

Passenger Car Equivalents of Light Duty Trucks and the Costs of Mixed Vehicle Traffic: Evidence from Michigan

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This study uses naturalistic data from drivers operating instrumented vehicles to estimate the following distance by vehicle type and compute the passenger car equivalents of light duty trucks (LDTs). Unlike most previous studies, this study separates LDTs by vehicle type and produces evidence that cars follow different types of LDTs at different distances. While car drivers follow pickup trucks more closely, they follow SUVs and minivans at a greater distance. The external cost on the transportation system is estimated to be approximately \$37 million annually in the Detroit area and \$2.05 billion annually for the United States as a whole.

INTRODUCTION

Traffic congestion is a growing problem in urban areas of the United States. According to the 2010 Urban Mobility Report (Schrank et al. 2010), traffic congestion levels have worsened in all of the 439 urban areas studied over the past 25 years. More specifically, roads are congested for an increasing portion of the day and more roads are congested. The costs of extra time and fuel due to congestion increased from \$24 billion in 1982 to \$115 billion in 2009, measured in constant 2009 dollars.

Sport utility vehicles (SUVs), pickup trucks, and minivans, collectively referred to hereafter as light duty trucks (LDTs), comprise a significant proportion of vehicles on the road today and add to the congestion problem because they require more space on the road than passenger cars, hereafter referred to as cars. According to the National Auto Dealers Association, from 2001 through 2009, an average of 52% of new vehicles sold each year were LDTs (AutoExec 2010). Several attributes of LDTs result in them requiring more space on the road than cars. First, LDTs are longer. Specifically, the average SUV is 6.7% longer, the average pickup truck is 28.2% longer, and the average minivan is 9.3% longer than the average car.¹ While LDTs are also significantly heavier and their drivers may perceive them to require more stopping distance, this aspect is conservatively ignored in this research.

In addition to their greater length, LDTs are higher (21% to 30%) and wider (5% to 17%) than cars. Using data from the Automotive News annual Market Data Books (for model years 2003-2006), weighted average characteristics were computed for cars, SUVs, pickup trucks, and minivans, weighted by total sales for the top 10 cars, top five SUVs and pickup trucks, and top three minivans from 2002-2005. The vehicles included in these calculations comprise 34% of new cars and 45% of new light duty trucks sold between 2002 and 2005. Table 1 collects data on the differences in length, height, width, and weight. For all vehicle types, the mean values are provided. In addition, for SUVs, pickup trucks, and minivans, the percentage difference from the mean car value is provided.

The greater height and width causes areas of blocked vision, or “blind spots,” for cars following LDTs. To maintain a consistent level of safety, the driver should allow a greater following distance behind an LDT than behind a car, given the unknown road situation in front of the LDT. In other words, the total road space needed by a vehicle while driving includes not only the length of the vehicle but also the following distance to the next vehicle. If data reveal that car drivers follow LDTs at a greater distance than they follow cars, then LDTs followed by cars require more total

road space than cars, both for their longer length and for the greater following distance of the car. This result would lead to important implications for traffic congestion and for the manner in which transportation planners compute road capacity. Cosgrove and Holahan (2010) provide evidence that the traffic flow rate with mixed vehicle types (cars and LDTs) is lower than uniform traffic flow. Thus, congestion time costs are higher than they would be with uniform traffic. Likewise, road capacity is reduced with mixed vehicle traffic compared with uniform traffic.

Table 1: Difference in Specifications by Vehicle Type and Percent Difference from Cars

	Length (in.)	Width (in.)	Height (in.)	Weight (lbs.)
Cars	181.1	70.1	56.9	3100.1
SUVs	193.2 (6.7%)	73.8 (5.3%)	71.7 (26.0%)	5943.7 (91.7%)
Pickup Trucks	232.3 (28.2%)	81.9 (16.8%)	74.3 (30.6%)	8702.8 (180.7%)
Minivans	198.0 (9.3%)	77.6 (10.7%)	69.0 (21.2%)	5729.2 (84.8%)

Note: Values are weighted averages of the specifications for top 10 cars, top five SUVs, top five pickup trucks, and top three minivans sold between 2002 and 2005. The autos included in these calculations comprise 34% of new cars and 45% of new light duty trucks sold between 2002 and 2005. In order of number sold, cars: Toyota Camry, Honda Accord, Honda Civic, Ford Taurus, Chevrolet Impala, Toyota Corolla, Chevrolet Cavalier/Cobalt, Nissan Altima, Ford Focus, Chevrolet Malibu; SUVs: Ford Explorer, Chevrolet Trailblazer, Jeep Grand Cherokee, Chevrolet Tahoe, Jeep Liberty; pickup trucks: Ford F series, Chevrolet Silverado, Dodge Ram, Chevrolet Sierra, Ford Ranger; minivans: Dodge Caravan, Honda Odyssey, Toyota Sienna.

This paper should be of interest to policymakers and transportation professionals because the country is experiencing increasing traffic congestion with little space and funding to expand highway capacity. In the event of highway expansion, the current capacity approach overstates the capacity by not accounting for the effects of mixed vehicle traffic. In the absence of highway expansion, the results of this study can be used to determine appropriate variable pricing by vehicle type to reduce the congestion problem.

This study has several objectives. The first objective is to determine whether car drivers behave differently when following LDTs than when following cars. More specifically, given the ambiguous results of previous work in the field, this study aims to clarify those mixed results and provide a more certain conclusion. Assuming there is a behavioral difference, the next objective is to develop an equation for an appropriate adjustment factor for LDTs to include in the standard capacity calculation in the Highway Capacity Manual (2000). Using that adjustment factor, this study predicts the relationship between the percentage of vehicles that are LDTs and capacity. Finally, a computation of the increased costs from mixed vehicle traffic is included.

The second section discusses the existing literature on the topic. The third section explains the data used in the study. The empirical model is presented in the next section. The fifth section explains the regression results. The sixth section explains the adjustment to the capacity calculation and discusses the relationship between vehicle mix and capacity. The next section discusses congestion costs from mixed vehicle traffic and is followed by the conclusion.

LITERATURE REVIEW

The existing literature on following behavior with mixed vehicle types provides ambiguous results on driver behavior. In an early study on the topic, Evans and Rothery (1976) found that lead vehicle size does not significantly affect following distance. In contrast, Yoo and Green (1999) found that drivers in a simulation followed cars approximately 10% closer than they followed pickup trucks,

school buses, and tractor trailers. The authors caution that all headways observed in the study were much greater than those typically reported in on-the-road studies.

Sayer et al. (2000) used instrumented passenger cars to derive naturalistic following data, i.e., driving as they “naturally” would, same speeds, routes, level of aggression, in a 1996-1997 Intelligent Cruise Control Field Operational Test.² The authors had 1,698 observations of 70 drivers and observed a vehicle mix of 65% passenger cars, 35% LDTs. They found that cars followed LDTs an average of 5.6 meters or 0.19 seconds in headway time margin more closely than they followed other cars, in contrast to their a priori expectation of driver behavior. The authors speculate that perhaps car drivers ignore the possible dangers in front of the LDTs because they are unable to see them, among other possible explanations.

Kockelman and Shabih (2000) assessed capacity at signalized intersections and found that it is reduced due to greater following distance of cars behind LDTs. They computed an aggregate LDT passenger car equivalency of 1.19, indicating that LDTs require approximately 20% more road space through intersections than cars.

Most recently, Brackstone et al. (2009) studied six subjects driving two test routes in an instrumented vehicle in the United Kingdom. They observed very few LDT following events in some speed categories, thus limiting their analysis to headways at speeds greater than 20 meters per second. They found that, in general, cars follow LDTs more closely than they follow cars and suggested the same reasons offered by Sayer et al. (2000).

Given the mixed results and limited number of observations or drivers in some studies, a current comprehensive analysis is in order. This study includes more current data, more observations, and more subjects than most previous studies. Moreover, subjects have free driving range on their typical daily routes and they were completely unaware that their following behavior by vehicle type would be assessed. Finally, and perhaps most importantly, this study separates the lead vehicle LDT into different types of LDTs and studies corresponding following behavior.

DATA TO ESTIMATE FOLLOWING DISTANCE

The University of Michigan Transportation Research Institute generously shared the rich dataset used for this study. The data were collected for the Road Departure Crash Warning (RDCW) System Field Operational Test from May 2004 through February 2005. Eleven Nissan Altima four-door sedans were equipped with two road departure warning systems, video cameras capturing the forward scene, and data collection systems, which recorded data continuously at 10Hz or higher while the car was being operated. The purpose of the test was to assess the effectiveness of the road departure warning systems; however, the extremely rich behavioral data collected in the test coupled with the videos of what drivers saw are ideal for a vehicle following study. Different from most previous studies on the topic, drivers were completely unaware that any of the data would be used for a vehicle following study because the data were collected for a distinctly different purpose. Therefore, the behavior captured is representative of their normal driving patterns.

Drivers were recruited from the general population in the southeast Michigan area including Detroit, surrounding suburbs, and rural areas and ranged in age from 20 to 70 years old. Each driver was instructed to use the instrumented car in place of their primary vehicle, driving where and how they normally would, for four weeks. The road departure warning systems were inactive during the first week for each driver to provide control data for the primary study and were activated for the remaining three weeks.³ Of the 87 original drivers, complete data for this study were available for 65 drivers.

To extract the relevant data for this study, a “following event” was defined as the instrumented vehicle maintaining a range rate, or rate of change of range to the lead vehicle, of \pm one meter per second (m/s). The observations were restricted to highway driving during daylight hours (defined as solar zenith angle between zero and 90 degrees) when windshield wipers were off to avoid driving in the dark and inclement weather, which may alter decisions about following distance. Because

the primary concern of this paper is the effects of any blind spot externality on congestion costs, the observations were further restricted to include only travel during dense traffic conditions when congestion would increase the time cost of travel.⁴ Presumably, in uncongested traffic if faced with a blind spot from a lead LDT, a car driver could change lanes with ease to alleviate the blind spot externality, thus the blind spot in uncongested traffic does not impose an external cost. Finally, a driver was excluded from the dataset if there were not at least two observations following a car and following an LDT.

Still video images for each observation were viewed to determine the type of vehicle the driver was following, hereafter, lead vehicle type. Lead vehicles could be accurately classified by type at a maximum of three seconds of headway time at highway speeds. Images were examined for the 4,010 observations that met the criteria specified above. Of these, 40 observations were dropped because the pictures were too bright, too dark, or completely black. Three additional observations were discarded because the road was snow covered, which likely affects driver following distance. Eight more observations were discarded because the lead vehicle type was a motorcycle and motorcycle following behavior may be different than car or LDT following behavior, with an insufficient number of observations to evaluate in its own category in this study. Thus, 3,959 observations remained. Summary statistics for all variables are provided in Table 2.

Table 2: Summary Statistics

Variable Name	Mean	Std Dev	Minimum	Maximum
dist (m)	29.35	15.96	1.69	120.69
secfol	1.17	0.65	0.50	6.30
leadpickup	0.12	0.32	0	1
leadsuv	0.25	0.43	0	1
leadminivan	0.12	0.32	0	1
leadhtruck	0.07	0.25	0	1
male	0.50	0.50	0	1
pickupprimary	0.13	0.33	0	1
suvprimary	0.11	0.32	0	1
minivanprimary	0.13	0.34	0	1
yearsdriving	25.24	14.69	2.5	54
engage	1.81	0.99	1	5
engagemale	0.87	1.06	0	4
speedcat5	0.02	0.15	0	1
speedcat10	0.05	0.21	0	1
bachelors	0.32	0.47	0	1
graduate	0.17	0.38	0	1
logincome	11.02	0.35	10.18	11.76
speedcat15	0.05	0.22	0	1
speedcat20	0.07	0.25	0	1
speedcat25	0.09	0.28	0	1
speedcat30	0.28	0.45	0	1
speedcat35	0.37	0.48	0	1
speedcat40	0.07	0.26	0	1
targets	4.70	2.01	0	12
RDCWdisabled	0.33	0.47	0	1

EMPIRICAL MODEL

To determine whether car drivers follow LDTs and heavy trucks at a greater distance than they follow other cars, an OLS regression model was used with two different dependent variables, following distance and following time. The model, while consistent with the general form of similar research in the field, includes a richer set of explanatory variables to capture the key variables of interest and control for driver characteristics that may affect following behavior. The model is shown in equation 1.

$$(1) \text{ dep}_{it} = \beta_1 \mathbf{LDT}_{it} + \beta_2 \mathbf{Htruck}_{it} + \beta_3 \mathbf{DEM}_i + \beta_4 \mathbf{Speedcat}_{it} + \beta_5 \mathbf{Targets}_{it} + \beta_6 \mathbf{RDCWdisabled}_{it} + \varepsilon_i$$

where

dep = *dist* or *secfol*

i = individual driver

t = following event

LDT_{it} is a vector of LDT lead vehicle types

DEM_i is a vector of demographic variables

Speedcat_{it} is a vector of speed categories

In addition to the OLS model, a fixed effects model was also estimated in case of endogeneity of driver characteristics for which demographic variables could not control. A comparison of the two models shows no bias in the OLS estimation coefficients. Thus, the OLS model is chosen because it provides some interesting information on the differences in driving behavior by demographics.⁵

Both time and distance are used as dependent variables in this study. Each instrumented vehicle was equipped with forward-looking radars to detect the distance to the lead vehicle. The variable *dist* is the following distance measured in meters. Time is measured as the number of seconds the instrumented vehicle is following behind the lead vehicle, indicated by variable *secfol*. Table 3 illustrates the mean values of following distance and following time by lead vehicle type and the comparison to a car following a car. The mean following distance and time are longer for cars following all categories of non-cars, except for pickup trucks.

Table 3: Summary of Dependent Variables by Lead Vehicle Type

Lead Vehicle Type	Following Distance (meters)		Seconds Following	
	Mean	% of Car	Mean	% of Car
Car	27.9	-	1.14	-
Pickup	27.1	-2.9%	1.09	-4.4%
SUV	32.4	16.1%	1.23	7.9%
Minivan	28.9	3.4%	1.16	1.8%
Heavy Truck	32.4	16.1%	1.34	17.5%

The key variable of interest in this empirical work is the lead vehicle type. While most previous studies grouped all LDTs in one category, the data in this study are rich enough to support separating LDTs into pickup trucks, SUVs, and minivans, creating three distinct variables: *leadpickup*, *leadSUV*, and *leadminivan*. This is an important advantage over previous work because following driver behavior may vary by these vehicle types due to their differences in size, window placement, and likelihood of windows being tinted. While there are clearly differences in the sizes of different models of pickup trucks and SUVs, some of the images were not clear enough to determine the exact make and model of the lead vehicle so these categories could not be defined more narrowly. A category for heavy trucks and a corresponding variable, *leadhtruck*, was also included where heavy trucks were defined as those with more than four tires, in accordance with the Highway Capacity

Manual's definition of heavy vehicles (2000). The expected signs on all these variables are positive, indicating that drivers follow LDTs and heavy trucks at a greater distance than they follow cars.

Several demographic variables were collected from the drivers, and are included in the analysis to control for differences in driving behavior. *Male* is an indicator variable for gender, taking a value of one for males and zero for females. Typically, males are considered to be more aggressive drivers than females so the expected sign of *male* is negative indicating that they follow more closely than females. More driving experience is expected to cause drivers to leave a bigger cushion between them and vehicles they follow. Thus, a *yearsdriving* variable is included to account for the number of years a subject has been driving and is expected to be positive. Because this variable is so closely correlated with age, no additional age variable is included. If drivers with higher incomes have a greater value of travel time, they may follow more closely. A *logincome* variable is included to capture this possible effect with an expected negative sign. Finally, categorical education variables for attaining a bachelor's degree, *bachelor*, and a graduate degree, *graduate*, are included to control for the fact that more educated drivers may be more cognizant of the risks of following too closely. If this hypothesis holds, the signs on the education variables will be positive.

In addition, because not all drivers in the study typically drive cars, it is important to consider the type of vehicle they drive on a routine basis. Drivers who typically drive LDTs may exhibit more caution when following LDTs in a car because they are unaccustomed to blocked vision from a lead vehicle. Indicator variables for drivers' primary vehicle type, *pickupprimary*, *suvsprimary*, and *minivanprimary*, take a value of one if the driver's primary vehicle is a pickup truck, SUV, or minivan, respectively, zero otherwise. These variables are expected to have a positive sign, indicating greater following distance.

All drivers participating in the study completed a behavioral questionnaire before they were given the instrumented vehicle. One question is particularly relevant to this study. Drivers were asked how often they engage in "tailgating," with responses varying from "never" (1) to "most of the time" (7). Driver responses to this question are indicated in the *engage* variable, which is expected to have a negative sign. Because men reported that they engaged in tailgating less frequently than women, an interaction term, *engagemale*, was included. While these types of self-reported behavioral questions do not tend to be particularly informative, they may serve to differentiate drivers by their degree of risk aversion.

Observation specific variables include speed categories, a measure of relative density, and whether the crash warning system was enabled. Following behavior inherently differs with the rate of traffic flow, thus some measure of speed is essential to the model. To avoid multicollinearity between speed and the dependent variable, either distance or time, speed is converted to a categorical variable in increments of five m/s. The variables are *speedcat* in eight increments and the fastest, *speedcat40*, is used as the base case. Given that the fastest speed is used as the base, the sign on the remaining speed category variables is expected to be negative, indicating that cars follow more closely at slower speeds. The *targets* variable counts the number of other vehicles detected by the radar in front and in the surrounding lanes of the instrumented vehicle and serves as a measure of traffic density. The expectation is that the *targets* variable will have a negative sign because more traffic density leads to following more closely. Finally, the *RDCWdisabled* variable takes a value of one when the Road Departure Crash Warning system is disabled. It may be important to control for the system if having it enabled prompts drivers to behave more cautiously, including following at a greater distance.⁶ In this case, the *RDCWdisabled* variable would have a negative sign.

REGRESSION RESULTS

The results of the regressions are presented in Table 4 and summarized below. The key variables tell an interesting story. *Ceteris paribus*, car drivers follow pickup trucks more closely than they follow cars, but car drivers leave a greater cushion between themselves and SUVs, minivans (insignificant in one model), and heavy trucks than other cars. In detail, cars follow pickup trucks 0.05 seconds

and 1.7 meters, about 5%, more closely than cars. However, cars follow SUVs at a mean time of 0.12 seconds and at a mean distance of 3.2 meters, about 9%, farther than they follow cars, and they follow minivans 0.06 seconds and 1.1 meters, about 3%, farther than they follow cars. Likewise, cars follow heavy trucks at a mean time of 0.15 seconds and at a mean distance of 2.9 meters, about 8%, farther than they follow cars. While these magnitudes are small, they may have a large effect on aggregate congestion costs. Two reasons may explain the difference in following time and distance between pickup trucks and other categories of LDTs. First, while most SUVs and minivans have tinted windows on the back of the vehicle, many pickup trucks do not. Clearly, tinted glass creates a greater visual barrier for the following driver. Secondly, pickup trucks without cabs create less of a visual barrier than SUVs and minivans, which have bodies that extend the full height and length of the vehicle.

Table 4: Results from Regression Analysis

Variable	Dist	std error	secfol	std error
constant	83.171*	9.645	3.095*	0.390
leadpickup	-1.672**	0.734	-0.053***	0.030
leadsuv	3.247*	0.559	0.121*	0.023
leadminivan	1.124	0.732	0.059**	0.030
leadhtruck	2.925*	0.939	0.150*	0.038
male	-6.538*	0.988	-0.296*	0.040
pickupprimary	1.553**	0.797	0.075**	0.032
suvprimary	-2.239*	0.842	-0.118*	0.034
minivanprimary	-1.954*	0.784	-0.036	0.032
yearsdriving	0.181*	0.020	0.006*	0.001
engage	-2.116*	0.493	-0.114*	0.014
engagemale	1.651*	0.493	0.096*	0.020
bachelors	2.515*	0.606	0.124*	0.024
graduate	0.324	0.734	0.007	0.030
income	-4.069*	0.919	-0.176*	0.037
speedcat5	-30.578*	1.758	1.464*	0.071
speedcat10	-23.751*	1.326	0.732*	0.054
speedcat15	-17.435*	1.312	0.465*	0.053
speedcat20	-12.515*	1.246	0.331*	0.050
speedcat25	-9.632*	1.138	0.161*	0.046
speedcat30	-4.540*	0.959	0.118*	0.039
speedcat35	-2.925*	0.912	0.023	0.037
Targets	-0.564*	0.122	-0.023*	0.005
RDCWdisabled	-0.001	0.487	0.032	0.020
F	53.07		55.24	
R ²	0.237		0.244	
Adj R ²	0.232		0.239	

*Denotes significance at the 1% level.

**Denotes significance at the 5% level.

***Denotes significance at the 10% level.

Two important outcomes can be drawn from these results. First, drivers following SUVs leave a distance and time cushion about equal to their cushion for tractor-trailers, school buses, and other heavy trucks. While the HCM applies an adjustment factor to heavy trucks when computing capacity, no such adjustment factor is currently applied to SUVs.⁷ The second significant outcome is that the results distinguish this study from previous similar studies because previous work did not separate the LDTs by type and, consequently, did not reveal the varying behavior by lead vehicle type. Perhaps this explains the ambiguous results of previous studies. It is likely, given these results, that studies with higher percentages of observations where the lead LDT was a pickup concluded that drivers follow LDTs more closely, while studies with higher percentages of observations where the lead LDT was an SUV concluded that drivers follow LDTs at a greater distance.

Before moving to the capacity implications and congestion costs from mixed vehicle traffic, several additional conclusions can be drawn from the results regarding driving habits. First, male drivers follow more closely than female drivers, *ceteris paribus*. Also, consistent with expectations, as driving experience increases, following distance increases. In addition, a 1% increase in income results in drivers following 4.1 meters more closely, perhaps indicating their higher time value of money. Interestingly, drivers with a bachelor's degree follow at a greater distance than drivers with a high school diploma and/or some college experience; however, following behavior of drivers with a graduate degree does not differ significantly from drivers with a high school diploma. Perhaps the drivers with graduate degrees have a higher time value of money.

Drivers' primary personal vehicle type influences their following distance. Drivers whose primary personal vehicle is a pickup truck allowed a larger cushion between their car and the lead vehicle than other drivers. Perhaps these drivers felt relatively less secure driving the small car compared with the large truck to which they are accustomed. However, drivers whose primary personal vehicle is an SUV or a minivan followed more closely than other drivers.

Drivers who stated in a questionnaire that they engaged in tailgating behavior frequently did follow more closely than drivers who denied frequently engaging in tailgating behavior. With regard to speed, there is a clear and expected pattern of following at a greater distance at higher speeds, compared with the base speed category of 40 m/s. Likewise, the seconds following are lower at higher speeds than the base speed category. Finally, when more targets, other persistent vehicles moving in the same direction, were present on the road, drivers followed more closely. This result is logical given that cars tend to group more closely with increased traffic.

THE EFFECTS OF VEHICLE MIX ON CAPACITY

The empirical results confirm that driver behavior differs depending on the type of vehicle the driver is following. As a result, it is important to consider the effects of vehicle mix on road capacity. Under conditions of uniform traffic, as additional vehicles are added to traffic flow, those vehicles travel at a free flow speed and incur no time cost of travel until a congestion point is reached, after which each additional vehicle added to the traffic flow increases its own travel time cost as well as the cost of other drivers on the road. This is shown by the well-known speed-flow curve (Walters 1961). Cosgrove and Holahan (2010) illustrate that the congestion point will be reached at a lower flow rate and the marginal and average time cost will increase more rapidly than with uniform traffic. The next step in this analysis is to compute the effects of mixed vehicle traffic on the traffic flow rate and evaluate consequent changes in time cost.

An adjustment factor, similar to the heavy vehicle factor in the HCM, is needed to evaluate the effect of mixed traffic on capacity. The standard HCM (2000) calculation for peak capacity is

$$(2) \text{ PeakCap} = \text{BaseCap} \times \text{PHF} \times N \times f_{HV} \times f_p$$

where:

PeakCap = peak capacity, in terms of vehicles per hour (all lanes, one direction)

BaseCap = base capacity, in terms of passenger cars per hour per lane

PHF = peak hour factor; a variable used to account for variations in flow within the peak hour, U.S. HCM recommends a default value of 0.92 for urban areas.

N = number of lanes in one direction

f_{HV} = adjustment factor for heavy vehicles

f_p = adjustment factor for driver population; value set to 1 on urban freeways indicating that the drivers are familiar with roadway and traffic conditions.

The HCM (2000) heavy vehicle adjustment factor is illustrated in equation (3).

$$(3) \quad f_{HV} = \frac{1}{1 + P_T(E_T - 1) + P_R(E_R - 1)}$$

where:

P_T = percentage of traffic that is heavy trucks and buses

E_T = passenger car equivalent for heavy trucks, which is 1.5 on level freeway segments

P_R = percentage of traffic that is recreational vehicles

E_R = passenger car equivalent for recreational vehicles, which is 1.2 on level freeway segments

To create an adjustment factor for LDTs, passenger car equivalents (PCEs) will need to be calculated for each type of LDT. There are several methods for computing PCEs. A form of a mean headway approach is chosen here due to the available data. Typically, headways are computed from the front bumper of the lead vehicle to the front bumper of the following vehicle. Each observation in this study shows following time and distance from the rear bumper of the lead vehicle. Due to the nature of the study, all following vehicles were cars. To accurately reflect the PCE for the different LDT types given the data in this study, the computation must include the length of the vehicle and the lagging headway. Thus, in this case, distances rather than times are used in the calculation, and the average length of the lead vehicle by vehicle type is added to the following distance. Equation (4) was used to compute the mean headways by vehicle type.

$$(4) \quad H_{v,s} = Length_v + FollowingDistance_{c,s} + \partial FollowingDistance_v$$

where

H = headway

V = vehicle type (cars, pickups, minivans, SUVs)

S = speed category

$FollowingDistance_{c,s}$ = following distance for car-car pairs by speed category

$\partial FollowingDistance_v$ = change in following distance by vehicle type

The average lengths by vehicle type are: cars—4.600 meters, pickups—5.900 meters, minivans—5.029 meters, and SUVs—4.907 meters.⁸ For a baseline, the car-car headways were computed at each of the eight speed categories using the regression results in Table 4. Next, the LDT-car headways were computed for each of the three LDT types at each of the eight speed categories. A weighted average of the headways by the number of observations from each speed category was taken to arrive at the final headway values for each vehicle type. Finally, equation (5) was used to compute the passenger car equivalencies for each LDT type.

$$(5) E_V = \frac{H_V}{H_C}$$

where:

E_V is the passenger car equivalency for each vehicle type

H_V is the weighted average headway by vehicle type from the front bumper of the lead vehicle to front bumper of the following vehicle

H_C is the mean headway for cars from the front bumper of the car to front bumper of the following car

The PCEs by vehicle type are: pickups—0.99, minivans—1.04, SUVs—.09.

These PCEs can now be incorporated into the standard HCM capacity equation (2000) to adjust for the effects of LDTs in traffic.⁹ Equation 6 shows the proposed LDT adjustment factor akin to the existing heavy vehicle adjustment factor from equation 3.

$$(6) f_{LDT} = \frac{1}{1 + P_p(E_p - 1) + P_m(E_m - 1) + P_s(E_s - 1)}$$

where:

P_p = percentage of traffic that is pickup trucks

E_p = passenger car equivalent for pickup trucks

P_m = percentage of traffic that is minivans

E_m = passenger car equivalent for minivans

P_s = percentage of traffic that is SUVs

E_s = passenger car equivalent for SUVs

In the sample studied, pickup trucks were the lead vehicle in 12% of the observations. Minivans were the lead vehicle in 12% of the observations and SUVs were the lead vehicle in 25% of the following events. These values are reasonable to use in the adjustment factor calculation as they combine to 49%, which is close to the 52% of new vehicles sold between 2001 and 2009 that were LDTs (AutoExec 2010). As a result, the LDT adjustment factor is 0.975. In other words, *ceteris paribus*, the presence of this combination of LDTs reduces highway capacity by 2.5%.

CONGESTION COSTS FROM MIXED VEHICLE TRAFFIC

Any estimation of the congestion costs from mixed vehicle traffic must be made and interpreted with caution given the number of variables involved. For a reasonable, albeit conservative, approximation, the 2010 Urban Mobility Report (UMR) data for the Detroit area can be used with the data above to estimate the spillover cost from mixed vehicle traffic. According to the UMR, the annual congestion cost for the Detroit area in 2009 was \$2.032 billion. UMR uses a value of time equal to \$16.01 per hour and a commercial value of time for heavy truck traffic equal to \$105.67 per hour. The report counts 250 working days per year and assumes a vehicle-occupancy rate of 1.25 passengers per vehicle. It is important to note that a disproportionate amount of the cost tallied in the UMR stems from heavy truck traffic, which would be present with or without LDTs. The UMR attributes \$551 million of the total cost for Detroit to heavy truck congestion costs (Schrank and Lomax 2010). The remaining \$1.481 billion results from mixed LDT and car traffic.

The relationship between capacity and delay costs is nonlinear. However, without a complex simulation that is outside of the scope of this paper, it is difficult to apply this nonlinear relationship to link the capacity reduction to delay costs. As a result, a linear relationship is assumed. This assumption could present two problems. The first would result in an overstatement of costs

associated with mixed vehicle traffic while the second would result in an understatement of these costs. First, when demand is relatively low, a reduction in capacity may not cause any delay at all. This problem does not affect the computations included in this paper because the UMR only accumulates costs when delay is occurring. Therefore, there is no overstatement of costs associated with mixed vehicle traffic. Second, when demand is relatively high, a reduction in capacity is likely to result in a much greater than proportional increase in delay. Assuming a linear relationship smooths the exponential increase in the speed-flow curve (Walters 1961) and, thus, understates the true costs of LDTs in the traffic mix. While this approach is suboptimal, it provides a conservative estimate of the effects of LDTs on delay costs.

Using the UMR data and the adjusted highway capacity level computed above, a comparison can be made between the costs when traffic comprises only cars and heavy trucks and when LDTs are added to the traffic mix. Compared with the mixed vehicle scenario, 2.5% more capacity would exist if only cars and heavy trucks were in traffic. Assuming a linear relationship between capacity and delay costs, \$37 million annually in congestion costs could be avoided without LDTs in the traffic mix.

Care must be taken in applying the estimates from Detroit to the remainder of the country because of potential differences in driving behavior, composition of traffic, and congestion levels. However, a rough estimate of the nationwide annual congestion cost from delay attributable to the mix of cars and LDTs can be derived in the same format described above. UMR estimates \$115 billion in annual congestion costs nationally, of which \$33 billion is attributed to heavy trucks (Schrank and Lomax 2010). Applying the 2.5% reduction in capacity found in the Detroit area, the additional congestion cost from LDTs in the vehicle mix is \$2.05 billion annually for the United States. It is important to point out that these conservative calculations account for congestion costs only. There are documented safety effects of vehicle mismatch and corresponding accident costs. The computation of those costs is outside the scope of this paper.

CONCLUSION

This analysis results in several interesting conclusions. For the first time in a study of mixed vehicle traffic, LDTs are divided into categories, and the estimates reveal that following behavior differs dramatically by these categories. Car drivers follow pickup trucks more closely than they follow cars, and car drivers leave a cushion behind SUVs about equal to the distance they leave behind heavy trucks. The additional following distance behind SUVs results in a PCE of 1.09, while pickup trucks are nearly equivalent to cars with a PCE of 0.99. The capacity of a highway computed using the standard HCM equations is overstated by 2.5%, given the percentages of each type of LDT present in this study. The external cost on the transportation system is estimated to be approximately \$37 million annually in the Detroit area and \$2.05 billion annually for the United States as a whole.

While the reduction in capacity and corresponding external time cost from mixed vehicle traffic is not huge, there are policy implications from these results. First, the effects of the blind spot externality could be internalized with a toll that varied by vehicle type. For a discussion of this approach, see Cosgrove and Holahan (2010). Moreover, transportation planners should incorporate the PCE for SUVs when computing expected capacity from lane additions or extensions so that they do not overstate the benefits of an expansion project.

Endnotes

1. Values are weighted averages of the specifications for the top 10 cars, top five SUVs, top five pickup trucks, and top three minivans sold between 2002 and 2005.
2. The cars were outfitted with cameras, radars, and computers to record extensive data every time the vehicle was being operated.

Passenger Car Equivalents

3. For additional details on the RDCW Field Operational Test, please see LeBlanc et al. (2006).
4. A density value was determined by computing a smoothed three-minute moving average of the number of persistent vehicles moving in the same direction as the instrumented vehicle. Traffic was classified as dense when the smoothed average was greater than four.
5. Results from the fixed effects model are available from the author by request.
6. The RDCW system alerts drivers when they are drifting from their lane and when they are approaching a curve too rapidly. As a result, there is no reason to think observations of following distance with the system enabled will be unduly biased. Still, the variable will be tested.
7. Following distance is one of several factors that should be considered in computing a passenger car equivalency (PCE) for heavy trucks. SUVs should not be counted as heavy trucks for capacity calculations, nor should they be considered identical to cars. The details of the recommended PCE for SUVs are discussed in the sixth section.
8. These are the values found in the first section converted to meters.
9. Including the E_s equation in the HCM capacity equation and examining the relationship between flow rate and vehicle mix reveals an asymmetric U-shaped curve where capacity is lowest with 75% SUVs.

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