma + \lambda EF_{mj} + \varepsilon_{mj}, \tag{13}$$

where δ_j is a model dummy, absorbing the utility that is constant for all households across the markets (including the utility derived from unobserved product attributes ξ_j). X_{mj} is a vector of model attributes that vary across MSAs. The vector includes, among other things, dollars per 100 miles (DPM), which captures the fuel cost of the vehicle. $EF_{mj} = \{EF_{mc}, EF_{mt}\}$ is the safety measure of vehicle j in market m. ε_{mj}, the error term, may capture that local unobservables that affect consumers preference for vehicle model j. Additional challenges arise in estimating λ due to the possible endogeneity of EF_{mj}. As shown by equation (1), this variable is affected by both the fleet composition and crash frequencies and these factors may be correlated with ε_{mj}. For example, unobserved MSA characters may cause consumers in the same area to prefer light trucks and hence induce a high proportion of light trucks in the vehicle fleet as well.

In order to control for the effect of local unobservables on vehicle preference, I include MSA dummies interacting with vehicle type dummies. That is, I allow consumer preferences for a certain vehicle type to be different across MSAs. Because EF_{mj} are derived based on lagged fleet composition and crash frequencies as shown in the appendix, the potential correlation between EF_{mj} and time-varying components of the error term ϵ_{mj} is unlikely to be significant (after time-constant components being controlled for by dummy variables). It is worth noting that since model dummies in the mean utility function absorb MSA-constant yearly variations, the identification of λ mostly relies on cross-sectional variations in the fleet composition and particularly crash frequencies. As shown in equation (2), given two MSAs with the same share of light trucks but with different multiple-vehicle crash frequencies, the safety advantage of a light truck will be larger in the MSA with a higher probability of multiple-vehicle crashes. Therefore consumers in this MSA may have stronger incentives to buy light trucks than consumers in the other MSA.

The estimation involves an iteration procedure with two steps in each iteration. Denote θ_1 as the vector of all the parameters in the mean utility function defined by equation (13) and θ_2 as the vector of all the parameters in the household specific utility defined by Equation (12). The first step uses a contraction mapping technique to recover the mean utility δ_{mj} for each product in each market as a nonlinear function of θ_2 by matching the predicted market shares of each model (as a function of θ_2 and δ_{mj}) to the observed market shares. The second step estimates the mean utility equation in (13) and then formulates an GMM objective function with two sets of moment conditions. The first set of moment conditions is from the exogeneity assumption in the mean utility equation that e_{mj} is mean independent of X_{mj}. I also include additional exclusion restrictions by interacting MSA-level demographics (average household size and the percentage of renters among househlds) with vehicle type dummies. The underlying assumption is that conditional on individual demographics being incorporated in the demand model through the household specific utility shown in Equation (12), their MSA-level average should not affect consumers' decisions. The second set of moment conditions includes micro-moments which match the model predictions to the observed conditional means from the 2001 NHTS as shown in Table 3. The procedure involves iteratively updating θ_2, δ_{mj}, and then θ_1 to minimize the GMM objective function.[15] With the demand side estimated, I can recover the marginal cost for each model based on firms' first order condition for profit maximization in Equation (9). The first order condition can then be used to simulate new equilibrium prices in counterfactual scenarios.

4.3 Estimation Results

I estimate the random coefficient model for the three definitions of an equivalent fatality. Model 1 is for the baseline definition where 20 incapacitating injuries is equivalent to 1 fatality. Models 2 and 3 use conversion factors of 10 and 30. The parameter estimates for the three estimations are presented in Tables 8 and 9. Table 8 reports the parameter estimates in the mean utility function defined by Equation (13). The last 2 columns report estimation results of a multinomial logit model for the purpose of comparison (with the conversion factor being 20). As shown by Berry (1994), the multinomial logit model can be transformed into a linear model and estimated using OLS. The dependent variable in the transformed model is $log(s_{mj})$-$log(s_{m0})$ where s_{mj} and s_{m0} are the market share of product j and the outside choice in market m, respectively. To allow consumer preference on vehicle prices to be affected by income, the multinomial logit model includes $log(p_j)/log(y_m)$ as an explanatory variable where y_m is the average household income in market m.

In all four regressions, we control for MSA-level unobserved preference/valuation for certain vehicle type (e.g., due to unobserved MSA-level characteristics such as travel and weather conditions) using MSA dummies interacting with vehicle type dummies. As discussed in the previous section, we use product fixed effects to control for unobserved product attributes such as product quality that could be correlated with vehicle price. The key variable of interest in these models is the safety advantage of light trucks over passenger cars measured by (EF_t - EF_c)* LTK dummy. EF_j is the number of equivalent fatalities sustained by 10,000 occupants in vehicles with type j. As shown in Table 13 in the appendix, the

[15] Household demographics are drawn from 2000 Census and are adjusted in different years based on Census data as well as American Community Survey 2000-2006. The unobserved household attributes are standard normal draws from Halton sequences. Due to computational intensity, I limit the number of random draws to 250 in each MSA. The convergence criterion for the simulated GMM is 10e-8 while that for the contraction mapping is set up to 10e-14.

Table 8: Parameters in Mean Utility Function

	Random Coefficient Model						Logit Model	
	Model 1		Model 2		Model 3		Model 4	
Variables	Para	S.E.	Para	S.E.	Para	S.E.	Para	S.E.
$\log(p_j)/\log(y_m)$							-7.622	0.499
(EF_t - EF_c) * LTK dummy	-2.983	1.524	-2.372	1.239	-3.202	1.606	-1.758	0.616
Gas price	8.877	0.321	8.875	0.321	8.881	0.321	0.966	0.169
Dollars per 100 miles (DPM)	-1.917	0.062	-1.917	0.062	-1.917	0.062	-0.173	0.033
P^{MV}	-10.114	0.914	-10.085	0.911	-10.136	0.912	-0.971	0.376
P^{MV} * S_t	0.179	0.015	0.179	0.015	0.179	0.015	0.004	0.007
P^{SV}	39.460	5.061	39.142	5.023	39.579	5.053	1.822	2.491

All regressions include five sets of dummy variables: MSA dummies (19), MSA dummies * Van dummy (19), MSA dummies * SUV dummy (19), MSA dummies * Pickup dummy (19), and product dummies (1608). The first four sets of dummy variables control for observed preferences for certain vehicle type at the MSA level while product dummies control for unobserved product characteristics (that are the same across the MSAs).

annual equivalent fatalities per million occupants in light trucks is on average about 25 less than that in passenger cars in the 20 MSAs. LTK dummy is a dummy variable equal to 1 for a light truck and 0 for passenger cars. The parameter on the interaction term captures consumers' willingness-to-pay for equivalent fatalities avoided by driving a light truck instead of a passenger car. The negative and significant coefficient shows that consumers obtain more utility from light trucks due to their better internal protection. The economic significance of the coefficient will be examined in the next section.

The parameters on gasoline price and dollars per 100 miles (DPM) captures consumer preference for the fuel cost of driving. The partial effect of the mean utility defined by Equation (13) with respect to gasoline price is given by: $\partial\delta_{mj}/\partial\text{Gasprice} = 8.87 - 1.917 * 100/\text{MPG}$. This suggests that with an increase in the gasoline price, the mean utility for vehicles with MPG larger than 21.61 increases while that for less fuel-efficiency vehicles decreases. Moreover, the smaller the vehicle MPG is, the larger the decrease in the mean utility will be.[16] Base on parameter estimates, I estimate the elasticity of the average MPG of new vehicles to the gasoline price at 0.118 for 1999-2006 and 0.207 for 2006. These estimates are similar to some recent estimates that are based on different empirical methodologies.

[16] 21.61 is about the 45 percentile of the MPG distribution for vehicle models in the data. Note that although 21.61 is the cutoff point for the effect of gasoline price on the mean utility, it may not directly apply to the effect on vehicle sales as shown in Equation (6).

Small and Van Dender (2007) obtain an estimate of 0.21 for 1997-2001 using U.S. state level time-series data on vehicle fuel efficiency and gasoline prices. Using a similar data set as the one in this paper but a different empirical method, Li, Timmins, and von Haefen (2009) estimate the MPG elasticity to the gasoline price to be 0.148 from 1999-2005 and 0.204 in 2005. The last 3 variables in the table are solely for the purpose of normalization (the utility from the outside good being 0). It is straightforward to show that these variables specify the relative safety advantage of a passenger car over an outside good. Although the coefficient estimates on the first variable is different across the three random coefficient models, other parameters are almost identical.

Table 9: Parameters in Household Specific Utility Function

	Model 1		Model 2		Model 3	
Variables	Para	S.E.	Para	S.E.	Para	S.E.
Heterogeneous Coefficients						
Log(y_i - p_j) if y_i<75,000	20.049	0.270	20.046	0.270	20.042	0.254
Log(y_i - p_j) if $y_i \leq$75,000	17.636	0.387	17.633	0.387	17.637	0.377
Household size * Car dummy	0.777	0.052	0.777	0.052	0.774	0.052
Household size * Van dummy	1.228	0.061	1.227	0.061	1.230	0.060
Household size * SUV dummy	0.897	0.052	0.897	0.052	0.896	0.051
Household size * Pickup dummy	0.732	0.054	0.732	0.054	0.733	0.053
House tenure * Car dummy	-2.793	0.064	-2.793	0.064	-2.791	0.062
House tenure * Van dummy	-3.228	0.108	-3.228	0.108	-3.227	0.106
House tenure * SUV dummy	-3.495	0.130	-3.495	0.131	-3.494	0.128
House tenure * Pickup dummy	-4.643	0.105	-4.643	0.105	-4.643	0.104
Children dummy * Vehicle size	1.764	0.071	1.764	0.071	1.763	0.069
Travel Time * Vehicle size	-0.048	0.001	-0.048	0.001	-0.048	0.001
Random Coefficients						
Vehicle Size	7.293	0.086	7.292	0.086	7.296	0.079
Dollars per 100 miles (DPM)	0.175	0.015	0.175	0.015	0.175	0.015
Car dummy	2.430	0.166	2.430	0.166	2.431	0.164
Van dummy	1.398	0.837	1.398	0.837	1.397	0.813
SUV dummy	2.106	0.513	2.107	0.514	2.107	0.502
Pickup dummy	2.310	0.497	2.310	0.497	2.312	0.489

Table 9 presents the estimates of the parameters in the household specific utility defined by Equation (12). These parameters capture consumer heterogeneity due to observed and unobserved household demographics. As discussed above, the three models use different definitions of equivalent fatality. Nevertheless, the coefficient estimates are very close across the models. The first two coefficients capture consumer heterogeneity for other goods and services after spending p_j on a new vehicle. The coefficient for low income groups being larger implies households with low income are more price sensitive. The next four parameters are for the interaction terms between household size and vehicle type dummies. The positive coefficients on these interaction terms suggest that large households are more likely to buy new vehicles (versus choosing the outside good). Moreover, large households have stronger preference for vans than for other vehicles. I also interact house tenure (1 if the house is rented) with vehicle type dummies. The negative coefficients suggest that a household in a rented house are less likely to buy a new vehicle, especially a new pickup truck. Table 9 also reports the estimates of 6 random coefficients, which measure the dispersion of heterogeneous consumer preference. These coefficients are the standard deviations of consumer preferences for the corresponding product attributes. For example, based on results from Tables 8 and 9 for model 1, consumer preference for dollars per 100 miles has a standard normal distribution with a mean of -1.917 and a standard deviation of 0.175.

The heterogenous coefficient and more importantly random coefficients break the independence of irrelevant alternatives (IIA) property of a logit model. Under the random coefficient models, the introduction of a new vehicle model into the choice set will draw disproportionately more consumers to the new model from similar products than from others. To illustrate the importance of modeling consumer heterogeneity, we present a sample of own- and cross-price elasticities in Table 10 for 11 products in 2006. One obvious pattern in the table is that cross-price elasticities are larger among similar products, suggesting that substitutions occur more often across similar products than dissimilar ones when prices change. The cross-price elasticities for Ford Escort suggest that when its prices increase, consumers are most likely to switch to Toyota Camry than any of the 10 other models presented in the table. However, the multinomial logit model would predict substitutions that are proportional to vehicles shares regardless the level of similarities across vehicle models.[17]

[17] For example, since Ford F-150 has the largest market share among all models in the data, the multinomial logit model would predict that a change in the price of Ford Escort (or any other model) would result in more consumers to switch to Ford F-150 than to other models.

Table 10: A Sample of Own- and Cross-price Elasticities and Price-cost Margins

Products in 2006	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	Price	Margin(%)
Cars													
Ford Escort (1)	-8.89	0.12	0.01	0.00	0.02	0.01	0.07	0.00	0.03	0.01	0.00	15,260	12.70
Toyota Camry (2)	0.43	-6.80	0.09	0.03	0.09	0.07	0.11	0.03	0.11	0.04	0.01	19,855	16.58
BMW 325 (3)	0.02	0.05	-4.66	0.07	0.02	0.02	0.01	0.02	0.01	0.02	0.01	31,595	21.91
Mercedez-Benz E class (4)	0.00	0.01	0.05	-4.61	0.01	0.01	0.00	0.01	0.00	0.01	0.02	51,825	22.60
Vans													
Kia Sedona (5)	0.01	0.02	0.01	0.00	-6.51	0.09	0.03	0.02	0.02	0.01	0.00	23,665	15.61
Honda Odyssey (6)	0.02	0.04	0.03	0.01	0.31	-5.68	0.07	0.06	0.06	0.05	0.01	25,895	18.46
Pickups													
Ford Ranger (7)	0.05	0.02	0.00	0.00	0.03	0.02	-7.31	0.06	0.04	0.01	0.00	18,775	16.63
Toyota Tacoma (8)	0.01	0.02	0.02	0.02	0.06	0.07	0.21	-4.79	0.04	0.04	0.02	28,530	22.79
SUVs													
Honda CR-V (9)	0.06	0.05	0.01	0.00	0.06	0.04	0.10	0.03	-7.44	0.12	0.01	22,145	14.58
Jeep Grand Cherokee (10)	0.01	0.02	0.02	0.01	0.04	0.04	0.03	0.03	0.14	-5.93	0.03	28,010	18.74
Cadillac Escalade (11)	0.00	0.00	0.01	0.03	0.01	0.01	0.00	0.02	0.01	0.04	-4.53	57,280	25.33

Note: Columns labeled (1) to (11), corresponding to the 11 products, present the matrix of own- and cross-price elasticities. The last column in the table gives the price-cost margins. These numbers are based on parameter estimates for the benchmark model presented in Tables 8 and 9. The sales-weighted average of own-price elasticities and price-cost margins among all 1,608 products are -6.69 and 18.13%, respectively.

The second pattern from the table is that the demand for cheaper products tends to be more price sensitive. Among the 11 vehicle models, the cheapest Ford Escort has the largest own-price elasticity (in absolute value) while the most expensive Cadillac Escalade has the smallest price elasticity. The sales-weighted average price elasticity among all 1,608 products is -6.69. Based on recovered marginal costs, I calculate price-cost margins, $\frac{p_j - mc_j}{p_j}$. The last column of Table 10 reports the margins for the 11 models. Products with more elastic demand tend to have lower price-cost margins than products with less elastic demand. The price-cost margins for 2006 Ford Escort and Cadillac Escalade are 12.70 percent and 25.33 percent, respectively. The sales-weighted average price-cost margin among all products in 18.13 percent. This estimate is close to Petrin (2002)'s estimate of 16.7 percent which is based on vehicles sold from 1981 to 1993. The average benchmark margin in BLP is estimated at 23.9 percent for cars sold between 1971 and 1990 while Goldberg (1995) recovers a much larger estimate of 38 percent for cars from 1983 to 1987.

5 Post-estimation Analysis

The preceding demand estimation confirms the presence of the arms race on American roads by showing that consumers have a higher willingness-to-pay for light trucks due to their better internal safety. The purpose of this section is to further examine the economic significance of the willingness-to-pay and to investigate different policy alternatives on consumer demand, industry performance, as well as traffic safety. To facilitate the analysis, I start the section with estimating the value of a statistical life based on consumers' willingness-to-pay for avoided equivalent fatalities.

5.1 Value of A Statistical Life

The value of a statistical life (VSL) is measured based on economic agents' willingness-to-pay (WTP) for a marginal change in mortality risk: $\text{VSL} = \frac{\text{WTP}}{\text{Reduced Mortality Risk}}$. It is often used to evaluate life-saving benefits of government regulations and programs. There have been numerous estimates of the VSL based on consumer decisions in the labor market or housing and product markets. The dominant framework in these studies is the hedonic models where wage (or price) differentials are explained by the difference in the risk level involved in different occupations (or products). Viscusi and Aldy (2003) provides a comprehensive survey on these studies and find a large variation in the estimates, with the range being \$0.5-20.8 million in 2000 dollars and the median 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 and claims that the best estimate of the VSL based on these studies is \$4 million in 2000 dollars. A significant challenge in the hedonic framework is to control for the unobserved choice attributes that are correlated with risk differentials as well as unobserved characteristics of the decision makers. Both type of unobservables can lead to biased estimates of the VSL. For example, a recent study by DeLeire and Timmins (2007) shows that occupational sorting based on unobserved worker characteristics can lead to large downward bias in the wage-hedonic framework. After correcting for the sorting, they recover VSL estimates at around 12 millions in 2005 dollars, much larger than those based on the traditional wage-hedonic model.

The existence of various methods to reduce fatality risk in automobile driving has been exploited by researchers to estimate the VSL. Atkinson and Halvorsen (1990) employ the hedonic framework to estimate the premium for a safer vehicle and find an estimate of 5.3 million in 2000 dollars. In a similar study, Dreyfus and Viscusi (1995) provide an estimate of \$3.8-5.4 million. Based on the time cost and disutility of safety device usage, Blomquist, Miller, and Levy (1996) obtain an estimate of \$2.8-4.6 million. Ashenfelter and Greenstone (2004) estimate the VSL based on the tradeoff between increased fatality risk and time savings associated with increasing the speed limit on rural interstate roads. They provide an upper bound of the VSL estimate of \$1.7 million.

The structural demand model in Section 4 provides a straightforward framework to estimate the VSL based on consumers' revealed preference. The demand model controls for unobserved product attributes that may be correlated with both prices and vehicle safety. Moreover, the model allows for unobserved household characteristics that introduce heterogeneity in the WTP for the reduced risk even conditional on observed household demographics. The demand estimation shows that consumers are willing to pay a premium for the the reduced fatality risk in the light trucks. The annual reduction of the fatality risk per occupant, different across MSAs and years, is given by $EF_c - EF_t$. The willingness-to-pay can be estimated based on the compensated variation: the amount of money a a household needed to be compensated with in exchange for the reduced fatality risk in light trucks. The VSL for a given household is then defined by: $\frac{\text{WTP}}{10*1.4*(\text{EF}_c\text{ - EF}_t)}$, assuming a 10 year discounted lifespan for a vehicle and 1.4 occupants per vehicle.[18] Assuming that 20 incapacitating injuries are equivalent to 1 fatality, the average VSL is 10.14 million in 2006 dollars with the interquantile range to be 3.75 and 13.16 million dollars with high income households having higher VSL. The average VSL is estimated to be 8.09 and 10.91 million dollars in 2006 dollars assuming that 10 and 30 incapacitating injuries are equivalent to 1 fatality, respectively. In comparison, the VSL based on the parameter estimates for the multinomial logit model shown in the last two columns of Table 8 is only 2.2 million dollars.

5.2 Corrective Tax on Light Trucks

A significant change in the U.S. auto industry in the past two decades is the strong growth in the light truck segment. Traditionally, the Big Three have been the major producers of light trucks. However, Japanese firms have increased their offering of light trucks in recent years and raised their U.S. market share in this segment from less than 10 percent in early 1990's to more than 30 percent in 2006. Our previous analysis suggests that the arms race could have been a significant factor behind the trend of increasing share of light trucks among vehicle fleet. The goal of this section is to quantify the effects of the arms race on consumer demand, industry performance, and overall traffic safety. To do so, I first calculate the monetary cost of the accident externality of light trucks based on vehicle safety effects in Section 3 as well as VSL estimates in the previous section.

As shown in Table 5, a light truck increases the equivalent fatality rate per occupant in a colliding car from 1.622 to 2.130 in 1,000 two-vehicle crashes while increasing the equivalent fatality rate per occupant in a colliding light truck from 0.902 to 1.216. The greater risk posed by light trucks (compared to those by cars) to others is considered as the accident

[18]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.

externality. Table 7 shows that the probability of a multiple-vehicle crash is close to 0.04 per year in recent years. To calculate the accident externality from a light truck, I further assume that the probability of a light truck colliding with a car is 0.6 and the probability of colliding with another light truck is 0.4 based on the U.S. fleet composition in recent years and that the average number of occupants per vehicle is 1.4 following the discussed in Footnote 3.3. The accident externality in equivalent fatalities imposed by a light truck during a 10 year discounted vehicle lifetime is equal to $\big[(2.130 - 1.622) * 0.6 + (1.216 - 0.902) * 0.4\big] * 0.04 * 1.4 * 10/1000 = 0.00024102$.[19] Taking the VSL being 10.14 million in 2006 dollars, the accident externality of a light truck during its lifetime is valued at $2,444.

The above calculation is based on the baseline definition of an equivalent fatality whereby 20 incapacitating injuries are converted to 1 fatality. Columns 2 and 3 in Table 6 presents vehicle safety effects when 10 and 30 incapacitating injuries are converted to 1 fatality, respectively. Based on these estimates of safety effects and corresponding VSL estimates of 8.09 and 10.91 million dollars, similar analysis shows that the accident externality imposed by a light truck over vehicle lifetime amounts to $1,950 and $2,630 for the two alternative definitions of an equivalent fatality.

I now examine how a corrective tax levied on light trucks affects both the demand and supply sides. The corrective tax is a per-unit tax (e.g., a special excise tax) and the amount is equal to the monetary cost of accident externality estimated above. Following Equation 9, I obtain new new equilibrium prices and sales under the tax. Table 11 reports changes in price and sales for passenger cars and light trucks under three tax levels corresponding to each of the three definitions of an equivalent fatality. Panel 1 of the table shows the effects in 1999 while panel 2 presents the effects in 2006, with the effects being similar across years.

There are several interesting findings. First, although the unit-tax is imposed only on lights trucks, the price of passenger cars increases. Under a $2,444 tax per light truck, the sales-weighted average price of cars in 1999 increases by $278 in 2006 dollars. The increase in the price of cars is due to the fact that cars and light trucks are substitutes.

[19] The magnitude of accident externality decreases with the share of light trucks on the road and ranges from 0.000176 to 0.000284 depending on the probability of a light truck colliding with a car in a two-vehicle accident.

The greater the substitution between the two types of vehicles, the larger the effect on car prices would be under a tax on light trucks. Second, with a $2,444 per-unit tax on light trucks, the average price of light trucks faced by consumers increases by $1,870 in 1999. This suggests that consumers bear over 75 percent of the tax burden on light trucks. The tax incidence is determined by the imperfect competition nature of the supply side as well as price elasticities of demand for light trucks (as a whole): the large (smaller) producers' market power (consumer price sensitivity) is, the larger the tax burden consumers will bear. Third, the sales of cars increase while those of light trucks decrease as a result of the tax. For example, a $2,444 per-unit tax on light trucks increases car sales by 0.79 million and reduces light trucks sales by about 1.20 million in 1999. The difference of 0.41 million reflects the increase in the choice of the outside good: some consumers choose not to buy new vehicles as new vehicles become more expensive. It is worthwhile to point out that the multinomial logit model as reported in the last 2 columns of Table 8 would lead to very different results. Since the IIA property of the multinomial logit model implies that the substitution among products will be based only on the share of the products rather than similarity of the product, the multinomial logit model would predict smaller increases in the price of light trucks and larger increases in the price of cars.

Table 11: Effect of Corrective Tax on Price and Sales in 1999 and 2006

	Price Change				Sales Change			
	Cars		Light Trucks		Cars		Light Trucks	
	in $	in %	in $	in %	in mil.	in %	in mil.	in %
Panel 1: Year 1999								
Tax = 2,444	278	0.90	1,870	6.47	0.79	9.27	-1.20	-14.54
Tax = 1,950	228	0.74	1,494	5.16	0.63	7.49	-0.97	-11.81
Tax = 2,630	299	0.97	2,016	6.97	0.84	9.92	-1.28	-15.54
Panel 2: Year 2006								
Tax = 2,444	283	0.96	1,907	6.04	0.69	8.77	1.02	12.31
Tax = 1,950	217	0.74	1,521	4.81	0.56	7.07	-0.82	-9.97
Tax = 2,630	304	1.03	2,056	6.51	0.74	9.40	-1.09	-13.17

Table 12 presents the impacts of the corrective tax on the variable profit of seven major automakers and the industry as a whole in 1999 and 2006. The numbers shows that a $2,444 per-unit tax on light trucks would reduce the industry profit by $3.61 billion and

$3.79 billion in 1999 and 2006, respectively. These losses amount to 4-5 percent of the total variable profit of the industry. However, this aggregate effect masks important heterogeneity that arises from the differences in firms' product mix both across firms and over time . The negative effect of the corrective tax on firm profit would mostly be felt by the Big Three while Volkswagen would see a positive effect on its profit because it introduced its first light truck (an SUV) only in 2003 into the U.S. market. Although the tax would increase the profit of Honda in 1999, it will reduce its profit in 2006, reflecting the fact that Honda has been introducing more light trucks in recent years.

Table 12: Effect of Corrective Tax on Firm Profits in 1999 and 2006

	Tax = $2,444		Tax = $1,950		Tax = $2,630	
	in bil. $	in %	in bil. $	in %	in bil. $	in %
Panel 1: Year 1999						
Industry	-3.61	-4.47	-3.08	-3.82	-3.78	-4.68
GM	-0.97	-3.89	-0.84	-3.34	-1.02	-4.07
Ford	-1.64	-8.47	-1.37	-7.07	-1.73	-8.96
Chrysler	-1.59	-12.68	-1.31	-10.46	-1.69	-13.48
Toyota	-0.07	-1.14	-0.07	-1.15	-0.07	-1.10
Honda	0.25	6.49	0.20	5.09	0.27	7.02
Nissan	-0.03	-1.19	-0.03	-1.31	-0.03	-1.11
Volkswagen	0.21	12.61	0.17	10.03	0.23	13.59
Panel 2: Year 2006						
Industry	-3.79	-5.02	-3.19	-4.23	-3.99	-5.29
GM	-1.45	-7.65	-1.20	-6.33	-1.54	-8.12
Ford	-1.09	-8.38	-0.90	-6.94	-1.15	-8.90
Chrysler	-1.03	-12.42	-0.85	-10.29	-1.09	-13.17
Toyota	-0.34	-3.00	-0.29	-2.58	-0.35	-3.14
Honda	-0.18	-2.81	-0.15	-2.48	-0.18	-2.91
Nissan	-0.13	-2.97	-0.12	-2.54	-0.14	-3.11
Volkswagen	0.17	10.79	0.14	8.56	0.19	11.63

I now turn to the effect of the corrective tax on overall traffic safety. As shown in Section 3, light trucks protect their occupants better at the greater expense of the occupants in other vehicles. The total number of equivalent fatalities in the U.S. is estimated at 51,474 in 2006.[20] The simulation shows that a $2,444 per-unit tax on light trucks reduces the sales of light trucks by 13.87 percent on average from 1999 to 2006. Assuming that the corrective

[20]This is based on the predicted rates of equivalent fatalities per occupant shown in column 2 of Table 6. These rates take into account vehicles of all vintages and thus reflect closely the traffic safety of the vehicle fleet in 2006.

tax would have resulted in the reduction of 13.87 percent (12.91 millions) of all light trucks in service, the number of equivalent fatalities would have been 204 less in 2006. Under a $1,950 or $2,630 per-unit tax, the reduction in equivalent fatalities would be 166 and 217, respectively.

6 Conclusion

The strong growth of the light truck segment is one of the most significant changes in the U.S. auto industry during the last two decades. Light trucks have been shown to protect their occupants better while posing greater risks to other vehicles, largely due to their higher front-ends, stiffer rail frames, and heavier body mass compared to passenger cars. In view of the increasing market share of light trucks, particularly SUVs, in recent years, many have suggested that U.S. drivers have engaged in an "arms race" by buying larger and heavier light trucks.

This paper takes a two-pronged approach to investigate the interrelationship between traffic safety and vehicle choice. Utilizing rich traffic accident data, I confirm that light trucks offer better overall protection to their occupants than passenger cars and that the better protection provided by the light trucks comes at the greater expense of others. These findings allude to the possibility of the arms race in vehicle demand in that demand for light trucks for the purpose of self-protection nevertheless leads to worse overall traffic safety.

To empirically examine the effect of traffic safety on vehicle demand, I estimate a random coefficient discrete choice model based on vehicle sales data in 20 MSAs from 1999 to 2006. The estimation results show that consumers are indeed willing to pay a premium for the safety advantage of light trucks. The implied willingness-to-pay for the reduced fatality risk provides an estimate of the value of a statistical life at $10.14 million in 2006 dollars. Together with the results on vehicle safety effects, the VSL estimate suggests that the accident externality posed by a light truck amounts to $2,444 during vehicle lifetime. I then conduct counterfactual analysis where a per-unit tax is levied on light trucks in order to correct for their accident externality. This analysis shows that a $2,444 tax per light truck would have reduced the sales of new light trucks by 12.31 percent in 2006 while increasing the sales of new cars by 8.77 percent. This finding suggests that the arms race has been an important force behind the growth of the light truck segment. The counterfactual analysis further shows the arms race has significant and heterogenous impacts on the profit of automakers with the Big Three receiving the largest benefit. The simulation results also show that the corrective tax of $2,444 would have resulted in a reduction of 204 equivalent fatalities in 2006.

Largely due to the lobbying efforts by the Big Three, light trucks, originally intended for business usage, have been subject to less stringent regulations in vehicle fuel economy, emissions, and body design as well. However, the majority of light trucks now serve as passenger vehicles just like passenger cars. This paper shows that the interaction between vehicle choice and traffic safety gives rise to an inefficient vehicle fleet composition. The significant accident cost from the arms race calls for more attention from regulatory agencies on the crash incompatibility problem due to the design of the light trucks. Many industry experts believe that light trucks, particularly SUVs, could be redesigned to be safer to others without sacrificing utility. The introduction of crossover utility vehicles that are based on passenger car platforms may represent a promising alternative solution to the problem.

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Appendix: Measure of Internal Vehicle Safety

This section describes the construction of the variable that captures the internal vehicle safety for a passenger car or a light truck in the 20 MSAs under study from 1999 to 2006. The internal vehicle safety is measured by the annual probability of an equivalent fatality per occupant in a certain type of vehicles. The baseline definition of an equivalent fatality used in this study corresponds to 1 fatality or 20 incapacitating injuries. If data on all traffic accidents at an MSA were available, the internal vehicle safety of a vehicle type for this MSA can be computed directly based on the outcomes of all the accidents. However, the most comprehensive traffic accident data, the General Estimate System (GES), only draw samples from police reports in 60 geographic sites.

I construct this variable based on two existing data sets on traffic accidents. The probability of an equivalent fatality per occupant in a type j vehicle in market m, EF_{mj}, can be defined by the following equation (suppressing the time index):

$$EF_{mj} \equiv (D_{jc}S_{mc} + D_{jt}S_{mt})P_{mj}^{MV} + D_j P_{mj}^{SV},\ j = \{c, t\}.$$

As discussed in Section 3.2, D_{jk} is the equivalent fatality rate per occupant in a vehicle of type j when colliding with a vehicle of type k. P^{MV} and P^{SV} are the probabilities of multiple-vehicle and single-vehicle crashes, respectively. Bearing in mind that P^{MV} should be considered as the two-vehicle crash equivalence of all multiple-vehicle crashes given that D's measure the severity of two-vehicle crashes. EF_{mj} varies between the two types of vehicles: passenger cars and light trucks. The above equation also shows that it can differ across markets due to variations in crash frequencies as well in the fleet composition. D's can be estimated based on the regression results of tobit models in Section 3.1 using the GES data. Crash frequencies at the MSA level are the remaining missing pieces.

To obtain crash frequencies, I take advantage of the Fatality Reporting Analysis System (FARS), also maintained by the NHTSA. The FARS data set contains detailed information on all fatal crashes in the country. For each year, I obtain the total number of fatalities involved in both types of crashes separately for each of the 20 MSAs. Assuming that the crash frequency of multiple-vehicle accidents is the same across vehicle types, the total number of fatalities involved in multiple-vehicle crashes in a year should equal to:

$$TF_m \equiv P_m^{MV}\Big[CAR_m\ OCC_c\ (F_{cc}S_{mc} + F_{ct}S_{mt}) + LTK_m\ OCC_t\ (F_{tc}S_{mc} + F_{tt}S_{mt})\Big].$$

CAR_m and LTK_m are the number of passenger cars and light trucks in the vehicle fleet of market m in the given year. They are available from the vehicle stock data set. OCC_j is the average number of occupants in type j vehicle and is estimated from the FARS data. F's are the average fatality rate per occupant in different types of accidents. They are estimated based on tobit regression, similarly to D's in Section 3.1. A key difference between them is that F's are based on tobit models where the dependent variable is the fatality rate per occupant (all the non-fatal outcomes are treated the same) for vehicles of all vintage models. P_m^{MV} can then be derived based on the above equation. The frequency of single-vehicle accidents, P_m^{SV} can be obtained similarly. It is worth noting that the crash frequency could theoretically be calculated for each of two type of vehicles separately since the data set contains vehicle type information. However, small MSAs often do not observe large enough number of fatal crashes to allow a robust measure of crash frequencies separately for each type. For large MSAs, I indeed find that crash frequencies are almost the same across the two types with those for light trucks being marginally smaller. This is consistent with the evidence from the national level data presented in Table 7.

Table 13: Crash Frequencies and Vehicle Safety at the 20 MSAs

	Mean	S.D.	Min	Max
P^{MV}	0.0526	0.0219	0.0212	0.1015
P^{SV}	0.0074	0.0026	0.0040	0.0183
EF_t - EF_c	-0.0253	0.0133	-0.0613	-0.0077

Table 13 presents summary statistics for frequencies of both types of crashes per 1,000 vehicles as well as for the safety advantage of light trucks measured by the reduced equivalent fatality rate per 1,000 occupants. The average frequency of single-vehicle crashes in the 20 MSAs (weighted by the number of households) is close to the national average presented in Table 7 while that of multiple-vehicle crashes is slightly larger than the national average. This is consistent with the finding from the GES data that the ratio of multiple-vehicle crashes to single-vehicle crashes is higher in populated areas, implying a bigger safety advantage for light trucks in these areas. Among the 20 MSAs, Phoenix has the highest frequency of multiple-vehicle crashes while San Francisco has the lowest. Similarly, the safety advantage of light trucks, EF_t-EF_c, is biggest in San Francisco while smallest in Phoenix.