Behavioral Distinctions: The Use of Light-Duty Trucks and Passenger Cars

KARA MARIA KOCKELMAN YONG ZHAO

University of Texas at Austin

ABSTRACT

In the United States, pickup trucks, sport utility vehicles (SUVs), and minivans are classified as light-duty trucks (LDTs), resulting in a variety of regulatory protections. Production and purchase trends suggest that Americans have shifted toward a significantly higher use of such vehicles for personal travel. Using the 1995 Nationwide Personal Transportation Survey (NPTS) data set, this research explores the subtle differences in ownership and use patterns between LDTs and passenger cars. Based on a variety of model specifications and response variables, the results suggest that the average LDT is used over longer distances with more people aboard and is purchased by wealthier households in less dense neighborhoods. Pickups tend to be driven by males, be owned by smaller households, and carry fewer people. There is no indication that SUVs or minivans serve additional work purposes for American households; however, their occupancies and total annual mileages are higher than those of passenger cars. Additionally, SUVs are relatively popular for weekend travel.

Kara Maria Kockelman, University of Texas at Austin, 6.90 E. Cockrell Jr. Hall, Austin, TX 78712–1076. Email: kkockelm@mail.utexas.edu.

INTRODUCTION

Before purchasing a vehicle today, many American households consider pickups, minivans, sport utility vehicles (SUVs), and passenger cars. These first three vehicle types are classified as light-duty trucks (LDTs) and currently capture 51% of new U.S. passenger vehicle sales,¹ a share much larger than the 9.8% they had in 1972 (64 Federal Register 82). Due to differences in federal regulation of passenger cars and LDTs, this shift in ownership and use is marked by reductions in fleetwide fuel economy, relative increases in pollutant emissions, and changes in crash frequency and severity. Ideally, regulatory differences across vehicle manufacturers and vehicle types should counterbalance differences in consumption externalities, both positive and negative. If regulations favor goods that do not provide external benefits, markets are likely to be inefficient (see, for example, Varian 1992). To illuminate the differences in household use of various vehicle types, this paper analyzes the 1995 Nationwide Personal Transportation Survey (NPTS) data (USDOT FHWA 1995).

When the Corporate Average Fuel Economy legislation was introduced in the early 1970s (Public Law 94–163), the argument for distinct classification was that light-duty² pickups and cargo vans were almost exclusively used as work vehicles for hauling cargo rather than for personal travel. At that time, economic censuses suggested that about 50% of U.S. trucks under 10,000 pounds of gross vehicle weight were used primarily for personal transportation; this figure is 75% today (USDOC 1985 and 1999). Also at that time, manufacturers specializing in light trucks and vans argued that, due to differences in body and engine types, they would not be able to meet the standards set for passenger cars requiring an average fuel economy of 27.5 miles per gallon (mpg) in 1985 and beyond. These arguments prevailed, and LDTs were subjected to a significantly lower standard, 20.7 mpg.³ For reasons also largely related to body and engine differences, LDTs enjoy higher emissions caps⁴ and do not endure luxury goods or gas guzzler taxes. Pickups also enjoy substantial import tax protection.

On the basis of structural similarities, particularly in early models, minivans and sport utility vehicles (SUVs) also were classified as LDTs, rather than as passenger cars, in the legislation. As these vehicles become more prevalent for personal travel, policymakers may question whether these vehicles also deserve regulatory protections. Analysis of household purchase and use patterns can suggest whether certain differences exist. By employing the 1995 National Personal Travel Survey data, this research estimates a variety of models that illuminate these behaviors and identify any behavioral distinctions. In identifying such distinctions, this research aims to educate policymakers and others on American travel habits across vehicle types so that related policies can be tailored most appropriately.

DATA SET, MODELS USED, AND RESULTS

The data come from the 1995 Nationwide Personal Transportation Survey (NPTS), which offers travel-behavior information for a broad cross-section of roughly 42,000 American house-

¹ The source of these 1999 data is the Polk Company (without Hummer, Winnebago, and Workhorse truck makes). While these data are the most recent available, they are unpublished, and Polk restricts their use.

² The Code of Federal Regulations (CFR) defines a lightduty truck to be any motor vehicle having a gross vehicle weight rating (curb weight plus payload) of no more than 8,500 pounds, "1) Designed primarily for purposes of transportation of property or is a derivation of such a vehicle or 2) Designed primarily for transportation of persons and has a capacity of more than 12 persons or 3) Available with special features enabling off-street or offhighway operation and use." (40 CFR 86.082-2.) The "special features" enabling off-road use are four-wheel drive and at least four of the following five clearance characteristics: an approach angle of not less than 28 degrees, a breakover angle of not less than 14 degrees; a departure angle of not less than 20 degrees, a running clearance of not less than 8 inches, and front and rear axle clearances of not less than 7 inches each. (40 CFR 86.084-2.)

³ The LDT fuel-economy standard is set by Department of Transportation rule-making; it is not incorporated into formal statute, as in the case of passenger-car fuel economy.

⁴ The EPA's Tier II plans for 2009 call for averaging emissions across a manufacturer's entire fleet of vehicles. Under this plan, LDTs are likely to continue emitting more than cars, on average, but low-emitting vehicles will have to be sold to meet the average, forcing individual manufacturers to balance emissions impacts of their LDT fleets against emissions benefits of their car sales. Ideally, manufacturers should be able to trade credits with one another, but the rule-making does not allow this.

holds, with members of at least five years of age recording all trips on a single day. The specific NPTS data incorporated here as explanatory and response variables are shown in table 1. Unfortunately, due to non-reporting of variables like annual income and VMT, many records are not complete. However, comparisons of variable distributions before and after record removal suggests that there are no sig-

- ·r ·····		Mean*	SD*	
Annual VMT	Annual vehicle-miles traveled in vehicle, as estimated by household respondent.	11,040	8,230	
Number of person-trips	Number of person-trips in the vehicle on the survey day	7.11	6.20	
Number of recreational person-trips	Number of person-trips in the vehicle on the survey day for trips of recreational purpose (including social, shopping, and eating-out purposes)	2.20	3.06	
Trip occupancy: all purposes	Number of vehicle occupants during trip	1.84	1.10	
Trip occupancy: recreational purposes	Number of vehicle occupants during recreational trip (including social, shopping, and eating-out purposes)	1.71	0.99	
Vehicle type choses for trip	Type of vehicle chosen by driver for trip (all purposes included)	NA	NA	
Newest vehicle owned	Type of newest-vehicle owned (identified by latest model year); includes passenger car, SUV, pickup, & minivan	NA	NA	
Explanatory variables:				
Population density	Population density of census tract (persons per square mile)	3,858	5,306	
Income per household member	Annual household income (1995 US\$) divided by house- hold size (where income is taken to be middle of class range)	\$19,075	\$13,56	
Vehicle age	1996 minus model year of vehicle	6.02	4.96	
Household members per vehicle owned	Household size divided by vehicles owned by household	1.48	0.80	
LDT indicator	Equals one for SUVs, pickups & minivans (zero otherwise)	0.26	0.44	
SUV indicator	Equals one for SUVs (zero otherwise)	0.08	0.27	
Pickup indicator	Equals one for pickups (zero otherwise)	0.11	0.31	
Minivan indicator	Equals one for minivans (zero otherwise)	0.08	0.27	
Vehicle price/income	Average purchase price of new vehicle (based on 1997 sales data) divided by annual household income)	0.74	0.14	
Household size	Number of household members	2.83	1.31	
Number of vehicles already owned	Number of vehicles already owned by household, of that vehicle type	0.92	0.87	
Number of cars already owned	Number of passenger cars already owned by household	0.56	0.69	
Weekend day	Equals one for Saturday and Sunday trips (zero otherwise)	0.22	0.42	
Vehicle occupancy	Number of vehicle occupants (for model of vehicle-type choice)	1.58	0.99	
Trip length	Self-reported trip travel time (minutes)	14.21	13.0	

nificant distinctions in the full and culled samples. Thus, the analysis of the various models presented use only complete record. These models estimate vehicle-miles traveled (VMT) per vehicle, number of person-trips per vehicle, vehicle occupancy, vehicle choice for trip making, and vehicle ownership. Several statistical specifications are necessary to model the different response variables most appropriately. Numeric results follow the description of all model specifications.

Models of Vehicle-Miles Traveled

With household estimates of annual VMT for each vehicle owned, two weighted least squares (WLS) models of VMT were developed. One model groups all LDTs together in a single class, while the second permits distinct VMT effects for each of the LDT vehicle types. With everything else constant, additional household members add driving distance to individual vehicles; therefore, the variance associated with VMT is expected to rise with household size. Thus, the weights used in these models are the inverse of household size. Finally, the decision to use only complete vehicle records required the removal of 42% of the records due to the lack of VMT information.

The results are shown in table 2, which suggests that all parameter estimates differ from zero in a highly statistically significant way, evidenced by negligible p-values. As expected, newer vehicles

Variable	Beta	SE	<i>t</i> -stat	P-value
Constant	9,979	174.7	57.12	0.000
Population density	-0.151	0.009	-16.21	0.000
íncome per household member	4.010E-02	0.003	12.72	0.000
Vehicle age	-408.0	8.753	- 46.62	0.000
HH members per vehicle owned	1,883	84.55	22.27	0.000
LDT indicator	1,162	1,11.0	10.47	0.000
Number of observations: 26,398 vehicles Weighted by: 1/household size Model form: VMT = $\beta' \chi + \varepsilon$, where $\varepsilon \sim N(0,$	$\sigma^2 imes$ household size)			
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Number of observations: 26,398 vehicles Weighted by: 1/household size Model form: VMT = $\beta' \chi + \varepsilon$, where $\varepsilon \sim N(0,$ Dependent variable: annual VMT Variable Constant	$\sigma^2 \times \text{household size})$ Beta 10,043	SE 175.0	<i>t-</i> stat 57.40	P-value 0.000
Number of observations: 26,398 vehicles Weighted by: 1/household size Model form: VMT = $\beta' \chi + \varepsilon$, where $\varepsilon \sim N(0,$ Dependent variable: annual VMT Variable Constant Population density	$\sigma^2 \times \text{household size}$ Beta 10,043 -0.153	SE 175.0 0.009	<i>t-</i> stat 57.40 –16.30	P-value 0.000 0.000
Number of observations: 26,398 vehicles Weighted by: 1/household size Model form: VMT = $\beta'\chi + \varepsilon$, where $\varepsilon \sim N(0,$ Dependent variable: annual VMT Variable Constant Population density income per household member	$\sigma^2 \times \text{household size}$ Beta 10,043 -0.153 4.00E-02	SE 175.0 0.009 0.003	<i>t-stat</i> 57.40 –16.30 12.60	P-value 0.000 0.000 0.000
Number of observations: 26,398 vehicles Weighted by: 1/household size Model form: VMT = $\beta'\chi + \varepsilon$, where $\varepsilon \sim N(0,$ Dependent variable: annual VMT Variable Constant Population density income per household member Vehicle age	$\sigma^2 \times \text{household size}$ Beta 10,043 -0.153 4.00E-02 -405.4	SE 175.0 0.009 0.003 8.76	<i>t</i> -stat 57.40 -16.30 12.60 -46.20	P-value 0.000 0.000 0.000 0.000
Number of observations: 26,398 vehicles Weighted by: 1/household size Model form: VMT = $\beta' \chi + \varepsilon$, where $\varepsilon \sim N(0,$ Dependent variable: annual VMT Variable Constant Population density Income per household member Vehicle age HH members per vehicle owned	$\sigma^2 \times \text{household size}$ Beta 10,043 -0.153 4.00E-02 -405.4 1,821	SE 175.0 0.009 0.003 8.76 85.2	<i>t</i> -stat 57.40 -16.30 12.60 -46.20 21.40	P-value 0.000 0.000 0.000 0.000 0.000
Number of observations: 26,398 vehicles Weighted by: 1/household size Model form: VMT = $\beta' \chi + \varepsilon$, where $\varepsilon \sim N(0,$ Dependent variable: annual VMT Variable Constant Population density Income per household member Vehicle age HH members per vehicle owned SUV indicator	$\sigma^2 \times \text{household size}$ Beta 10,043 -0.153 4.00E-02 -405.4 1,821 1,027 	SE 175.0 0.009 0.003 8.76 85.2 189	t-stat 57.40 -16.30 12.60 -46.20 21.40 5.44	P-value 0.000 0.000 0.000 0.000 0.000 0.000
Number of observations: 26,398 vehicles Weighted by: 1/household size Model form: VMT = $\beta'\chi + \varepsilon$, where $\varepsilon \sim N(0,$ Dependent variable: annual VMT Variable Constant Population density Income per household member Vehicle age HH members per vehicle owned SUV indicator Pickup indicator		SE 175.0 0.009 0.003 8.76 85.2 189 152	t-stat 57.40 -16.30 12.60 -46.20 21.40 5.44 4.74	P-value 0.000 0.000 0.000 0.000 0.000 0.000 0.000

driven by wealthier households residing in less population-dense neighborhoods appear to be driven longer distances. Also, as the number of household members per vehicle owned increases, a vehicle's annual mileage increases. What is surprising is that after controlling for all these factors, LDTs are found to be driven substantially more than passenger cars, particularly minivans and SUVs. All else unchanged, the additional mileage driven in an SUV, pickup, and minivan is estimated to represent 9.3%, 6.5%, and 20% of a passenger car's VMT, respectively. Such figures suggest that these vehicles are more popular or more useful to households or both. Their larger carrying capacity (eight passengers in many minivans and towing options for virtually all pickups) and offroad capability, in the case of many SUVs and pickups, make these vehicles more versatile. Such qualities are a large part of the reason these vehicles generally cost significantly more than passenger cars. In 1997, the average SUV, pickup, and minivan cost about 58%, 39%, and 21% more than the average passenger car sold.⁵ Applying the numeric results from table 2, we find that a doubling of population density, from its mean value of 3,858 people per square mile (6 people per acre or 4.9 people per hectare) to 7,716 would provoke, on average, a per-vehicle VMT drop of 590 miles. This suggests a very significant density shift, but its effect is much lesser than the extra VMT associated with SUVs (1,027 miles) and minivans (2,150). Of course, one's vehicle choice is, to some extent, a function of environmental qualities such as density since, for example, it may be harder to park a larger vehicle in a denser environment, and people seeking denser living environments may prefer to drive less. Density may be proxying for some effects of unobserved personal preferences. Thus, if LDT sales decline or densities increase, VMT is not guaranteed to fall. But, a comparison of mileages across distinct densities and vehicle types illustrates a rather remarkable magnitude of difference. This is also apparent in the effects of the income variable: if we double mean incomes per household member, the effect on VMT is a rather negligible 76 miles per year per vehicle. It seems clear that LDTs are driven substantially further, on average, even after controlling for their age.

Models of Person-Trips per Vehicle

Due to its non-negative integer nature, the number of person-trips per vehicle in the data set was estimated using negative binomial regression models.⁶ This variable's mean was specified as an exponential function so that the expected number of trips is equal to $\exp(\beta X)$. Unlike a Poisson distribution, which implies that the variance equal the mean, a negative binomial specification permits over-dispersion in observed values. Its variance equals its mean times the quantity one plus a non-negative over-dispersion parameter. Log-likelihood results are shown for the assumption of a Poisson model, alongside the results for the negative binomial specification.

The results of person-trip-per-vehicle models raise the question of whether one vehicle type is used more than another and whether this differs by trip type. Since SUVs are heavily marketed for their off-road abilities and cargo space for long trips, one may expect to find evidence of this in the nature of their use. For example, they may be used more often, particularly for trips of a recreational nature. In contrast, pickups have been portrayed as providing non-recreational, heavy work uses, and they generally safely seat no more than three occupants.⁷ Therefore, one may expect pickups to make fewer recreational trips.

Originally, three person-trip models were estimated: one counts trips of all purpose types, another counts only those trips of a recreational nature, and a third counts those trips with a work purpose. Almost all parameters are estimated to differ significantly from zero in a statistical sense. The empirical results of the third, work-purpose model are not provided because their overall predictive value is almost zero (pseudo- R^2 s < 0.01). Their low predictive value is probably due to the fact that most work trips are made solo since two U.S. workers rarely share the same workplace location.

⁵ These numbers come from *Ward's Automotive Yearbook* (1997) prices and Automotive News (1998) sales data. They are based on sales-weighted values.

⁶ See Cameron and Trivedi's 1986 discussion of such models. ⁷ However, this is changing via new four-door "car-plustruck" models.

TABLE 3 Negative Binomial Regressions for Number of Person-Trips: All Purposes and Recreational PurposesDependent variable: number of person-trips for all purposes

Variable	Beta	SE	<i>t</i> -stat	P-value
Constant	1.672	0.012	138.00	0.000
HH members per vehicle owned	0.255	0.004	59.20	0.000
Income per household member	-3.16E-06	2.77E-07	-11.40	0.000
Population density	-4.42E-06	6.10E-07	-7.25	0.000
Vehicle age	-0.014	0.001	-20.80	0.000
Weekend day indicator	0.100	0.007	13.50	0.000
SUV indicator	0.045	0.012	3.85	0.000
Pickup indicator	-0.164	0.011	-14.90	0.000
Minivan indicator	0.302	0.011	28.50	0.000
Over-dispersion parameter	0.351	0.004	97.10	0.000
Log-likelihood Function	Negative binomial rea	Negative binomial regression Poisson regression		
Constant only	-121,113.3	_	160,951.3	
Convergence	-117,983.1	_	148,642.7	
Pseudo-R ²	0.026		0.076	

Number of observations: 41,538 vehicles

Model form: Number of person-trips ~ negative binomial with expected value $\exp((\beta' X))$ and non-negative over-dispersion parameter

Dependent variable: number of person-trips for recreational purposes

Beta	SE	t-stat	P-value
0.485	0.021	22.80	0.000
0.204	0.008	25.90	0.000
-3.14E-06	4.73E-07	-6.60	0.000
-6.12E-06	1.09E-06	-5.60	0.000
-0.018	0.001	-15.60	0.000
0.590	0.014	41.40	0.000
0.005	0.021	0.20	0.814
-0.292	0.019	-15.20	0.000
0.308	0.020	15.70	0.000
1.009	0.011	93.40	0.000
Negative binomial reg	gression Poi	sson regression	
-82,460.37	-	-10,6536.4	
-80,612.10	-	-99,753.51	
0.022		0.064	
	Beta 0.485 0.204 -3.14E-06 -6.12E-06 -0.018 0.590 0.005 -0.292 0.308 1.009 Negative binomial reg -82,460.37 -80,612.10 0.022	Beta SE 0.485 0.021 0.204 0.008 -3.14E-06 4.73E-07 -6.12E-06 1.09E-06 -0.018 0.001 -0.018 0.014 0.005 0.021 -0.292 0.019 0.308 0.020 1.009 0.011 Negative binomial regression Poi -82,460.37 - -80,612.10 -	Beta SE t-stat 0.485 0.021 22.80 0.204 0.008 25.90 3.14E-06 4.73E-07 -6.60 -6.12E-06 1.09E-06 -5.60 -0.018 0.001 -15.60 0.590 0.014 41.40 0.005 0.021 0.20 -0.292 0.019 -15.20 0.308 0.020 15.70 1.009 0.011 93.40 Negative binomial regression -82,460.37 -10,6536.4 -80,612.10 -99,753.51 0.022 0.064

Number of observations: 41,538 vehicles

Model form: Number of person-trips ~ negative binomial with expected value $\exp{(\boldsymbol{\beta}' X)}$ and non-negative over-dispersion parameter

Table 3 provides the estimates resulting from application of the all-purposes and recreationalpurposes person-trip models. These data are based on a single day's trips, introducing much random variation. This variation is evident in a low goodness-of-fit, as measured by pseudo- R^2 . While a Poisson stochastic specification superficially suggests better fit, the negative binomial specifications are statistically superior (the addition of a single parameter, the over-dispersion coefficient, increases the log-likelihood significantly).

Table 3 shows that newer vehicles belonging to households in lower density environments with higher incomes and more household members per vehicle owned carry more person-trips per day. However, these models' mean values are characterized by exponential functions, and halving density from its average value reduces person-trips by just one percent. Doubling incomes (per household member) from their current mean produces only a six percent change. Of all trip types, 10% more person-trips are estimated to occur on weekends (versus weekdays); this difference becomes a significant 80% when trips are of a recreational nature.

The general distinctions among different vehicle types in table 3 are not surprising: minivans make the most person-trips per day, followed by SUVs, passenger cars, and finally pickups. SUVs are estimated to make, on average, 4.6% more person-trips per day than passenger cars, while pickups average 15% fewer, and minivans average an impressive 35% more. For recreational purposes, the figures are less than 1% more for SUVs, a remarkable 25% fewer for pickups, and 36% more for minivans. Person-trip models bundling all LDTs into a single category show the average differences translate to six percent more person-trips across all trip purposes carried by LDTs and only one percent more for recreational purposes.⁸

In summary, these results suggest that SUV and "average" LDT person-trip counts are very close to those of passenger cars. However, minivans are estimated to make significantly more person-trips and pickups, significantly fewer. It is surprising that SUVs are not making more recreational persontrips, on average, than passenger cars. The 58% higher purchase price and performance distinctions of the average new SUV, relative to the average new car, are not reflected in this form of use.

Models of Vehicle Occupancy

Ordered probit models were used to study vehicle occupancy during trip-making.9 Relative to the negative binomial specifications used above (for estimation of person-trip counts), an ordered probit specification can provide some important flexibility by removing implications of cardinality. For example, it can distinguish two-person vehicle occupancy from two times single-person occupancy. Additional occupants are frequently non-driving children or others whose reasons for travel may be distinct from those of the vehicle's driver. For this reason, we hypothesize the existence of latent variables whose thresholds, which essentially are cut-off points for integer occupancy values, differ only ordinally. This set up contrasts with underlying, cardinal rates fundamental to Poisson and negative binomial specifications.

Tables 4a and 4b provide the results of the tripoccupancy estimations for trips of all types and for only those trips with a recreational purpose. Without cardinality, the magnitudes of ordered probit parameters are not as easily interpreted as those of the WLS and negative binomial models; however, it is clear that trips made by lower income households for shopping, eating out, or other, recreational purposes tend to exhibit higher occupancies. The same is true of weekend trips made by households having more members per vehicle. In general, minivans draw the largest occupancies, followed by SUVs, cars, and, lastly, pickups.

In the all-trip-purposes model of occupancies (Table 4a), the minivan, eating out, and weekend indicator variables have coefficients high enough to almost raise expected occupancy by one, while few of the other variables exert comparable effects. For example, occupancy appears to be negligibly influenced by income levels and population density: the parameter estimates suggest it would take more than a \$47,000 reduction in the average income per household member or almost 90 more persons per acre (36 more per hectare) to find people occupying passenger cars to the degree they occup minivans.

⁸ In the interest of space, these models are not shown.

⁹ See Greene's (1993) discussion of this model specification.

TABLE 4a Ordered Probit Model for Trip Occupancy: All Trip Purposes

Dependent variable: trip occupancy (all purposes)

Variable	Beta	SE	<i>t</i> -stat	P-value
Constant	-0.565	0.007	-79.90	0.000
HH members per vehicle owned	0.340	0.002	153.00	0.000
Income per household member	-1.06E-05	2.05E-07	-51.50	0.000
Population density	-8.79E-06	4.27E-07	-20.60	0.000
Weekend day indicator	0.474	0.005	91.20	0.000
SUV indicator	0.174	0.008	20.90	0.000
Pickup indicator	-0.229	0.008	-30.40	0.000
Minivan indicator	0.500	0.006	78.80	0.000
Shopping indicator	0.021	0.006	3.21	0.001
Eat out indicator	0.544	0.011	49.20	0.000
$\mu_{ m o}$	0.000	na	na	na
μ_1	0.875	0.003	302.00	0.000
μ_2	1.431	0.004	365.00	0.000
μ_3	2.039	0.006	368.00	0.000

Log-likelihood function		
Constant only	-324471.0	
Convergence	-298694.3	
Pseudo-R ²	0.079	

Number of observations: 263,031 trips

Model form: $\Pr(\text{Occupancy} = 1) = \Pr(\mu^* \le \mu_0)$, $\Pr(\text{Occupancy} = 2) = \Pr(\mu_0 \le \mu^* \le m1)$, $\Pr(\text{Occupancy} = 3) = \Pr(\mu 1 \le \mu^* \le \mu_2)$, $\Pr(\text{Occupancy} = 3) = \Pr(\mu 1 \le \mu^* \le \mu^* \le \mu^* \le \mu^* \le \mu^* \le \mu^* \ge \mu^* \le \mu^* \le \mu^* \le \mu^* \le \mu^* \le \mu^* \ge \mu^* \le \mu^* \le \mu^* \le \mu^* \le \mu^* \le \mu^* \le \mu^* \ge \mu^*$

= 4) = $\Pr(\mu_2 \le \mu^* \le \mu_3)$, and $\Pr(\text{Occupancy} \ge 5) = \Pr(\mu_3 \le \mu^*)$, where $\mu^* = \beta'X + \varepsilon$, and $\varepsilon \sim \text{Normal}(0, 1)$

In the recreational-trip-purposes model of occupancies (Table 4b), the minivan indicator variable has a coefficient estimate that almost raises expected occupancy by one. Weekend day and members-per-vehicle variables also exert strong effects. In contrast, recreational-trip occupancy appears to be only very slightly influenced by income levels and population density: the parameter estimates suggest it would require more than a \$53,000 reduction in average income per house-hold member to find people occupying passenger cars to the degree they occupy minivans.

Note that the parameter sign on the variable of population density changes between the two tripoccupancy models. Neighborhood density is associated with reduced occupancies in general (that is, across all trip types) but with higher occupancies for recreational trips. In practical terms, density's effect on recreational-trip occupancy is estimated to be effectively zero. It appears that density does not affect that decision.

In general, these occupancy results across vehicle types are consistent with expectations and the person-trips-per-vehicle results. Minivans carry significantly more occupants per trip than do passenger cars, while pickups carry fewer. In regard to the other variables, density and income do not exert very strong effects, but day of the week, trip purpose, and number of household members per vehicle owned do.

TABLE 4b Ordered Probit Model for Trip Occupancy: All Recreational Purposes

Dependent variable: trip occupancy (all recreational purposes)

Variable	Beta	SE	<i>t</i> -stat	P-value
Constant	0.043	0.020	2.136	0.033
HH members per vehicle owned	0.349	0.006	57.435	0.000
Income per household member	-9.77E-06	5.55E-07	-17.622	0.000
Population density	1.95E-07	8.11E-08	2.404	0.016
Weekend day indicator	0.341	0.014	24.810	0.000
SUV indicator	0.316	0.027	11.925	0.000
Pickup indicator	-0.196	0.025	-7.802	0.000
Minivan indicator	0.524	0.019	27.929	0.000
$\mu_{ m o}$	0.000	na	na	na
μ_1	1.055	0.009	113.721	0.000
μ_2	1.612	0.011	146.304	0.000
μ_3	2.247	0.014	160.105	0.000
Note: Trip occupancy is grouped into 1, 2, 3, 4	, and 5+ person levels.			
Log-likelihood function				
Constant only	-38686.52			
Convergence	-35948.44			
Pseudo-R ²	0.071			

Number of observations:26,190 trips

Model form: $Pr(Occupancy = 1) = Pr(\mu^* \le \mu_o)$, $Pr(Occupancy = 2) = Pr(\mu_o \le \mu^* \le m1)$, $Pr(Occupancy = 3) = Pr(\mu^* \le \mu_2)$, $Pr(Occupancy = 4) = Pr(\mu_2 \le \mu^* \le \mu_3)$, and $Pr(Occupancy \ge 5) = Pr(\mu_3 \le \mu^*)$, where $\mu^* = \beta' X + \varepsilon$, and $\varepsilon \sim Normal(0, 1)$

Model of Mode Choice

Another model of vehicle use emphasizes a driver's vehicle choice. When multiple vehicle types are available, the driver's probabilities of electing each type can be examined. Here the choices are clearly discrete so a multinomial logit (MNL) specification provides estimation.¹⁰ To avoid issues of correlation in unobserved components of similar vehicle types, only trip records by drivers residing in households with no more than one vehicle of each type are examined.¹¹

Since all explanatory variables, except that of vehicle age, are constant across driver trip records, they are interacted with indicator variables of vehicle type. In addition, a reference alternative is necessary for parameter identifiability. Therefore, all parameter estimates are relative to choice of a passenger car, whose parameter estimates effectively are forced to equal zero here. As a consequence, three parameters are estimated for all but the vehicle age variable; these correspond to the three noncar vehicle types.

Table 5 shows the results of this model's estimation, and they suggest that in general cars are more likely to be chosen, or assigned, depending on household vehicle use constraints. Driver age plays a role for SUV use, with drivers in their late 40s most likely to be using an SUV when other alternatives exist. The role of driver age is not

¹⁰ See, for example, Greene's (1993) discussion of this model. ¹¹ A nested-logit specification would avoid the record removal used here. In such a framework, all passenger cars available to a household form one nest of choices: all minivans form a different nest, and so on. Our interest lies in distinctions across vehicle types, rather than among vehicles of a single type (that is, within a nest), so the removal of households with more than one vehicle of any type was adopted, simplifying the estimation.

TABLE 5 Multinomial Logit Model for Vehicle Type Chosen for Trip by Driver

Dependent variable: vehicle type choice

Variable		Beta	SE	<i>t</i> -stat	P-value
	SUV	-2.464	0.244	-10.108	0.000
Constant	Pickup	-2.322	0.145	-16.046	0.000
	Minivan	-2.687	0.183	-14.653	0.000
Vehicle age		-0.056	0.002	-31.158	0.000
_	SUV	0.077	0.012	6.550	0.000
Age of traveler	Pickup	0.047	0.006	7.239	0.000
	Minivan	0.112	0.008	13.575	0.000
	SUV	-8.34E-04	1.36E-04	-6.119	0.000
Age ² of traveler	Pickup	-5.71E-04	7.04E-05	-8.111	0.000
	Minivan	-1.09E-03	9.09E-05	-11.977	0.000
	SUV	0.550	0.048	11.401	0.000
Male driver	Pickup	3.172	0.035	91.060	0.000
	Minivan	-0.411	0.035	-11.806	0.000
	SUV	0.119	0.071	1.685	0.092
Employed driver	Pickup	0.089	0.046	1.927	0.054
	Minivan	-0.330	0.048	-6.824	0.000
	SUV	0.058	0.063	0.919	0.358
Work trip	Pickup	0.359	0.042	8.549	0.000
-	Minivan	-0.034	0.048	-0.713	0.476
	SUV	0.056	0.059	0.947	0.344
Recreational trip	Pickup	-0.170	0.037	-4.579	0.000
	Minivan	-0.032	0.041	-0.773	0.440
	SUV	8.37E-06	5.34E-06	1.567	0.117
Population density	Pickup	-1.54E-06	4.15E-06	-0.370	0.711
	Minivan	1.66E-06	3.75E-06	0.443	0.658
	SUV	6.21E-07	1.67E-06	0.371	0.710
Income per person	Pickup	-6.29E-06	1.40E-06	-4.509	0.000
	Minivan	4.76E-06	1.64E-06	2.896	0.004
	SUV	0.169	0.053	3.199	0.001
Weekend indictor	Pickup	-0.046	0.033	-1.387	0.166
	Minivan	-0.042	0.037	-1.138	0.255
	SUV	0.229	0.029	7.970	0.000
Vehicle occupancy	Pickup	-0.449	0.020	-22.796	0.000
	Minivan	0.385	0.017	22.138	0.000
	SUV	-0.40E-03	0.17E-02	0.228	0.820
Trip length (min.)	Pickup	-1.00E-03	0.11E-02	-0.882	0.378
	Minivan	-0.51E-02	0.13E-02	-3.866	0.001
Log-likelihood function					
Constant only	-36009.5				
Convergence	-27703.3				
Pseudo–R ²	0.231				
Number of observations: 50,865	5 vehicle trips				

Model form: Pr(vehicle chosen) = Pr($u_i \ge u_j \forall \ge j$) = Pr($\beta'_i x_i + \varepsilon_i \ge \beta'_j x_i + \varepsilon_j \forall i > j$)

$$= \frac{\exp(\boldsymbol{\beta}_{i}^{\prime} \boldsymbol{x}_{i})}{\sum_{i} \exp(\boldsymbol{\beta}_{i}^{\prime} \boldsymbol{x}_{i})}, \text{ where } \boldsymbol{\varepsilon}_{i} \sim \text{iid Gumbel}$$

practically significant, however, for minivan or pickup choice/assignment. Males are far more likely to use pickups and somewhat more likely to use SUVs, while women have a tendency to drive minivans. Employed persons have a slight tendency to favor pickups and SUVs but a stronger tendency to avoid minivans. If the trip's purpose is work-related, pickups are more likely, and if the purpose is recreational in nature, the converse is true. In contrast, trip purpose effects for minivans and SUVs are not statistically significant. Population density does not show statistical significance for any of the these vehicle choices relative to passenger cars.

On weekend days, the model results suggest that an SUV is a more likely choice and a pickup somewhat less likely. Its effect, however, is not quite significant, in neither a statistical nor a practical sense. Vehicle trips made with more occupants lead to a higher probablity of SUV and minivan choice but lower likelihood of pickup. This result echoes the results of the occupancy models. Perhaps unexpectedly, trip length, as measured in time units reported by drivers, does not have an impact on SUV and pickup choices but negatively affects the likelihood of minivan choice.

Models of Vehicle Ownership

The final pair of models estimated center on vehicle ownership. Similar to the above analysis of vehicle types chosen for specific trips, a multinomial logit model was used first. This specification predicts the type of "newest vehicle owned," as measured by model year, in a household's fleet. In addition, a set of simultaneous Poisson regression equations, for the various numbers of different vehicle types owned, was estimated. The simultaneity in this second form of ownership model results from restricting the parameter of vehicle price-over-income variable to be the same for all of the exponential equations.¹² Tables 6 and 7 show the results of these models. As is evident in the negative constant terms for various LDT vehicle types in both these tables, passenger cars are relatively favored, on average. However, current total sales figures indicate that LDTs as a class are catching up and starting to surpass passenger car sales. Moreover, some LDTs are held longer by households than are passenger cars, suggesting that household vehicle holdings may differ substantially in the coming years.¹³ As results reported above suggest, LDTs are driven significantly more miles each year and minivans serve substantially more person-trips than passenger cars. Therefore, LDTs contribute significantly more toward congestion, pollution, and crashes than ownership information alone suggests.

Results of tables 6 and 7 results also suggest that as household sizes increase, SUVs and minivans are more popular choices than passenger cars, while pickups are becoming a slightly less likely choice. Furthermore, as incomes per household member increase, SUVs become more common, and pickups become less common. Minivan ownership response to higher incomes is not as significant, statistically or practically.

Table 6 suggests that when a household owns multiple cars, the addition of minivans and pickups is favored, but an SUV's addition is not affected in a statistically significant way. Ownership of a relatively new minivan becomes less likely as a household's overall fleet size increases. Finally, results of both tables 6 and 7 indicate that LDTs are more popular in lower density environments. This result may be reflective of longer travel distances in such locations and fewer parking issues for these larger vehicles.¹⁴

¹² A series of independent Poissons or simultaneous-inunknown-parameters Poissons (as specified here), conditioned on the sum, is equivalent to a multinomial distribution for the combinations of vehicles owned. The price-over-income variable was restricted to a single coefficient because the prices were constant for each vehicle type here (using 1997 average sales prices). Thus, this variable would have simply reflected the inverse of income had its parameters been allowed to vary. A multiariate

negative binomial also was attempted to allow heterogeneity across the vehicle ownership levels (see Kockelman [2000b] for an example application of this specification); however, this model's maximum-likelihood estimation would not converge due to the dispersion parameter's tendency for near-zero values. Finally, a series of independent, non-simultaneous Poissons was run, without the price-over-income variable, and the pseudo- R^2 of this model was 4.93%.

¹³ For example, the average household pickup age in the 1995 NPTS data set was 8.22 years, versus 6.83 for passenger cars. The average age of minivans and SUVs in the sample was just 4.72 and 5.16 years, which may be due to the fact that these body types have not been available in the market for nearly as long as pickups and passenger cars.

¹⁴ The average van and pickup sold in 1997 were 8.2 and 16.2% longer and 9.2 and 12.2% wider, respectively, than the average car.

TABLE 6 Multinomial Logit Model for Newest Vehicle Owned

Variable		Beta	SE	<i>t</i> -stat	P-value
	SUV	-3.137	0.096	-32.6	0.000
Constant	Pickup	-1.258	0.067	-18.9	0.000
	Minivan	-3.515	0.093	-38.0	0.000
Vehicle price/household in	ncome	-0.660	0.074	-9.0	0.000
	SUV	0.242	0.020	11.9	0.000
Household size	Pickup	-0.058	0.016	-3.5	0.000
	Minivan	0.542	0.018	30.6	0.000
	SUV	-2.81E-05	4.19E-06	-6.7	0.000
Population density	Pickup	-6.91E-05	4.21E-06	-16.4	0.000
	Minivan	-3.93E-05	4.25E-06	-9.3	0.000
Incomo por	SUV	1.78E-05	1.58E-06	11.2	0.000
household member	Pickup	-1.55E-05	1.58E-06	-9.8	0.000
nousenoid member	Minivan	1.15E-06	2.08E-06	0.6	0.580
Number of vahialas	SUV	0.206	0.04	5.9	0.000
already owned	Pickup	0.193	0.03	6.9	0.000
alleady Owned	Minivan	-0.046	0.04	-1.3	0.209
Number of cars	SUV	0.016	0.04	0.4	0.696
already owned	Pickup	0.362	0.03	10.8	0.000
	Minivan	0.135	0.04	3.2	0.001
Log-likelihood function					
Constant only	-28,725.37	,			
Convergence	-27,080.58				
Pseudo-R ²	0.057				
Number of observations: 30,9	49 households				
Model form: Pr(ushicle cho	$(an) = \Pr(u > u) \forall i$	$+i - (\theta' + \alpha) > \theta$	$V' = \alpha \forall i \neq i$		

Dependent variable: newest vehicle owned

These ownership models are based on a single, 1995 cross-section of data. In reality, preferences, products, and markets change over time. With a panel data set, temporal ownership patterns could be analyzed, illuminating consumer trends and providing more insights to policymakers. However, the 1995 NPTS data are useful in that they validate many commonly held perceptions about present consumption of light-duty trucks versus passenger cars. For example, larger household sizes favor minivans the most, SUVs next, and pickups least. Higher income households favor SUVs but not pickups, and lower population densities favor pickups the most and passenger cars the least.

 $\sum \exp(\boldsymbol{\beta}_i' \boldsymbol{x}_i)$

CONCLUSIONS

The U.S. government has taken an active regulatory stance in the area of emissions, as well as the safety, fuel economy, and size of different vehicle types. In many ways, cars and light-duty trucks, including minivans, SUVs, and pickups, are regulated very differently even though households may use them for very similar purposes. This paper presented an investigation of the 1995 Nationwide Personal Transportation Survey data set for evidence of household use differences across lightduty trucks and passenger cars in the United States.

Total vehicle-miles traveled, daily person-trips served, vehicle occupancies, drivers' vehicle type choices, and household ownership choices were analyzed to illuminate any significant differences in

Variable	Beta	SE	<i>t</i> -stat	P-value
Vehicle price/income	-0.2213	0.0075	-29.40	0.000
Car:				
Constant	0.148	0.021	7.03	0.000
Household size	0.0699	0.0043	16.30	0.000
Population density	-0.1519	0.0081	-18.70	0.000
Income per HH member	0.02	0.0042	4.77	0.000
SUV:				
Constant	-2.8437	0.0553	-51.40	0.000
Household size	0.273	0.0118	23.10	0.000
Population density	-0.4526	0.0311	-14.60	0.000
Income per HH member	0.1899	0.0095	20.00	0.000
Pickup:				
Constant	-0.6725	0.0383	-17.60	0.000
Household size	0.0715	0.008	8.92	0.000
Population density	-0.9598	0.0281	-34.20	0.000
Income per HH member	-0.1102	0.0093	-11.80	0.000
Minivan:				
Constant	-3.1526	0.058	-54.30	0.000
Household size	0.4446	0.0103	43.00	0.000
Population density	-0.3993	0.0303	-13.20	0.000
Income per HH member	0.0262	0.0141	1.86	0.031
Log-likelihood function				
Constant only	-89026.8			
Convergence	-84399.8			
Pseudo-R ²	0.0520			

TABLE 7 Simultaneous Poissons Model for Vehicle Fleet Ownership

Model form: Number of vehicles of type *i* owned ~ Poisson (λ_i) with $\lambda_i = \exp(\beta_i X_i) + \beta_{\text{price/income}} \times \text{Price/Income}$

vehicle use. Weighted least squares (for VMT), negative binomials (for person-trips), ordered probit (for occupancy), multinomial logits (for vehicles chosen by drivers [for trip-making] and for newest vehicle owned), and an MNL conditioned on a Poisson (for fleet combinations) were the stochastic specifications employed.

While the NPTS questionnaires do not target special uses of LDTs by households specifically, analysis of these data offers insights and does suggest use differences. In general, it appears that households drive LDTs significantly more miles (up to 25% more, on average). Minivans are found to carry more occupants on any given trip and serve 35% more person-trips over the course of a day than passenger cars, while pickups are associated with significantly fewer occupants per trip and 15% fewer person-trips. SUVs, on the other

hand, are used for the same number of person-trips as passenger cars, and their occupancies are quite similar, except in the case of vehicle trips made for recreational purposes.

Light-duty-truck ownership decisions are strongly associated with household size, incomes, population density, and vehicles already owned. For example, SUVs are more likely to be found in higher income, larger households in low-density environments with multiple vehicles. In terms of within fleet vehicle choice for trip making, several driver and trip characteristics are relevant. For example, males are far more likely to drive a pickup, and employed persons are unlikely to drive the household minivan. Pickups are more common for work-related trips, and SUVs are a more likely choice for weekend trips.

Taken together, the various models' results suggest that, when available, LDTs are used more regularly than cars for trips of a personal nature. However, the NPTS data offer no strong indications that minivans and SUVs are used as "work" vehicles, the original basis for separate classification of LDTs from passenger cars. Pickups are more popular among households than they were 20 years ago when American life was less urban, so it is not clear that pickups are performing unusual services either.

Even if LDTs perform special services for their owners, such as towing boats, hauling home furniture, or carrying many occupants, these benefits largely accrue only to their owners. In fact, such vehicles impose many negative externalities (Kockelman 2000a, Kockelman and Shabih 2000). Thus, it may be argued that their owners should be paying for these impacts rather than enjoying more lenient regulation.

ACKNOWLEDGMENTS

The authors wish to acknowledge the University of Texas at Austin Department of Civil Engineering and the Luce Foundation for their support of this research effort.

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