Analysis of Automobile Travel Demand Elasticities With Respect To Travel Cost

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1. INTRODUCTION

The purpose of this project is to establish quantitative relationships between automobile travel demand and cost. There is a large body of empirical evidence showing that as the cost of traveling goes up the amount of vehicle travel people engage in goes down. The measure of travel demand can be the number of trips taken over a given time period, or it can be the vehicle miles of travel engaged in by such trips. The most popular approach to measuring the sensitivity of household travel volumes to changes in travel costs is to compute elasticity. The simplest definition of such elasticity is the percentage change in the volume of travel demanded that results from a one percentage change in some measure of travel cost. The price elasticity of demand for automobile travel, concerning the monetary cost, is often computed as the proportional changes in the demand for automobile travel, such as annual vehicle miles of travel or number of trips made annually, in response to the proportional change in the price paid to make such trips. More generally, travel elasticities may be derived from any measure associated with the utility or disutility of travel, such as changes in travel times, or changes in the quality of travel service offered (e.g., levels of comfort, safety, or on time reliability), or in terms of some weighted combination of all of the above types of cost.

The oil embargos of the 1970's led to many studies, in various countries, of the elasticity of gasoline demand with respect to its price. Most of the literature on travel demand elasticities to date has focused on the effects of rising or falling motor fuel prices, and their effects on tripmaking propensities and on household vehicle miles of travel (VMT). The American Automobile Association (AAA, 2011) puts the daily operating costs for an average automobile (a sedan) in 2011 at 17.74 cents per mile, of which 12.34 cents is spent on fuel (at $2.88 per gallon), and 5.4 cents per mile is spent on maintenance and tires. If driven 15,000 miles per year this comes to an annual operating cost of $2,662. If we then add in the cost of vehicle ownership, including licensing, insurance, finance charges and asset depreciation this comes to an additional $6,114 per year. Adding up these operating and ownership costs comes to $8,776 per year, or 58.5 cents per mile. Taken over a range of the most popular personal vehicle classes, and over annual vehicle mileages ranging from 10,000 to 20,000 miles, these per mile costs vary between 38 cents per mile (for a small sedan doing 20,000 miles per year), and 98 cents per mile (for a 4-Wheel Drive Sports Utility Vehicle doing only 10,000 miles per year): a range of about 2.7 to 1 from most to least expensive. Of note, given the emphasis on fuel price effects in the travel demand literature, these two estimates put fuel costs at between 27% and 17% of full per mile private vehicle operating plus ownership costs. Using a U.S. household vehicle fleet weighted average fuel economy of 20.66 miles per gallon, and an annual average mileage of 11,300 miles (Davis et al., 2011) yields an average fuel cost share of 20.5% for the U.S. household vehicle fleet. This also means that almost 80% of travel costs are not directly fuel related. And to these daily vehicle operating costs we should also add the costs of vehicle parking and any tolls or congestion fees incurred on a regular basis.

Furthermore, travel demand elasticities are often classified as either *short-run* or *long-run* elasticities. The former usually (but not always) refer to annually based elasticities, the latter to anything from 2 or more years into the future. Most of the literature on elasticities considers a long-run elasticity to be one that is capable of capturing demand changes that result from a household's ability to add or change the number and types of vehicles it owns and operates, as well as to change job and/or residence locations, and also change family size: all factors that can have a substantial impact on the household's travel costs as well as its annual VMT. Short run elasticities are assumed to capture the more readily adopted changes in behavior, including making fewer vehicle trips, making shorter trips (to alternative destinations), chaining more trip destinations, shifting to non-auto modes (taking public transit, ridesharing, walking or biking), and using the latest in-vehicle navigation technologies to plan shorter routes. Where an aggregate time-series of data on VMT and fuel prices has been used to estimate elasticity, both short and long run elasticities are possible based on the use of lagged variables in the regression equations. Where disaggregate, cross-sectional data sets have been used, such as the household specific data supplied by the National Household Travel Surveys (NHTS) in the United States, it is usual to refer to the resulting elasticities as long run estimates. However, a number of studies do not follow this convention. Also, a few studies have managed to pool disaggregate time-series with cross-sectional data sources, and in doing so include vehicle purchase costs in their short run elasticity estimates (e.g., Feng et al., 2005; Dargay, 2007). Whether based on this sort of data, or on pooled data of a more aggregated (typically state-level) form, significant changes over time in real vehicle retail prices can prove to be an important costing factor in explaining household level trade-offs between the type of vehicle(s) driven and the use (i.e., the VMT) to which each vehicle is being put.

This report summarizes the auto travel demand elasticities with respect to different cost variables. The dependent variable of interest is VMT of personally owned vehicles by U.S. households. Trip frequency, in terms of the number of trips made per day, is also considered as a dependent variable, though it requires a conversion (i.e., a trip length assumption) to put trip frequency into VMT terms. A relationship between household-level VMT and a set of explanatory variables is established using the direct demand approach. In particular, a log-log regression model is formulated and calibrated using the 2009 National Household Travel Survey (NHTS) dataset, supplemented with the national transit database and other data sources. Household-level travel demand elasticities with regards to fuel cost, maintenance cost, transit services, income and other socioeconomic characteristics are derived from the VMT regression model. A Poisson regression model is used to describe the relationship between trip frequency and various travel cost variables. In addition, to examine the effect of travel time and cost on the mode choice between flying and driving a personal vehicle, the long distance passenger travel mode choice is represented by a discrete choice model. Using a subset of 2001 NHTS long trip samples, a binary logit choice model is developed and calibrated, which includes access distance, travel time, cost, income, and travel party size as explanatory variables. Aggregate elasticities of long distance trips by personal vehicles are derived from the discrete choice model.

2. LITERATURE REVIEW

This section provides a concise review of the effects of increases or decreases in monetary travel costs on the demand for personal vehicle travel.

To date the elasticity literature has been dominated by changes in travel volumes as a result of changes in motor fuel prices, with much less study devoted to the effects of other types of driving costs. These other costs, which in total account from some 70% to 80% of the costs of owning and operating a private household vehicle (AAA, 2011), include year-to-year vehicle insurance, maintenance, tire replacement, and road taxes. Ideally they should also include parking and any toll or congestion fee costs. Looked at over a number of years, such driving costs also include the significant costs associated with vehicle purchases or leasing arrangements. Trips of more than 75 miles (or so), and especially trips of over 300 miles, place the automobile in competition with very different modes of transport to those associated with daily commuting, shopping, and other frequent local area trips. Public transit, ridesharing, walking and cycling alternatives to the automobile are replaced here with inter-city bus, rail, and air transport, and the very different comparative costs these modes incur.

2.1 METHODS USED TO DERIVE TRAVEL DEMAND ELASTICITIES

It is usual to derive both direct and cross-elasticities of demand as outputs from a travel demand model. This includes not only the monetary cost or price-based elasticities of interest to this present review, but also income elasticities and elasticities associated with non-monetary costs. This includes travel time based elasticities, which in most travel demand models are combined with monetary costs to produce a total or generalized cost of travel, for which sensitivities of demands are derived for VMT forecasting purposes.

However these travel costs are constructed, similar econometric methods have been applied to the problem, and there are a number of ways to divide up the various modeling approaches. Policy driven reasons for deriving travel demand elasticities play a leading role here in determining the methodology employed. Where the interest is in understanding highway investment needs or in forecasting the effects of cost changes on traffic congestion, a direct, single equation estimate of VMT has often been used. However, where the objective of a study is to assess the potential for reducing petroleum consumption or mobile source (including greenhouse gas) emissions, a VMT estimate is usually one result produced by a multi-equation approach that also produces estimates of the number and types of vehicle owned.

The types and sources of data available for estimating elasticities also go a long way to determining the methodology adopted. Some travel demand models focus on capturing and comparing the temporal changes in both travel volumes and travel costs from year to year, while others are based on single period sampling of a large cross-section of households of different types. An important advantage of using time-series data is the ability to capture the effects on VMT of significant fuel price increases, such as those occurring during the oil embargoes of the 1970's; as well as the effects of significant trend altering non-price variables, such as the introduction of the Corporate Average Fuel Economy (CAFÉ) standards in the 1980's. The most successful time-series models to date have used aggregate, state level data, drawing on a long time series of federal and state reporting of VMT, fuel use, and fuel prices. Especially useful is the ability to introduce lagged effects into such equations, in order to pick up recent trends in vehicle stock as well as vehicle miles of travel growth or decline, and to allow time for cost changes to impact travel volumes. For the most part this has been accomplished by using simple, one period (annual) lags in travel volumes. Examples discussed below include the U.S. studies by Schimek (1997a), Small and Van Dender, (2007a, b), Hymel et al., (2010), Hagemann et al., (2011), and the Canadian study by Barla et al., (2009). Time-series studies carried out over the past decade have become increasingly more sophisticated in their application of econometric techniques. In particular, they identify non-stationary relationships between dependent and independent variables, and derive long run elasticities based on cointegration regression, subsequently applying error correction models to identify time period-specific short-run elasticities within these longer run trends (see Graham and Glaister's 2002 review for references to numerous studies applying these techniques to fuel price sensitive gasoline demands).

In the United States many of the cross-sectional studies of VMT make use of the NHTS, and most recently the 2001 and 2009 surveys. This data is collected at the level of the individual household and brings with it a rich set of trip purpose, trip frequency and trip length details that can be linked to a household's socio-economic-demographic and also locational (e.g., metropolitan, small urban, rural) characteristics. The survey also provides details on the number and types of vehicles owned by each household sampled; and via an Energy Information Administration (EIA) matching of vehicle make and model to fleet averaged miles per gallon data, it also provides estimates of household vehicle fuel consumption.

A few studies have also managed to create pooled times-series/cross-sectional databases using similarly disaggregate datasets. This includes studies that use time series data on individual household expenditure profiles, including the money spent on fuel as well as vehicle purchases (for example, Greene et al, 1999 using the Residential Transportation Energy Consumption Surveys; and Feng, et al., 2005, using the U.S. Bureau of Labor's quarterly Consumer Expenditure Survey data; and Dargay, 2007, in the United Kingdom using a similar household expenditures dataset). One recent California study (Gillingham, 2010) was able to use the reporting of over two million individual vehicle odometer readings, collected over a number of years as part of a government mandated vehicle inspection and maintenance program.

All of the above studies using government supported data sources to analyze trends in broad statewide or national travel demands. In addition, a number of more regionally and locally based studies also offer insight into the relationship between auto demand and travel cost. These include a large number of discrete choice demand models that support the metropolitan area-wide or statewide transportation planning process as it is carried out across the nation on a regular basis: and in particular the analysis of travel mode choice and its sensitivity to both auto and public transit costs. Example North American mode choice studies reviewed in Section 4 include Hess (2001), Wamablaba, et al., (2004), Washbrook et al., (2006), and Salom (2009). de Jong and Gunn (2001) summarize the elasticities coming out of such models in Europe.

Another group of studies to shed light on the cost sensitivity of travel do so by evaluating the effects of congestion fees, and highway tolls on specific highway corridors. In the U.S. this includes the work reported by Small, et al. (2002, 2006), Yan, et al., (2002), Burris (2003), and Austin (2008). While it is difficult to translate empirical results from one traffic corridor to another, these studies at least offer a very direct measurement of both traffic volumes, tolls paid, and also vehicle speeds, from which not only vehicle operating costs but also in-vehicle travel time versus monetary travel cost trade-offs can be evaluated. Their down-side is that 'lost' corridor traffic may simply appear elsewhere in the network, and may even lead to increased daily VMT. Because of this last effect, these corridor–specific studies are not reviewed further here.

2.2 SYNTHESIS OF THE EMPIRICAL EVIDENCE

This section summarizes the empirical findings obtained from the above mentioned travel demand modeling exercises. Table 1 shows the elasticities of automobile demand with respect to auto fuel (usually gasoline) price and the monetary cost of operating and maintaining a vehicle, as reported by a number of recent, or frequently cited travel demand studies, including both domestic and foreign studies, and including the summarized findings from a number of past review articles on the topic. The most recent studies are listed at the top of either cost category.

An immediate observation on these numbers is the wide range of elasticity values reported, both across and often also within studies, and for both short-run and long-run elasticity estimates. In all cases the elasticities fall between 0.0 and -1.0, with larger absolute values for Operating and Maintenance (O&M) elasticities that combine fuel with other cost components. The reasons for this variability can be placed under three general categories: (1) structural (pertaining to the nature of the travel involved: notably its purpose, trip length, geographic setting, and to the availability of public transit and other modal alternatives), (2) behavioral (i.e., as a result of different cost sensitivities across different types of traveler), and (3) methodological (pertaining to the type of data, study purpose and model formulation used). While a good deal of light is shed by these studies collectively on specific influences on the dollar cost-based elasticities of travel, it is often the interaction between two or more of these influences that make it difficult to place strong reliance on any one elasticity measure.

Table 1. Example Fuel, and Vehicle Operating and Maintenance Cost Elasticities with Respect to Vehicle Miles Traveled

List of Example Studies	Short Run Elasticities		Long Run Elasticities	
	Fuel	Vehicle O&M[1] costs	Fuel	Vehicle O&M[1] costs
Hagemann, et al 2011 (Draft)	-0.07			
Li, et al, 2011[2]			-0.24 to -0.34	
Gillingham, 2010	-0.15 to -0.20			
Hymel , et al (2010)	-0.03 to -0.05		-0.13 to -0.24	
Karpus, 2010	<-0.01 to -0.19			
Barla et al , 2009	-0.08		-0.18 to -0.19	
Brand, 2009	-0.13 to -0.21			
McMullen & Zhang, 2008			-0.47 to -2.23	
Austin, 2008	-0.06		-0.4	
Dargay, 2007	-0.1		-0.11 to -0.18	
Small & Van Dender, 2007a	-0.02 to -0.08		-0.06 to -0.34	
Small & Van Dender, 2007b	-0.01 to -0.04		-0.06 to -0.21	
Feng et al, 2005	-0.02 to -0.07			
Goodwin, et al 2004*	-0.06 to -0.14		-0.10 to -0.63	
Graham & Glaister 2002,2004*	-0.15		-0.31	
de Jong & Gun, 2002* (shares)	-0.02 to -0.2		-0.20 to -0.41	
Brons, et al ,2002*	-0.02		-0.33	
Goodwin , 2002*	-0.16		-0.32	
Greene et al, 1999			-0.17 to -0.28	
TRACE, 1999 (Travel shares)*	-0.02 to -0.22		-0.20 to -0.52	
Johannson & Shipper, 1997			-0.55 to -0.05	
Schimek, 1996a	-0.06		-0.26	
Blundell et al, 2011			-0.35	-0.33 to-0.83
Souche, 2010				-0.52 to -0.86
Bento et al, 2009				-0.46 to-0.83
Salon (2009)		-0.24 to -0.68		
Ingram and Liu, 1999		-0.06 to -0.28		
Small and Winston, 1999		-0.06 to -0.23		-0.10 to -0.28
Oum et al, 1992		-0.09 to -0.52		

Notes: * refers to the results summarized in a review article. [1] O&M = Operating and Maintenance. [2] Not clear whether short, intermediate, or long run elasticities, i.e., placed under long run here because of their relatively high values.

From the 1990's on there has been a steady stream of review articles synthesizing the elasticity with respect to fuel price and the subsequent literature (see Goodwin, 1992; Oum et al., 1992; Graham and Glaister, 2002, 2004; Goodwin, 2002; Goodwin et al., 2004; Brons et al., 2006; Austin, 2008; Brand, 2009; Raborn, 2009; Litman, 2011). As a set they report consistently lower short run (annual) fuel price elasticities, most falling in the range -0.02 to -0.22 (average around -0.15), with longer-run elasticities falling mostly in the range -0.06 to -0.60 (average around -0.3) for the most common trip purposes. As discussed earlier, the most common explanation for these higher long-run elasticities is that given more time, travelers have more options for reducing their travel expenditures. The more elaborate econometric analyses try to measure the relative importance of these various options.

The amount of travel we use our vehicles for is clearly dependent on income. Small and Van Dender (2007a) estimate a short run, annual income elasticity with respect to travel of 0.11, and a long-run elasticity of 0.51. That is, as income rises so does household VMT. Graham and Glaister's (2004) review led them to conclude that long-run income elasticities of fuel demand typically fell in the range 1.1 to 1.3. Short run income elasticities were much lower, in the range 0.35 to 0.55. Goodwin's et al., (2004) review reports short and long run fuel price elasticities with regards to VMT of around -0.1 and -0.3 respectively, with income elasticities with regards to VMT of 0.3 and 0.73. Being larger in all studies reviewed than the equivalent long run and short run fuel price elasticities implies that fuel prices must rise faster than the rate of income growth even to stabilize fuel consumption (and VMT) at existing levels. Some of the more recent time-series based modeling of income elasticities, however, suggests that income elasticities with regards to travel demand may have been falling in recent years, especially if looked at over the longer term (Small and Van Dender, 2007a; Barla, et al., 2009), and the question of whether this is true for the past 2 or 3 years is currently open to speculation.

A few of studies have found ways to use existing datasets to generate vehicle O&M based cost elasticities. Eight estimates are reported in Table 1, drawn from seven different studies. Most of the elasticities reported in the short-run studies cover a range of -0.06 to 0.4 (the Salon study has a much higher estimate for Manhattan than for the rest of New York City, and also includes parking costs which are not present in the other studies). The long run elasticities are generally a good bit higher, mirroring the results for fuel price only elasticities, with most in the range -0.3 to -0.9. And as with the fuel cost estimates, the use of different model specifications and different types of data sources make it difficult to separate out behavioral and structural effects from study and modeling context. Discrepancies between studies may also result from the way in which each study calculates its vehicle O&M costs, and especially what variables go into it. Formulas used vary from a simple average of O&M costs per mile, or they may be constructed to include the fuel efficiency and other attributes of the specific vehicle type(s) being modeled (e.g., Bento et al., 2009).

The overall price elasticity of demand for automobiles is often taken to be in the vicinity of -1.0 (Greene, et al., 1999). McCarthy (1996), for example, estimated a -0.87 price elasticity of demand for automobiles in the U S market. Litman's (2011) review puts it in a wider range, between -0.4 and -1.0. Bento et al. (2009) estimate a mean long run vehicle 'rental price" elasticity of -0.88, and for new vehicles of -1.97, with much higher elasticities associated with newer and more expensive vehicles. These price sensitivities need to be seen against the equivalent income elasticities with respect to vehicle purchase and ownership costs. Goodwin et al.'s (2004) review puts vehicle ownership elasticities with regards to income at around 0.32 in the short run, rising to 0.81 in the long run. Using disaggregate household data for the U.S., Schimek (1996b) puts it somewhat lower, at 0.22. For Canada, Barla, et al., (2009) put the short run elasticity of vehicle ownership with regards to income between 0.28 and 0.35, with the long run elasticity only rising to about 0.4. However, these average elasticities can hide a good deal of variability. In particular, household income level and number of vehicles owned matter a great deal. For example, for New York City's Five Boroughs, Salon (2009) puts these short run income elasticities at -0.5 for zero-vehicle households, 0.10 for one vehicle households, and at 0.58 for two vehicle households.

At least two studies have also estimated the effect of new vehicle purchase price on VMT directly. Small and Van Dender (2007a) estimate this short-run elasticity to be negligible (around -0.003), rising to just under 0.1 in the long run. Hagemann et al.'s (2011) preliminary estimate is similarly small, at -0.024 in the short run. Capturing this effect more consistently in future VMT forecasting models appears to be a worthwhile area for further exploration.

2.3 CAUSES OF VARIABILITY IN TRAVEL COST ELASTICITIES

The wide range of fuel price and other cost-based elasticity values leaves a lot of room for speculation. A good deal of this variability is explained in the literature as being either structurally (pertaining to the nature of the travel involved: notably its purpose, trip length, and to the availability of public transit and other modal alternatives), or behaviorally (i.e., as a result of different cost sensitivities across different types of travelers and households) motivated.

Table 2 provides a concise, qualitative summary of what the literature appears to support. Not all factors are reported for all studies. Example studies are referenced where a particular factor was well researched and had a major direct impact on the range of elasticities reported. This usually means that a separate elasticity value was estimated for different levels of that factor, or a factor was combined with a travel cost variable to capture its impact. Many other structural and behavioral factors affecting travel demand are not listed, but play an indirect role through the way they improve model fits to the observed data, thereby presumably improving the elasticity estimates that come out of the models. Between them, trip purpose, availability of an automobile, and urban location appear to have significant effects on the elasticity of auto use as the cost of travel changes. Commuting, business, and school trips are inelastic with respect to costs, while the more (temporally) discretionary activities such as shopping, social, and recreational tripmaking have higher elasticity values, often on the order of 2 to 1. Households with two vehicles are consistently found to be less elastic with respect to costs, presumably because they can switch to a less expensive-to-operate vehicle for some trips. This may mean using a sedan instead of a pickup or SUV. Rural households tend to have lower travel cost elasticities than urban ones, possibly because of their more limited travel options, and perhaps because they make fewer trips in the first place and so have less slack in their weekly activity schedules.

Table 2. Some Causes of Variation in Auto Fuel Cost Elasticities

Structural Factors	*Lower Elasticity*	*Higher Elasticity*
Trip Purpose *(de* *(Jong and Gunn,Litman 2011,TRACE)*	Business , Commuting, Education (short-run)	Social/Recreational, Shopping, Education (long-run)
Public Transit Options *(Kim, Litman 2004 & 2011, TRACE)*	Fare Increase	LOS[1] Improvement
Urban Location & Density *(Gillingham,Karpus,Salon, Wadud et al)*	Rural	Urban
Behavioral Factors	*Lower Elasticity*	*Higher Elasticity*
Household Income [2] *(Gillingham, Karpus, Kim, Litman 2011, McMullen et al, Wadud et al)*	Low Very High	Very Low Medium, High
Number of Vehicles *(Feng et al, Greene et al, Karpus, McMullen et al)*	Two or More	One
Vehicle Types & Ages *(Bento et al 2009, Feng et al, Gillingham, McMullen et al)*	Auto	Auto/SUV Mix

Notes: [1] LOS = level or service (or service quality). [2] Mixed results across studies.

Household income and the availability of good quality public transit service are also found to have significant impact on the cost based elasticity of auto use. However, the current evidence appears to be somewhat mixed in both these cases. That is, we might expect higher income households to be less price sensitive than lower income ones, but then realize that poorer people spend a good deal more of their travel budgets on necessary trips, such as commuting. So they may have little choice but to pay the extra travel cost imposed: or they may have to stay home if the trip is of a more discretionary nature. Either way, they are often dependent on their current travel option. Higher and middle income households, in contrast, may find it easier to drop some discretionary trips if fuel or other prices rise sharply. Over the longer run they also have more opportunities to adapt their lifestyle to absorb additional travel expenditures.

The empirical evidence is certainly mixed. McMullen et al.'s (2008) log-log VMT regressions on 2001 NHTS data for the northwestern U.S. states show a gradual transition from high to low elasticities as one moves from the lowest (<$10,000) to the highest (>$100,000) income group. In contrast, a recent study by Blundell et al., (2011), also using NHTS 2001 disaggregate household travel data, fits log-log regressions of gasoline demand that associates much larger price elasticities with middle income households, while the highest of his three income groups has the lowest elasticity. Different model formulations, different income grouping, and different data samples may account for these discrepancies. However, it is clear that income's role in travel price elasticity requires more attention if we are to get a clear picture of its true effects.

Wadud et al., (2009) review a number of past studies that report both fuel price and income elasticities associated with the demand for auto travel and find that as a set they provide contradictory conclusions. They fit log-log regression models to obtain income and price elasticities of gasoline demand for different household income quintiles, using groupings of like income households to fit time-series data on fuel and other expenditures from the US Consumer Expenditure Survey, for the years 1984-2003. The price elasticity of gasoline demand is found to be largest in absolute value for the poorest income group though demand is still fairly inelastic (-0.35), at its lowest for the middle quintile group (-0.20) and to increase for the highest income group (to -0.29). They speculate that for the lowest income group a price increase may result in an increased propensity to use public transport and other alternatives or perhaps to forego some trips altogether. In contrast, households from the wealthiest income group may have less need to respond to higher gasoline prices, yet it may also be easier for them to do so, as much of their consumption may not be a necessity. They also note that these wealthier households are also, on average, larger households, and may have more options at their disposal for arranging their travel more efficiently (including the possibility of substituting air travel for long distance auto travel for vacation purposes). Fitting separate regressions to representative samples of urban and rural US households these authors also found rural households to be less price sensitive that their urban counterparts, with rural fuel price elasticities of demand for gasoline between -0.17 and -0.21, depending on the type of regression model used, and urban elasticities of around -0.30. The presence of a greater proportion of wealthier households in urban settings appears to be influencing this result.

Kim (2007) reports findings that may help to explain some of these mixed results with respect both to income level and transit ridership. He fits a discrete-continuous vehicle choice and VMT estimation model, also to 2001 NHTS data, and also using other data sources that allow him to estimate a per mile vehicle operating cost (which includes fuel, maintenance and tire costs, and a vehicle annual 'rental cost' that captures depreciation, state taxes, and interest).

Based on these data, fuel demand elasticities were derived for a range of household income classes, with each class also divided into high and low transit supply areas. Also pointing to the mixed results of past studies and the very limited evidence for transit's impact on auto price elasticities per se (rather than on auto demand or gasoline consumption levels directly), he questions the past representation of transit supply in such analyses. Using annual transit service miles as a measure of high versus low transit supply (above and below the mean level for the nation), he finds that urban households in high transit supply areas had significantly less elastic demand for gasoline use as vehicle operating cost increased (elasticity around -0.15) than did urban households in low transit supply areas (elasticity around -0.82). Breaking this down by income level, he found that in high transit supply areas the poorest travelers have by far the smallest elasticity in absolute value, and that this value increases as income level increases. Ten different income levels were used. In low transit supply areas, however, this relationship displays the opposite tendency, with the poorest travelers having much the highest auto operating cost elasticity of all travelers, at -1.3. These results suggests that poor households with limited access to transit are much more severely impacted in terms of their travel opportunities by rising auto operating costs than are households close to transit options. At the other end of the income scale, high income travelers, while less damaged than poorer travelers, are still comparatively more elastic in their responses to auto operating costs where transit supply is limited (-0.77 versus -0.30).

These studies make it clear that if we are to identify with consistency the price elasticities of travel demand associated with different household characteristics, we need to capture the joint effects of both the behavioral (income, family size, and vehicle ownership grouping) and the structural (urban/rural, good transit service proximity) factors affecting travel volumes.

3. METHODOLOGY

Elasticity is a popular measure to capture the sensitivity of household travel volumes or trip frequency to changes in travel costs. By definition, elasticity is the ratio of the percentage change in one variable y to the percentage change in another variable x, denoted as

$$E_x^y = \left|\frac{\partial \log y}{\partial \log x}\right| = \left|\frac{\partial y}{\partial x} \cdot \frac{x}{y}\right| \approx \left|\frac{\%\Delta y}{\%\Delta x}\right|. \tag{1}$$

In the context of travel demand analysis, elasticity represents the percentage change in travel demand resulting from a one percentage change in the travel cost variables. Both direct and cross-elasticities can be derived from a travel demand model, which include not only the price-based elasticities, but also income elasticities and elasticities associated with non-monetary costs (Southworth, 2011).

3.1 DIRECT DEMAND MODEL

A straightforward approach for modeling travel demand is to characterize travel activity as a multiplicative function of socioeconomic variables and level-of-service attributes in the following form:

$$M = \theta \cdot \prod_i P_i^{\beta_i} \tag{2}$$

where

M = dependent variable that measures personal travel activity, such as annual miles of automobile travel, averaged annual miles per household, per person, or per driver;

P_i = explanatory variables, such as fuel prices, travelers' disposable income, the convenience and the cost to ride other modes (e.g., transit); and

θ , β_i = model parameters.

By taking the natural logs of both sides, we can obtain the following log-log linear regression model

$$\log M = \beta_0 + \sum_i \beta_i \cdot \log P_i \tag{3}$$

Based on the definition of elasticity given in Equation (1), β_i 's represent the elasticities associated with the corresponding explanatory variables Pi. Thus, a common practice to obtain elasticities is to estimate the parameters (i.e. β_i 's) of the log-log linear demand model using the ordinary least squares (OLS) method.

3.2 POISSON REGRESSION MODEL

Consider the number of vehicle trips, or trip count, as the dependent variable y_i . Due to its discrete nature, the Poisson regression model is used. Assume that y_i is drawn from a Poisson distribution, which is related to the regressors X_i , that is,

$$\Pr(Y = y_i | X_i) = \frac{e^{-\lambda_i} \cdot \lambda_i^{y_i}}{y_i!}; y = 0,1,2,\cdots \tag{4}$$

where

λ_i = parameter of the Poisson distribution;

$y_i!$ = factorial of y_i ;

The expected trip frequency is given by

$$E[y_i | X_i] = \lambda_i = e^{\beta X_i} \tag{5}$$

where

β = coefficients of the regressors;

Note that the Poisson assumes that the variance equal the mean. If over dispersion is detected in the observed values, a negative binomial specification could be used instead.

The relationship between the response and the regressors (i.e., explanatory variables) can be expressed in a log-linear form:

$$\log(\lambda_i) = \beta X_i \tag{6}$$

Similar to the above-mentioned log-log VMT regression model, for the explanatory variable that is in its nature log form, the corresponding coefficient is the elasticity.

3.3 MULTINOMIAL LOGIT MODEL

Another approach used in the present study to estimate travel elasticities is deriving them from the discrete choice models. As part of the traditional transportation planning model suite, transportation planning agencies usually use discrete choice models to estimate the demand for particular travel frequencies, modes, destinations, routes, and departure times. The observed traveler utility is represented by the value function

$$V_{ij} = \alpha_j + \beta x_{ij} + \gamma_j z_i + \delta_j w_{ij} \tag{7}$$

where

α_j = alternative specific constant;

x_{ij} = alternative specific variable with a generic coefficient β;

z_i = individual specific variable with an alternative specific coefficients γ_j, assuming $\gamma_1 = 0$; and

w_{ij} = alternative specific variable with an alternative specific coefficients δ_j.

If the random residuals are independent and identically Gumbel distributed, the multinomial logit (MNL) model is used to estimate choice decisions. In particular, the probability of individual *i* choosing alternative *j* can be computed based on the formula

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_j e^{V_{ij}}}, \tag{8}$$

where

P_{ij} = probability of individual *i* choosing alternative *j*.

Elasticities at both disaggregate and aggregate levels can be derived from the calibrated logit models. A *disaggregate* elasticity represents the responsiveness of an individual's choice probability to a change in the value of some attribute. For an individual specific variable z_i, the disaggregate elasticity can be computed as follow:

$$E_{z_i}^{P_{ij}} = \frac{\partial \ln P_{ij}}{\partial \ln z_i} = z_i(\gamma_j - \sum_l P_{il}\gamma_l). \tag{9}$$

For an alternative specific variable x_{ij}, the disaggregate direct elasticity is given by

$$E_{x_{ij}}^{P_{ij}} = \frac{\partial \ln P_{ij}}{\partial \ln x_{ij}} = \beta x_{ij}(1-P_{ij}), \tag{10}$$

and the disaggregate cross elasticity is given by

$$E_{x_{il}}^{P_{ij}} = \frac{\partial \ln P_{ij}}{\partial \ln x_{il}} = -\beta x_{il} P_{il}, \;\; j \neq l\,. \tag{11}$$

Rather than that of any individual, *aggregate* elasticities summarize the responsiveness of all or some group of decision makers. For the entire sample set, let $\overline{P}_j$ represent the expected share of all the decision makers choosing alternative *j*. We have

$$\overline{P}_j = \frac{\sum_{i=1}^{N} P_{ij}}{N}, \tag{12}$$

where

$\overline{P}_j$ = the expected share of alternative *j*, and

N = the number of decision makers in the sample set.

The aggregate elasticity describes the changes in the expected share in response to altering the value of variable x_{ij} by a uniform percentage change for all the decision makers when $j \neq l$ Equation (10) calculates aggregate cross elasticity, otherwise, the direct elasticity:

$$\overline{E}_{\overline{x}_l}^{\overline{P}_j} = \frac{\sum_{i=1}^{N} P_{ij} \cdot E_{x_{il}}^{P_{ij}}}{\sum_{i=1}^{N} P_{ij}}. \tag{13}$$

A similar approach can be used to compute aggregate elasticities of a subset of the samples (e.g., decision makers sharing some socioeconomic attribute). Assume the entire population is divided into several market segments, or groups. Let N_{gj} denote the number of observations in the group *g* choosing alternative *j*.

$$\sum_j N_{gj} = N_g, \tag{14}$$

where

N_{gj} = the number of decision makers in market segment g choosing alternative j, and

N_g = the number of decision makers in market segment g.

The expected share of alternative j in the market segment g can be calculated based on the choice probabilities predicted by the logit model:

$$\overline{P}_{gj} = \sum_{i=1}^{N_g} P_{ij} \Big/ N_g \,, \tag{15}$$

where

$\overline{P}_{gj}$ = the expected share of alternative j in market segment g, and

P_{ij} = the probability of individual i choosing alternative j.

The aggregate elastcities of market segment g can be computed as

$$\overline{E}_{\overline{x}_l}^{\overline{P}_{gj}} = \frac{\sum_{i=1}^{N_g} P_{ij} \cdot E_{x_{il}}^{P_{ij}}}{\sum_{i=1}^{N_g} P_{ij}} \,. \tag{16}$$

4. ANNUAL HOUSEHOLD VMT MODEL

To better understand highway investment needs and forecast the effects of cost changes on traffic congestion, a direct, single equation estimate of vehicle miles has often been used. Though changes in travel cost might affect vehicle purchase and ownership decisions, the dominating effect on travel demand is reflected in miles traveled rather than fleet composition (Bento et al., 2006). In this section, we establish a relationship between household-level VMTs and a set of explanatory variables using a log-log regression model. VMT elasticities with respect to fuel prices, transit service coverage and some socioeconomic factors are estimated using the 2009 NHTS dataset, supplemented with data from the National Transit Database.

4.1 2009 NHTS DATASET

The 2009 NHTS data was collected at the individual household level, which entails households' socio-economic-demographic and locational (e.g., urban or rural) characteristics, as well as trip information such as trip purpose, trip frequency and trip length. In addition, by matching the vehicle make and model to the fleet averaged fuel economy data from Energy Information Administration (EIA), 2009 NHTS also provides estimates of household vehicle fuel consumption and cost.

The dependent variable of interest is VMT by U.S. households (or, household VMT) measured as an annual VMT total. ORNL has estimated the number of miles driven by each vehicle sampled in the NHTS based on the best available data, called the BESTMILE. The miles traveled by each household are obtained by summing up the VMTs of all vehicles owned by the household. To eliminate the outliers, only vehicles that traveled more than 1,000 miles annually are considered. As shown in Table 3, on average, each household drives more than 22,000 miles annually and each vehicle is driven for about 11,000 miles.

Table 3. Summary Statistics

Average household vehicle miles of travel	22,623 miles
Average vehicle miles of travel	10,999 miles
Average fuel price	$2.79 per gasoline gallon equivalent

After examining a set of potential predictors, the following explanatory variables that have a significant effect on auto travel demand are extracted from 2009 NHTS.

(1) Fuel cost in nominal US dollars per gasoline gallon equivalent (gge),

(2) Household income,
(3) Life cycle,
(4) Race,
(5) Household size,
(6) Number of drivers,
(7) Employment status, and
(8) Household located in urban or rural area.

In particular, life cycle is categorized into adults with no child, adults with the youngest child under 16, adults with the child 16 or older and retired. The average annual VMT per household and per capita for each life cycle category are compared in Figure 1. Households with 16+ child travel the most miles, as such households tend to have more drivers.

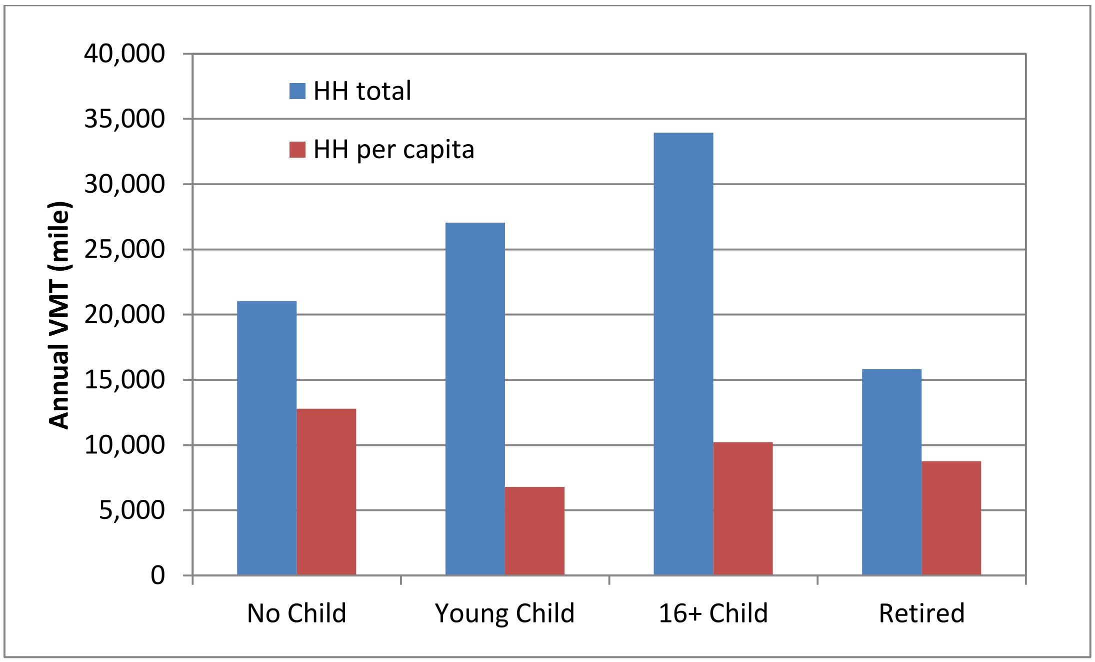

Figure 1. Average annual VMT by life cycle

Note: HH = household; VMT = vehicle miles of travel.

In 2009 NHTS the race is classified into the following categories: White; African American, Black; Asian; American Indian, Alaskan Native; Native Hawaiian, other Pacific Islander; Hispanic, Mexican Only; White & African American and Other Specify. Figure 2 shows that Hispanic households travel the most in terms of total VMT, probably due to the large household size. White households travel the most miles per capita.

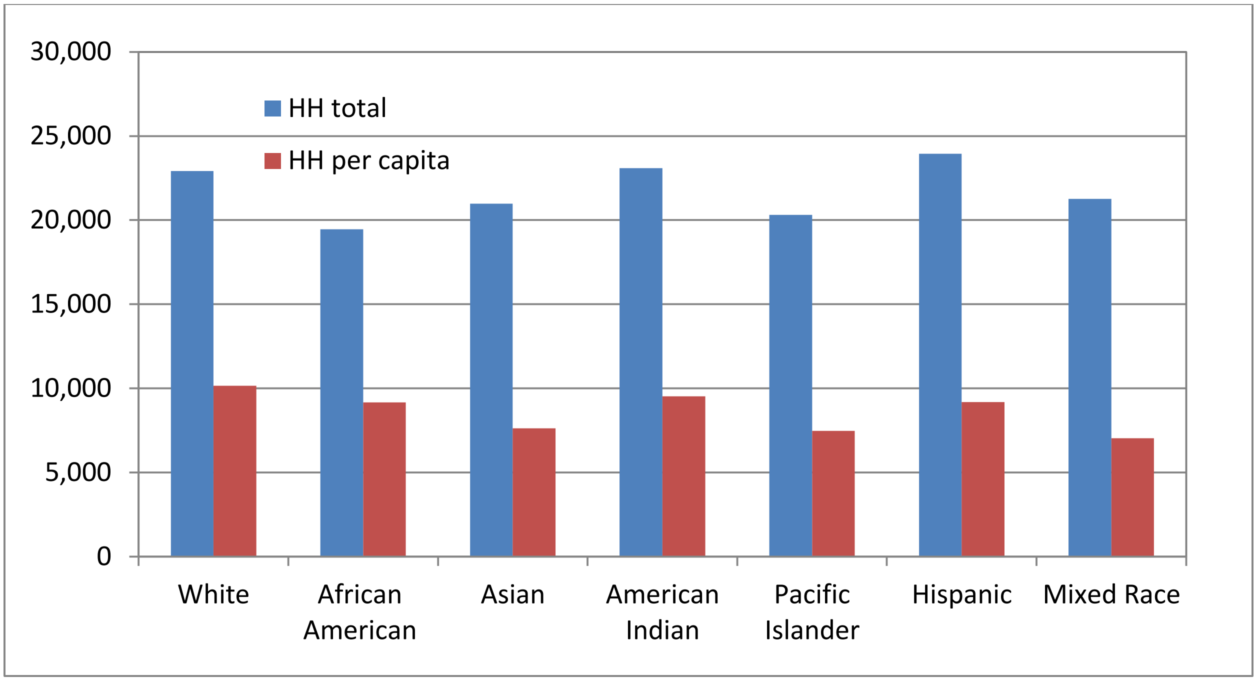

Figure 2. Average annual VMT by race

Note: HH = household; VMT = vehicle miles of travel.

4.2 NON-FUEL VEHICLE COST

The effects of changes in the non-fuel components of travel cost on travel volumes have received less attention than fuel price changes. One reason is the greater difficulty of establishing a time series of these cost changes. An advantage of using fuel pricing data to assess the elasticity of demand for personal travel is the availability of a long time series of data on such prices, on a monthly and year-to-year basis, including the taxes levied on each gallon consumed. Though NHTS provides a linkage between its individual household data, including data on the number of trips made, vehicle miles of travel, and vehicle type(s), as well as an (EIA derived) estimate of each vehicle's fuel consumption, vehicle maintenance, parking, purchase, leasing and insurance costs must be approximated based on other data sources.

The EIA produced a variable called VEHCLASS (Vehicle Class) in the process of adding miles per gallon and fuel cost variables to the NHTS. Using this variable, one can match the AAA categories of Small, Medium, and Large sedans. The Table 4 contains the mapping for the NHTS vehicle type "Automobile/car/station wagon":

Table 4. Vehicle Class

NHTS VEHCLASS Value	AAA Category
Compact	Small Sedan
Mini-compact	Small Sedan
Subcompact	Small Sedan
Two Seater	Small Sedan
Midsize	Medium Sedan
Large	Large Sedan
Not Known	Average Sedan

All vehicles of NHTS vehicle type "Van (mini, cargo, or passenger)" were mapped to the AAA category "Mini Van," and all vehicles with NHTS vehicle type "Sports utility vehicle" were mapped to AAA's "4WD Sport Utility Vehicle." Some of these may not be precise matches (e.g., not all SUV's are 4WD, etc.), but represent the best available information. Approximately 20% of NHTS household vehicles are pickup trucks, and have no equivalent in the AAA data. The best match of available information in the AAA driving cost table is "4WD Sport Utility Vehicle," and as such Pickups were treated as Sport Utility Vehicles. Finally, 5% of total vehicles (mainly motorcycles) are not covered by any of the previous categories. Since these vehicles typically do not account for much of the VMT in a household, no match was attempted.

As a result, maintenance cost, including tire cost, is estimated for each sampled vehicle in the 2009 NHTS dataset. The per mile maintenance cost for each household, together with other explanatory variables discussed in the previous section, is included in the household VMT regression model.

4.3 PUBLIC TRANSIT CROSS-ELASTICITIES

There is a significant body of literature on the effects of public transit fares, as well as levels of service, on the demand for bus and rail ridership, both in the United States and abroad. Litman (2004, also 2011) provides a comprehensive survey of public transit cost and other related elasticities, including examples from the limited amount of direct empirical evidence on the cross-elasticities of both transit fare effects on auto travel and of automobile cost effects on transit patronage. He concludes that short-run direct, fare based transit ridership elasticities commonly fall in the range of -0.2 to -0.6, and long-run elasticities in the range -0.4 to 1.0. Off-peak period elasticities tend to be 1.5 to 2 times those for peak period travel, and suburban commuters tend to have some of the highest elasticities. Paulley et al., (2004) found a similar result for peak and off-peak fare elasticities for all transit modes in Europe, noting that off-peak discount fares as well as travel for different, largely non-commute purposes in the off-peak are likely responsible for this difference. McCollom and Pratt et al., (2004) also summarize the earlier transit elasticity literature, reporting on studies from the 1970s and 1980s that show significant differences in fare elasticities across trip purpose, vehicle ownership, income (mixed results), and time of day (less elastic in the peak period), and also by traveler age (older = less elastic). Most of the inelasticity in ridership with respect to transit fares comes from transit-dependent, lower income riders.

Litman also summarizes the past literature on transit ridership cross-elasticities with respect to increases in auto driving costs. He reports cross-elasticities in the range 0.05 to 0.15 in the short run and between 0.3 and 0.4 in the longer term. Auto travel cross-elasticities with respect to transit fares are a little lower, between 0.03 and 0.1 in the short run and between 0.15 and 0.3 long run. Based on a review of European transit studies, Balcombe et al., (2004) report a similar range of direct fare price elasticities, and also similar bus cross-elasticities with respect to changes in gasoline prices: of around 0.17 in the short run and 0.3 to 0.45 in long run (but based on only 2 studies).

Holmgren (2007), looking at 17 past studies from around the world, found that transit elasticity of demand with respect to gasoline price covered a wide range of values, from almost zero to 1.04, with a mean value of 0.38. For the U.S. his meta-study of past models gives a short run cross-elasticity of transit demand with regards to gasoline price of 0.4. Using aggregate, quarterly data from January 1998 to October 2005, Currie and Phung (2008a, b) provide some additional evidence. Their results for U.S. transit suggests a somewhat smaller transit ridership cross-elasticity with respect to auto fuel cost of 0.12, i.e., a 10% increase in gasoline prices would increase aggregate national transit demand by 1.2%. However, the type of transit mode matters a good deal here. Cross-elasticities were significantly higher for light rail (0.27 to 0.38), but lower for heavy rail (0.17), and much lower for bus (0.04). Espino et al., (2007) found similarly low cross-elasticities for bus ridership in Gran Canaria, Spain, with elasticities increasing from 0.05 to 0.09 as comfort levels on transit went down. Looked at from the opposite perspective, Vioth (1991, 1997) estimated that a 10 percent increase in commuter rail transit fares would reduce rail ridership by about 5 percent in the short run and by about 10 percent in the long run. Wambalaba, et al., (2004) also provide a brief literature review of auto/transit cross elasticities, and, using data from Puget Sound, Washington provide one of the few studies on vanpooling price elasticities. Using a logit mode share model, they estimate direct cost elasticities between -0.6 and -1.34, indicating a significant sensitivity to price changes for vanpool use. A summary of much of the pre-1997 transit price elasticities and cross-elasticities with regards to auto costs is also provided by TCRP Research Results Digest 14 (TRB 1997).

As a set, the papers reviewed testify to the significant difficulty associated with using transit fare reductions to influence shifts away from the automobile. And while increased auto costs can help to increase transit ridership, this effect is likely to remain small unless accompanied by other changes, such as improved transit service. Also, as Litman (2004) points out "not all increased transit ridership that results from fare reductions and service improvements represents a reduction in automobile travel. Much of this additional ridership may substitute for walking, cycling, or rideshare trips, or consist of absolute increases in total personal mobility." Based on his review of past studies, he concludes that in "typical situations" a quarter to a half of increased transit ridership represents a reduction in automobile travel, but that this varies considerably depending on specific conditions.

In the present study, due to the lack of detailed transit fare and level of service data, only the transit operating expenses data from the National Transit Database (NTD) is available to derive the transit service coverage in each of the urbanized area, measured as per square miles directional route miles (DRM). Based on the home location of the sampled households in 2009 NHTS, each household located in the urbanized area is associated with an urbanized area (UA) code. By matching the UA code with the operating expenses data from NTD, each household is assigned with a DRM per square mile value. A higher DRM per square mile value usually indicates a better coverage of transit services.

4.4 REGRESSION MODEL

The log-log regression model is used to represent the relationship between the household VMT and a set of explanatory variables. By using the log-log regression model the elasticity of automobile travel demand with respect to the explanatory variables that are in the natural log form comes directly out of the regression. Interaction terms could also be included in the model formulation (West, 2004). In addition, instead of taking the natural log of all of the explanatory variables, some variables on the right-hand side of Equation (3) could be in its original form (McMullen et. al., 2008).

In our analysis, we include fuel price and household income in logs, and household size, number of vehicles and number of workers in the household in the original form. We also include a dummy variable to indicate whether the household is located in urban or rural area. The direct demand model is specified as:

$$\log M = \beta_0 + \beta_P \cdot \log P + \beta_I \cdot \log I + \beta_M \cdot \log M + \beta_H \cdot H \tag{17}$$

where

M = annual household vehicle miles,

P = fuel price,

I = household income,

H = household characteristics, including household size, race, life cycle, number of drivers, employment status, and urban/rural location indicator, and

β*'s* = the parameters.

The weighted ordinary least squares (WOLS) method is used to estimate the coefficients in the regression model using the NHTS data, considering household weights. The coefficients associated with the variable in the natural log form are the elasticities. Thus, the income elasticity is given by

$$E_I = \beta_I \, . \tag{18}$$

The fuel cost and maintenance cost elasticities in this case are given by:

$$E_P = \beta_P \, , \, E_M = \beta_M \, . \tag{19}$$

To test the linear relationships between the explanatory variables, the variance inflation factor (VIF) is computed. When there is no linear relation between one explanatory variable and the other explanatory variables in the model $VIF = 1$. A larger VIF indicates a higher degree of multicollinearity. For an explanatory variable with $VIF > 1$, the standard error for that variable's coefficient is $\sqrt{VIF}$ times as large as compared to the case where it is uncorrelated with the other explanatory variables. For the explanatory variables that have more than 1 degree of freedom, such as race and life cycle, the generalized variance-inflation (GVIF) factors (Fox and Monette, 1992) are calculated.

4.5 RESULTS

The regression model, specified in Equation (14), is calibrated using the WOLS method. Table 5 and Table 6 list the estimated coefficients and the corresponding statistics. The GVIF is computed for each explanatory variable to quantify the severity of multicollinearity in the estimated regression model. As all the variables have a GVIF value close to 1, no significant linear correlation is detected between the explanatory variables.

The negative coefficient for the urban variable indicates that people who live in rural areas tend to drive more miles. This could be due to the lower density land use patterns and fewer travel options. More drivers in a household and being employed tend to generate more vehicle miles.

Table 5. Estimated Household VMT Regression Model: All Samples

Variable name	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**
Constant	6.7824	0.0495	137.11	<2e-16
Fuel price, *Log*(*P*)	-0.7107	0.0404	-17.596	<2e-16
Maintenance cost, *Log*(*M*)	-0.3673	0.0019	-189.029	<2e-16
Income, *Log*(*I*)	0.1809	0.0024	75.964	<2e-16
Life cycle				
No child				
Young child	0.0847	0.0045	19.017	< 2e-16
16+ child	0.0066	0.0081	0.82	0.4121
Retired	-0.0859	0.0054	-15.933	< 2e-16
Race				
White				
African American	-0.0368	0.0060	-6.096	1.09E-09
Asian	-0.1171	0.0111	-10.549	< 2e-16
Native	-0.0159	0.0183	-0.869	0.3848
Pacific Islander	-0.1789	0.0271	-6.598	4.17E-11
Hispanic	0.0437	0.0215	2.034	0.0419
White&African American	-0.0191	0.0090	-2.132	0.033
Other	-0.0342	0.0142	-2.408	0.016
Urban	-0.2323	0.0041	-56.343	<2e-16
Driver count	0.3717	0.0027	138.422	<2e-16
Employed	0.2048	0.0055	37.118	<2e-16
Residual standard error		16.57		
Adjusted R-squared		0.4795		

Table 6. F Test Statistic and Generalized VIF: All Samples

Variable name	**Degrees of Freedom**	**F-value**	**Pr(>F)**	**GVIF**
Fuel price, *Log(P)*	1	309.62	0.7487	1.045586
Maintenance cost, Log(*M*)	1	35732.14	3.11E-06	1.028915
Income, Log(*I*)	1	5770.48	< 2.2e-16	1.290997
Life cycle	3	328.87	< 2.2e-16	1.944721
Race	7	27.16	< 2.2e-16	1.142796
Urban, *U*	1	3174.56	< 2.2e-16	1.046605
Driver count, *D*	1	19160.63	< 2.2e-16	1.450885
Employed, *E*	1	1377.75	< 2.2e-16	1.667919

Focusing on the travelers who live in the urban area, where transit might be an option to substitute some vehicle miles, an explanatory variable that indicates transit coverage is added to the regression model.

$$\log M = \beta_0 + \beta_P \cdot \log P + \beta_I \cdot \log I + \beta_M \cdot \log M + \beta_M \cdot \log D + \beta_H \cdot H \quad (17)$$

where

D = directional route miles (DRM) per square miles.

The regression model is estimated using a subset of the NHTS samples (i.e., the travelers who live in an urbanized area). Table 7 and Table 8 list the estimated coefficients for each explanatory variable, as well as the corresponding GVIF indicating the severity of multicollinearity.

Table 7. Estimated Household VMT Regression Model: Urban Households

Variable name	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**
Constant	6.0909	0.0704	86.503	< 2e-16
Fuel price, *Log*(*P*)	-0.2928	0.0580	-5.051	4.42E-07
Maintenance cost, *Log*(*M*)	-0.3731	0.0026	-145.675	< 2e-16
DRM, *Log(D)*	-0.0445	0.0042	-10.475	< 2e-16
Income, *Log*(*I*)	0.1822	0.0033	55.817	< 2e-16
Life cycle				
No child				
Young child	0.1082	0.0060	18.096	< 2e-16
16+ child	0.0362	0.0109	3.324	0.000887
Retired	-0.0995	0.0074	-13.478	< 2e-16
Race				
White				
African American	-0.0237	0.0074	-3.215	0.001306
Asian	-0.0905	0.0128	-7.089	1.37E-12
Native	0.0160	0.0273	0.587	0.557157
Pacific Islander	-0.1777	0.0328	-5.418	6.04E-08
Hispanic	0.0508	0.0276	1.838	0.066035
White&African American	-0.0051	0.0112	-0.452	0.651252
Other	-0.0282	0.0167	-1.686	0.091758
Driver count, *D*	0.3736	0.0035	105.277	< 2e-16
Employed, *E*	0.1798	0.0076	23.614	< 2e-16
Residual standard error		17.45		
Adjusted R-squared		0.4683		

Table 8. F Test Statistic and Generalized VIF: Urban Households

Variable name	Degrees of Freedom	F-value	Pr(>F)	GVIF
Fuel price, *Log(P)*	1	25.51	4.42E-07	1.287695
Maintenance cost, Log(*M*)	1	21221.32	< 2.2e-16	1.027045
DRM, *Log(D)*	1	109.72	< 2.2e-16	1.277399
Income, Log(*I*)	1	3115.59	< 2.2e-16	1.281305
Life cycle	3	262.15	< 2.2e-16	1.925911
Race	7	13.05	< 2.2e-16	1.153147
Driver count, *D*	1	11083.22	< 2.2e-16	1.402385
Employed, *E*	1	557.61	< 2.2e-16	1.636849

The negative coefficient (i.e., elasticity) associated with the DRM variable indicates that providing more transit services in an area help to reduce the miles traveled by personal vehicles. The coefficients associated with driver count and employment status are comparable to the ones listed in Table 5. The elasticities estimated based on all samples and the urban samples are compared in Table 9. The elasticities with regards to per mile maintenance cost and household income are similar in both cases. However, fuel price elasticity associated with urban households is smaller, compared to the entire population.

Table 9. Household VMT Elasticities

Variable	All Samples	Urban Households
Fuel price	-0.7107	-0.2928
Maintenance cost	-0.3673	-0.3731
Income	0.1809	0.1822
DRM per square miles	-	-0.0445

5. DAILY VEHICLE TRIP AND VMT MODEL

This chapter studies the effect of gasoline prices, parking costs and socioeconomic variables on an individual's choice of daily vehicle trips and miles traveled. Both trip frequency and daily VMT are considered as dependent variables.

5.1 TRIP COUNT AND VMT

Studies in travel demand modeling and analysis have suggested great variation in travelers' trip making behavior, including daily variation in the trip frequency, trip chaining, departure time choice and its connections with demographic variables (e.g., Pas and Sundar, 1995; Elango et al., 2007; Ficklin, 2010). Figure 3 plots the distribution of daily vehicle travel distance per person. The majority of the samples are within the 10 to 40 miles range.

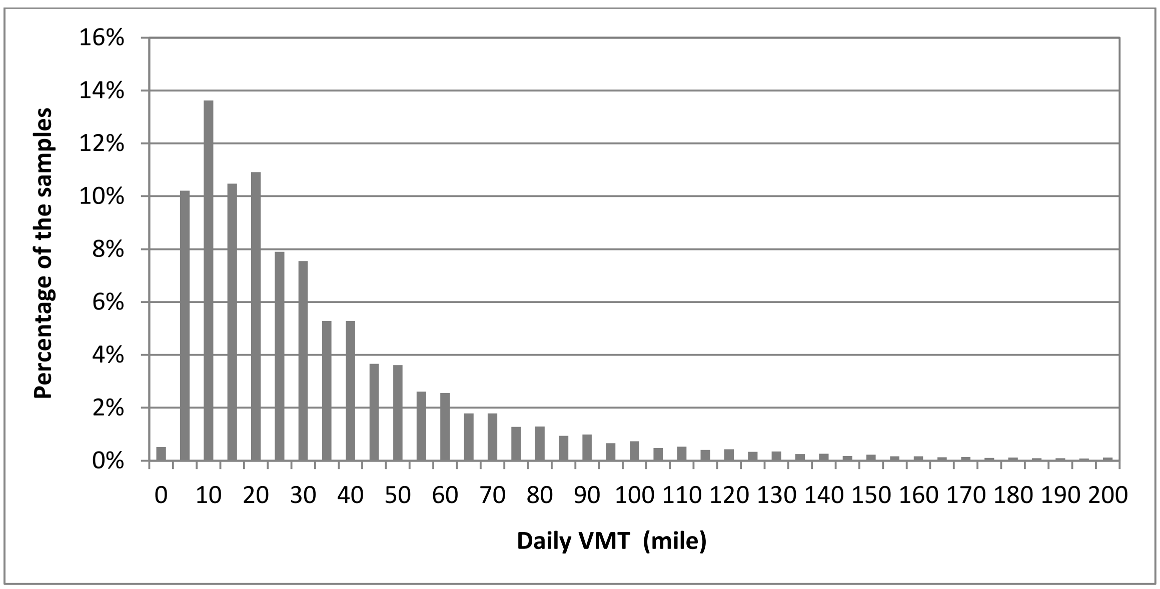

Figure 3. Daily VMT distribution

Figure 4 plots the number of trips taken by an individual during the designated 24-hour travel day, in terms of all trips (including both vehicle trips and non-vehicle trips), vehicle trips and trips that are part of a work trip chain. The majority of the population makes 2 to 4 trips per day. For commuters, over 50% of samples take 2 trips per day, presumably, drive to and from work.

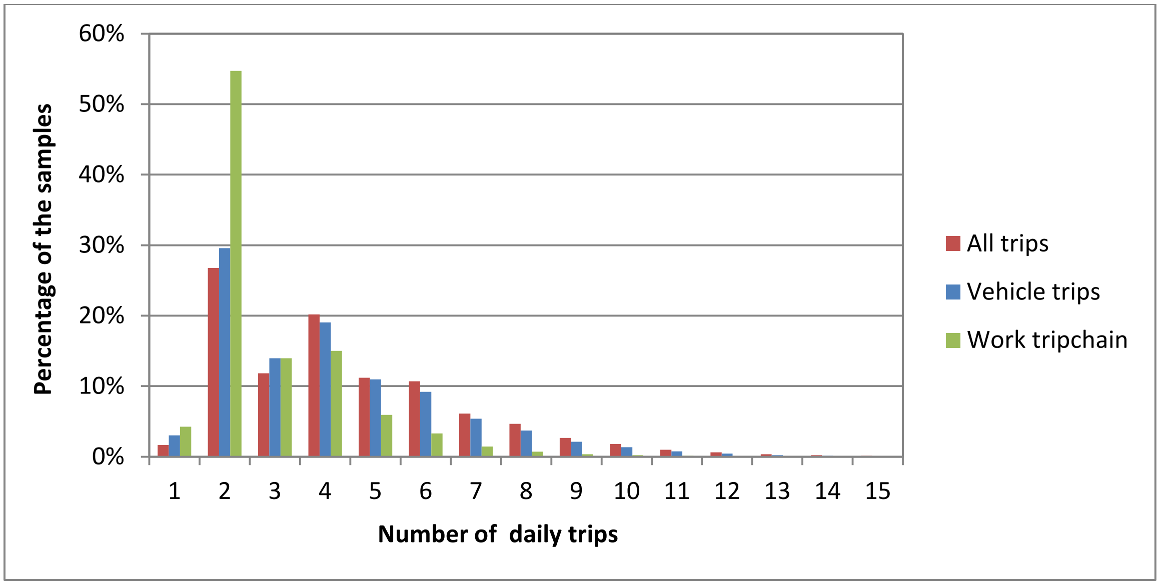

Figure 4. Daily trip frequency distribution

Though miles traveled and trips made are both an indicator of vehicle travel demand, some explanatory variables might have different effects on these dependent variables. For example, as shown in Table 10, men travel more miles than women, while women take more trips per day than men. As a result, the coefficients of the dummy variable indicating gender have opposite signs in the VMT and trip count regression models, discussed in Section 5.3 and 5.4, respectively.

Table 10. Average Daily Trip Count and VMT

	Male	Female	All
Average daily VMT (mile)	44.3	32.2	38.3
Average daily vehicle trip count	4.09	4.19	4.13

5.2 PARKING PRICE ELASTICITIES

Table 11 summarizes the elasticities reported by a number of recent parking price studies. As noted by Vaca and Kuzmyak et al. (2005) most studies of the effects of parking costs on automobile use have focused on commuting trips, and on elasticities associated with off –street parking options. They summarize the literature in the United States by noting that “Empirically derived as well as modeled parking demand elasticities for areawide changes in parking price generally range from -0.1 to -0.6, with -0.3 being the most frequently cited value”. They reference Shoup (1994), who reported the results of seven employer site specific studies in which the elasticity of travel with regards to parking fees fell between -0.08 and -0.22, averaging a value of -0.15. These parking elasticities are also usually reported in terms on the number of people who park, and hence in trips, rather than in VMT terms.

Table 11. Example Parking Price Elasticities

Study Author and Date	Parking Elasticity (Trips)
Hensher & King, 1997	-0.197
Hensher & King, 2001	-0.48 to -1.02
Hess, 2001	-0.44
Kelly and Clinch, 2009 (on-road,short-run)	-0.19 to -0.61
Shoup, 1994	-0.08 to -0.22
TRACE, 1999* (Trips) short-run	-0.00 to -0.46
TRACE, 1999* (VMT) short run	-0.00 to -0.08
TRACE, 1999* (Trips) long-run	-0.02 to -0.62
TRACE, 1999* (VMT) long run	-0.03 to -0.17
Washbrook et al, 2006	-0.23 to -0.46
Vaca and Kuzmyak, et al, 2005*	-0.1 to -0.6

In another North American study, Hess (2001) assessed the effect of free parking on commuter mode choice in the CBD of Portland, Oregon, while Washbrook et al., (2006) report on parking elasticities for commuters in Vancouver, Canada. Pratt (2000) found significantly high elasticities (-0.9 to -1.2) of parking price with higher commercial parking lot gross revenues, since motorists can respond to higher prices by reducing their parking duration or by changing to cheaper locations and times, as well as reducing total vehicle trips. Based on data from a Toronto, Canada parking study that begins with a point price elasticity of -0.33 for parking in the block adjacent to a trip's destination, Kuzmyak et al., (2003) report progressively higher price elasticities with greater parking distance from this destination: and with this increasing sensitivity to price with walking distance also paired with decreasing parking elasticities with respect to (with regards to) longer journey time costs.

Outside North America, the TRACE (1999) study in Europe provides a wide selection of estimates of both short and long run parking price elasticities broken down by trip purpose, percentage of trips by transit, and auto ownership levels. Their estimates are based on discrete choice modeling, with short-run elasticities associated with changes in mode only, while long run elasticities capture change in mode, destination, and trip frequency. Trip purpose appears to be an especially important determinant of the cost elasticity, from very inelastic trips for business, commuting and (in the short run) education trips, with all price elasticities below -0.1, to other (e.g., shopping, leisure) trips with much higher elasticities.

Marsden's (2006) review of parking studies, mainly outside the United States, similarly reports a limited number of non-commuting and on-street parking studies. Kelly and Clinch (2006, 2009) provide one of the few exceptions. Based on responses to a face-to-face survey of some 1,000 parkers in Dublin, Ireland, they employed an ordered probit model to assess parking price sensitivity. As in other parking studies, they found that people traveling on business are much less elastic than those on non-business trips, and that this difference increases with increasing prices. They also found that heavy users of this parking resource were significantly more sensitive to price changes than less frequent users. In their 2009 paper they report a representative elasticity of -0.29, with a range of elasticities spanning different weekdays and hours of the day from -0.19 to and -0.61, and with much lower price sensitivity during morning periods and also during a well know late night shopping period. Clinch and Kelly (2003) found the elasticity of parking frequency to be smaller (-0.11) than the elasticity of parking duration (-0.20), suggesting that some motorists respond to higher fees by reducing how long they park. Litman (2011) describes the findings from other, non-U.S. studies.

Consistent data on the effects of pre-paid or guaranteed parking slots versus unsecured spaces prior to arrival, or of on versus off-street, or street-level versus high rise parking could not be found. These differences may all be important. Litman (2011) notes that consumers tend to measure prices with respect to what they perceive as their endowment (what they consider is theirs) and place a greater value on losses than on gains, so that a typical motorist might be expected to respond 2.25 times as much to a new parking fee than to, for example, a parking cash out incentive scheme where they receive a rebate of the same amount for reducing their use of parking spaces (Shoup 1997; Litman, 2011).

Due to the data limitation, parking cost is represented by a surrogate, namely population density, as parking is usually more expensive in more populated areas. In particular, for the all workers in the dataset, census tract density data at their work location is derived from the 2009 American Community Survey (ACS) and incorporated in the corresponding regression model.

5.3 DAILY VMT REGRESSION MODEL

The daily VMT regression model is estimated using the daily travel distance per person. Table 12 and Table 13 list the estimated coefficients for each explanatory variable, as well as the corresponding GVIF indicating the severity of multicollinearity.

Table 12. Estimated Daily VMT Regression Model

Variable name	Estimate	Std. Error	t-value	Pr(>|t|)
Constant	2.0174	0.0775	26.043	<2e-16
Fuel price, *Log*(*P*)	-0.3148	0.0618	-5.091	3.57E-07
Income, *Log*(*I*)	0.1549	0.0037	41.406	< 2e-16
Driver age				
Age 25-64				
Young driver (<25)	-0.1570	0.0088	-17.878	<2e-16
Old driver (>64)	-0.1680	0.0102	-16.52	<2e-16
Female	-0.2149	0.0054	-39.651	<2e-16
Life cycle				
No child				
Young child	0.0555	0.0065	8.542	< 2e-16
16+ child	0.0279	0.0099	2.825	0.00472
Retired	-0.0068	0.0096	-0.712	0.47631
Race				
White				
African American	0.1641	0.0092	17.826	< 2e-16
Asian	-0.0641	0.0162	-3.951	7.78E-05
Native	0.0601	0.0260	2.309	0.02092
Pacific Islander	0.0301	0.0423	0.71	0.4774
Hispanic	0.1396	0.0308	4.529	5.93E-06
White&African American	-0.0676	0.0134	-5.037	4.74E-07
Other	-0.0807	0.0225	-3.583	0.00034
Urban, *U*	-0.4006	0.0063	-63.778	<2e-16
Employed, *E*	0.1982	0.0065	30.588	<2e-16
Residual standard error		32.35		
Adjusted R-squared		0.06615		

Table 13. F Test Statistic and Generalized VIF

Variable name	Degrees of Freedom	F-value	Pr(>F)	GVIF
Fuel price, *Log(P)*	1	25.92	3.57E-07	1.050708
Income, *Log(I)*	1	1714.45	< 2.2e-16	1.130291
Driver age	2	272.34	< 2.2e-16	1.787376
Female	1	1572.21	< 2.2e-16	1.016674
Life cycle	3	29.08	< 2.2e-16	1.872684
Race	7	60.87	< 2.2e-16	1.136256
Urban, *U*	1	4067.59	< 2.2e-16	1.042645
Employed, *E*	1	935.64	< 2.2e-16	1.261123

The coefficient associated with the “Employed” variable suggests that workers tend to travel more miles than the unemployed ones. It is also expected that workers are less elastic to travel cost. Therefore, the daily VMT regression model is estimated using a subset of the samples who are employed. The population density at the work locations is included in the model specification, which is used as indicator of the parking cost. The estimated coefficients for each explanatory variable, as well as the corresponding statistics are shown in Table 14 and Table 15.

Table 14. Estimated Daily VMT Regression Model for Workers

Variable name	Estimate	Std. Error	t-value	Pr(>|t|)
Constant	1.7984	0.1146	15.693	< 2e-16
Fuel price, *Log*(*P*)	-0.0287137	0.0896	-0.32	0.748725
Density, *Log*(*D*)	-0.0117	0.0025	-4.664	3.11E-06
Income, Log(*I*)	0.1722	0.0059	28.954	< 2e-16
Driver age				
Age 25-64				
Young driver (<25)	-0.1949	0.0127	-15.305	< 2e-16
Old driver (>64)	-0.1162	0.0201	-5.789	7.11E-09
Female	-0.2094	0.0079	-26.63	< 2e-16
Life cycle				
No child				
Young child	0.1128	0.0088	12.837	< 2e-16
16+ child	0.0158	0.0135	1.165	0.244164
Retired	0.0234	0.0159	1.47	0.141444
Race				
White				
African American	0.1810	0.0139	13.036	< 2e-16
Asian	0.0067	0.0223	0.3	0.76386
Native	0.0009	0.0359	0.025	0.979715
Pacific Islander	0.0752	0.0606	1.241	0.214714
Hispanic	0.1575	0.0430	3.662	0.000251
White&African American	-0.0300	0.0203	-1.479	0.139141
Other	0.0911	0.0327	2.781	0.005424
Urban, *U*	-0.3446	0.0095	-36.238	< 2e-16
Residual standard error		30.03		
Adjusted R-squared		0.06454		

Table 15. F Test Statistic and Generalized VIF

Variable name	Degrees of Freedom	F-value	Pr(>F)	GVIF
Fuel price, *Log(P)*	1	0.10	0.7487	1.058285
Income, *Log(I)*	1	21.75	0.000003107	1.190865
Driver age	1	838.36	< 2.2e-16	1.09673
Female	2	129.51	< 2.2e-16	1.236317
Life cycle	1	709.17	< 2.2e-16	1.025788
Race	3	59.93	< 2.2e-16	1.25681
Urban, *U*	7	27.71	< 2.2e-16	1.144672
Employed, *E*	1	1313.16	< 2.2e-16	1.155759

5.4 TRIP COUNT REGRESSION MODEL

Consider daily trip count, or trip frequency, as dependent variable. The Poisson regression model is estimated, as shown in Table 16 through Table 19.

Table 16. Estimated Daily Trip Count Regression Model

Variable name	Estimate	Std. Error	t-value	Pr(>|t|)
Constant	1.3940	0.0012	1178.13	< 2e-16
Fuel price, *Log*(*P*)	-0.2690	0.0009	-285.42	< 2e-16
Income, *Log*(*I*)	0.0242	0.0001	422.13	< 2e-16
Driver age				
Age 25-64				
Young driver (<25)	-0.1158	0.0001	-836.345	<2e-16
Old driver (>64)	0.0298	0.0002	192.249	<2e-16
Female	0.0392	0.0001	475.763	<2e-16
Life cycle				
No child				
Young child	0.0998	0.0001	1010.692	< 2e-16
16+ child	0.0310	0.0002	201.937	< 2e-16
Retired	-0.0129	0.0001	-87.334	< 2e-16
Race				
White				
African American	0.0409	0.0001	298.79	< 2e-16
Asian	-0.1238	0.0003	-476.804	< 2e-16
Native	-0.0165	0.0004	-41.294	< 2e-16
Pacific Islander	-0.0031	0.0006	-4.841	1.29E-06
Hispanic	0.0379	0.0005	82.442	< 2e-16
White&African American	-0.0085	0.0002	-41.752	< 2e-16
Other	-0.0122	0.0003	-35.126	< 2e-16
Urban, *U*	0.0572	0.0001	590.921	< 2e-16
Employed, *E*	-0.0432	0.0001	-426.112	< 2e-16
Residual standard error		32.18		
Adjusted R-squared		0.01962		

Table 17. F Test Statistic and Generalized VIF

Variable name	Degrees of Freedom	F-value	Pr(>F)	GVIF
Fuel price, *Log(P)*	1	71.76	3.57E-07	1.047632
Income, *Log(I)*	1	157.73	< 2.2e-16	1.132328
Driver age	2	345.90	< 2.2e-16	1.794412
Female	1	198.89	< 2.2e-16	1.019169
Life cycle	3	369.50	< 2.2e-16	1.88118
Race	7	44.79	< 2.2e-16	1.131914
Urban, *U*	1	309.71	< 2.2e-16	1.040617
Employed, *E*	1	162.16	< 2.2e-16	1.280651

Table 18. Estimated Daily Trip Count Regression Model for Workers

Variable name	Estimate	Std. Error	t-value	Pr(>|t|)
Constant	1.2240	0.0019	640.369	< 2e-16
Fuel price, *Log*(*P*)	-0.2156	0.0015	-144.775	< 2e-16
Density, *Log*(*D*)	-0.0097	0.0000	-232.799	< 2e-16
Income, Log(*I*)	0.0320	0.0001	321.006	< 2e-16
Driver age				
Age 25-64				
Young driver (<25)	-0.0567	0.0002	-262.955	<2e-16
Old driver (>64)	0.1033	0.0003	317.496	<2e-16
Female	0.0565	0.0001	434.351	<2e-16
Life cycle				
No child				
Young child	0.1094	0.0001	751.721	< 2e-16
16+ child	0.0473	0.0002	208.133	< 2e-16
Retired	-0.0158	0.0003	-58.485	< 2e-16
Race				
White				
African American	0.0573	0.0002	256.182	< 2e-16
Asian	-0.1213	0.0004	-312.015	< 2e-16
Native	-0.0593	0.0006	-97.406	< 2e-16
Pacific Islander	-0.0030	0.0010	-2.983	0.00285
Hispanic	0.1008	0.0007	148.463	< 2e-16
White&African American	-0.0277	0.0003	-81.364	< 2e-16
Other	-0.0322	0.0006	-57.854	< 2e-16
Urban, *U*	0.0704	0.0002	441.172	< 2e-16
Residual standard error		33.33		
Adjusted R-squared		0.02222		

Table 19. F Test Statistic and Generalized VIF

Variable name	Degrees of Freedom	F-value	Pr(>F)	GVIF
Fuel price, *Log(P)*	1	17.06	0.00003621	1.054802
Density *Log(D)*	1	43.90	3.481E-11	1.188111
Income, *Log(I)*	1	84.56	< 2.2e-16	1.096811
Driver age	2	72.09	< 2.2e-16	1.23657
Female	1	153.29	< 2.2e-16	1.026969
Life cycle	3	171.76	< 2.2e-16	1.254301
Race	7	25.63	< 2.2e-16	1.13996
Urban, *U*	1	159.83	< 2.2e-16	1.152516

The fuel price and income elasticities are summarized in Table 20. For the employed population the elasticity with regards to population density at the work location is also reported.

Table 20. Daily VMT and Trip Count Elasticities

Variable	Daily VMT		Trip Count	
	All Samples	Workers	All Samples	Workers
Fuel price	-0.3148	-0.0287	-0.2690	-0.2156
Income	0.1549	0.1722	0.0242	0.0320
Density	-	-0.0117	-	-0.0097

6. LONG DISTANCE TRAVEL DEMAND ELASTICITY

Instead of examining the vehicle miles traveled (as a continuous variable), some of the travel demand models estimate the effects of costs on mode split (as a discrete choice). With a trip length assumption trip frequencies can be converted into VMT terms. In this section, focusing on the long distance travel mode shift, automobile trip share elasticities with respect to cost, time and income are derived from a discrete choice model. The discrete choice model, as well as the supporting datasets, described in this section was developed in a preceding project that focused on long distance passenger travel mode choice. For the sake of completeness, the relevant material was drawn from the report by Dong et al., (2012) and included in the present report.

6.1 PREVIOUS STUDY

For trips over 75 miles (or so) one way, the automobile starts to compete with intercity rail, bus, and air modes. Factors found to affect mode choice are again both behavioral and structural, including trip length and trip purpose, as well as the time spent away from home, the number of people in the travel party, the relative ease of access to the primary mode of travel, and also the total visit costs (Southworth and Hu, 2010). That is, travel costs are often combined with hotel and other costs associated with business or leisure trips. A number of studies have measured the travel cost elasticities involved, with a handful also looking specifically at cross-price elasticities. While the nature of the dependent variable in these studies varies quite a bit, most are interested in modal shifts, and measure the elasticity associated with shifting trips, or patrons, from one mode to another.

An often quoted study by Oum, et al., (1992) provides one of the earliest reviews of long distance travel elasticities. They report significant differences across modes, across trip purposes and also significant differences across different data sources and types of demand model used. For air travel they found that most direct price elasticities produced by direct demand regression models varied between values of -0.8 and -0.20, but with significantly different results across fare classes, and with a lower elasticity usually associated with business versus non-business trips. They also found that cross-sectional, aggregate regression models yielded generally higher values than time-series model estimates. Their elasticities for intercity rail also showed considerable variation, ranging from values of -0.12 to -1.54, with elasticities generally below -1.0, in absolute terms, for business trips. The authors also looked at the modal shift elasticities produce by past studies based on disaggregate, discrete (mainly mode) choice models. Based on this (now somewhat dated) literature, intercity auto elasticities fall in the range -0.70 to -0.96, bus intercity elasticities in the range -0.32 to -0.69, and rail intercity elasticities in the range -0.32 to -1.20. Air travel elasticities fell in the range -0.18 to -0.62. In general these discrete choice based elasticities (which assume a fixed level of travel within which modal shifts take place, and are therefore essentially “short run”) are somewhat lower than their aggregate modeling counterparts.

Since this early work there appears to have been limited additional attention to the topic in the United States, and most of it, at least as published, has focused on the direct price elasticity of the various modes, with little attention to cross-elasticity effects. Presumably, the various air, rail, and intercity bus carriers collect this sort of information, on a corridor and/or market segment basis, but are not likely to publish their findings for reasons of inter-modal as well as inter-carrier competition. A recent study in the United Kingdom, by Dargay et al., (2010) suggests that there is a good deal of variability in price sensitivity that could be captured, given suitable long distance travel data. These authors calibrate both an aggregate time series model and a detailed disaggregate demand model based on U.K. National Travel Survey data for the years 2004 to 2006. Their aggregate time series model elasticities are both short run and long run, as follows in Table 21.

Table 21. Example Aggregate Time-Series Elasticities

	Short Run	Long Run
Auto	-0.3	-1
Coach (Bus)	-0.2	-0.8
Rail	-0.3	-1
Air	-0.1	-0.3

Source: Dargay, et al., (2010).

Using their disaggregate dataset they are able to develop a set of long-run, cross- as well as direct elasticities, broken down by mode, trip distance (<150 and >150 miles) and trip purpose (business, commuting, vacation, leisure, and visits to friends and relatives).

Table 22 shows some of these results for trips of 150 miles or more. The shaded diagonal cells are here the direct (or “own”) cost elasticities (all the negative valued cells), and the other cells are the (zero or positive valued) cross-elasticities. In viewing these results, it is important to remember that the passenger rail network in the United Kingdom is much denser than it is in the United States, with greater ease of access to rail from most urban locations in the U.K. than in the U.S.

Table 22. Direct and Cross-Elasticities Example (United Kingdom, 2004-6) (150+ mile trips only)

150+ miles		w.r.t. Costs of These Competing Modes:			
	Mode	Auto	Rail	Bus	Air
Business	Auto	-0.34	0.1	0	0.03
	Rail	0.25	-0.74	0.01	0.18
	Bus	0.25	0.31	-0.43	0
	Air	0.02	0.06	0	-0.42
Vacation	Auto	-0.79	0.11	0.06	0.05
("Holiday")	Rail	0.38	-1.68	0.44	0.48
	Bus	0.17	0.36	-0.86	0.02
	Air	0.08	0.21	0.01	-1.15
Leisure	Auto	-0.61	0.1	0.05	0.02
	Rail	0.23	-1.3	0.26	0.21
	Bus	0.21	0.5	-0.86	0.01
	Air	0.05	0.26	0.01	-1.14
VFR*	Auto	-0.6	0.15	0.01	0.03
	Rail	0.28	-1.19	0.05	0.06
	Bus	0.18	0.5	-0.86	0
	Air	0.11	0.13	0	-0.99

Source: Dargay et al., 2010. * VFR= visiting friends and relatives.

Gillen et al., (2002) provide a detailed assessment the air travel price elasticity literature prior to 2002. Based on 254 estimates taken from 21 different studies, they find most air travel price elasticities fall between zero and -2.5, with a maximum (absolute) value of -3.2, a minimum of -0.04, and a median value of -1.12. Looking further into the data, they identify six distinct markets for air travel, and report own-price elasticities for each of these distinct markets: (1) Short-haul business travel, (2) Short-haul leisure travel, (3) Long-haul, domestic business travel, (4) Long-haul, domestic leisure travel, (5) Long-haul, international business travel, and (6) Long-haul, international leisure travel, of which the top four are the most relevant to this present study of automobile travel options. Among other statistics and graphs of the spread of elasticity values in each of these markets, the authors report the median value air market-specific elasticities shown in Table 23.

Table 23. Example Air Travel Market Elasticities (median values, for studies between 1992 to 2002)

All long-haul domestic estimates	-1.15
All long-haul domestic business estimates	-1.15
All long-haul domestic leisure estimates	-1.12
All short/medium haul estimates	-1.15
All short/medium haul business estimates	-0.73
All short/medium haul leisure estimates	-1.52

Source: Gillen, et al., (2002).

There is a clear difference here between the sensitivity to air fares for short to medium distance leisure trips (-1.52) and business trips (-0.73) which has implications for auto travel competitiveness. The authors argue that elasticity values can and do differ significantly between travel distance and by type of traveler, including income classes, and note that route-specific data is especially valuable in capturing competitive, geographic and market differences. Also of note, these authors report a median elasticity estimate from cross-sectional data studies of -1.133, versus a much lower one for time-series studies of -0.847, supporting the previous finding by Oum et al., (1992). Based on a meta-analysis of air travel demand studies from around the world, Brons, et al., (2002) also obtained similar results, showing that class of ticket and trip purpose (economy, business) along with length of trip (<500,500-1500, > 1500 miles) have a significant effect on reducing the absolute value of elasticities, but once again the type of modeling (cross-sectional, time-series, or pooled data) as well as length of time period studied influence the results significantly.

In more recent modeling of auto versus air travel in the U.S., Ashiabor, et al., (2007) and Baik (2008) used data from the 1995 American Travel Survey (ATS) to fit a series of nested and mixed logit demand models. Noting not only that travelers tend to switch to faster modes of transportation for long trips, but also that higher income travelers tend to switch to the faster modes earlier (i.e., for shorter trips) than do low income travelers, they stratify their travel cost variable by 5 income groups. Of note, in computing auto trip costs they include overnight stay costs where these are necessary to get to a destination. Their results suggest that higher income travelers are less sensitive to increased travel cost, and again confirm that business trips are a little less elastic with respect monetary costs than are non-business trips in the middle and higher income ranges.[1]

[1] based on logit mode parameters, no elasticities are reported

Using data from a survey of air, rail, and auto travelers in the Toronto-Montreal corridor in Canada, Bhat (1995) calibrated a variety of discrete mode choice models. From his heteroscedastic extreme value model he obtained a direct travel cost elasticity for rail of -1.12, and cross-elasticities of air (0.29) and auto (-0.22) with which to assess the effects of changes in rail pricing. Intercity rail elasticities were also looked at in some detail by Wardman, et al., (1997) in Great Britain (but again with somewhat dated, 1990 data). Using rail passenger and also roadside interview data, they fit a logit model that allows for non-linearities in its utility function, from which they obtain a series of both direct and cross-elasticities with respect to auto travel. They report the results (among others) that are seen in Table 24.

Table 24. Example Auto-Rail Price Cross Elasticities

	Single Traveler	Travel Group	All Travelers
Auto Direct Price Elasticity:	-0.21	-0.09	-0.16
Rail Direct Price Elasticity:	-0.58	-0.34	-0.47
Auto Cross-Elasticity w.r.t. Rail Cost:	0.07	0.04	0.06
Rail Cross-Elasticity w.r.t. Auto Cost:	0.25	0.23	0.25

Source: Wardman, et al., (1997).

Significant differences are observed between those who traveled alone and those who were accompanied by others, and once again showing a greater sensitivity to cost among rail riders over travelers by automobile. With the growing interest in high-speed rail corridors in the U.S. we may expect more empirical work on such rail direct and cross-elasticities in the near future.

6.2 DATA

As part of the 2001 NHTS, the sampled households were asked to report their long distance tripmaking activity for one four-week travel recall period. The long distance trip is defined as travel to a destination 50 miles or more from home (i.e., the round trip distance is greater than 100 miles).

In addition to the publicly available 2001 NHTS data records, additional confidentiality-protected data fields were also used in the analysis, as well as the following data sources used to estimate additional mode specific variables and subsequently attached to the corresponding long distance trip records:

- Airport and Amtrak station location data from the National Transportation Atlas Database (NTAD) (BTS, 2011) is used to calculate private vehicle access distances to each sample household's nearest commercial airport.
- Average cost of owning and operating an automobile, published by American Automobile Association (AAA), is used to estimate per traveler monetary cost of origin-to-major destination travel by personal vehicle.
- Airline on-time data from BTS's Office of Airline Information (OAI) database is used to draw actual elapsed flight time between origin-destination (O-D) cities.
- Airline origin and destination survey (DB1B) database, containing a 10% sample of all airline tickets, is used to estimate air fare between O-D city pairs.

The great circle distances (GCDs) from each sample's household location to the nearest airport are computed to estimate the access distance for the air mode for each trip. The access distance for driving a personal vehicle is assumed to be zero. The NTAD contains location data for airports. Together with the household locations from the confidential 2001 NHTS dataset, the air travel access distance was estimated for each long distance trip record. For about half of the households, there is a commercial airport located less than 20 miles from home. The farthest access distance to an airport is 200 miles.

The average cost of owning and operating an automobile, travel distance, trip purpose and travel party size are used to estimate highway travel times and costs for long distance travel by personal vehicles. An average speed of 60 mph is assumed to calculate the travel time based on the distance. The overnight stay (hotel) costs for the traveling party are also considered, where appropriate. The Virginia Tech travel surveys indicated that travelers tended to stop for an overnight stay after 8 and 10 hours for business and non-business trips respectively (Ashiabor et. al., 2007). The lodging cost for business and non-business trips are assumed as $90 and $70 per night, respectively. The overnight stay cost is the product of number of overnight days and daily lodging cost. The average costs of owning and operating an automobile is 51 cents per mile for year 2001, including a variable cost of 13.6 cents per mile and a fixed cost of 37.4 cents per mile (AAA, 2001). For non-business trips, only the variable cost (i.e., 13.6 cent per mile) is considered for estimating the cost associated with long distance driving, as the fixed cost associated with owning a vehicle is usually indispensable, whether or not long distance travel occurs. For business trips, the total cost (i.e., 51 cents per mile) is assumed, which reflects the typical reimbursement rate for using a personal vehicle for business travel.

To estimate travel time and monetary cost for air travel, aviation fares data for O-D city and/or airport pairs published by the USDOT Office of Aviation Analysis, as well as flying time statistics published by the Bureau of Transportation Statistics' (BTS) Office of Airline Information were used. These datasets are merged with 2001 NHTS long distance trips to estimate the airborne time and the air fare associated with applicable long distance travel record. To utilize the flight time and air fare data, the O-D cities for the applicable long trip records in the 2001 NHTS database were identified first. Specifically, the origin city is determined based on the household location and the destination city is obtained from the confidential 2001 NHTS dataset. Then, trip time and monetary cost by air mode are estimated and attached to the corresponding 2001 NHTS long distance travel record. Trip time by air mode is estimated based on the flight time and connection time if nonstop scheduled-service is not available. Flight time is obtained or imputed from airline on-time data, which is reported to BTS by 16 U.S. air carriers that have at least 1 percent of total domestic scheduled-service passenger revenues, plus two other carriers that report voluntarily. The data cover nonstop scheduled-service flights between points within the United States (including territories). Detailed flight time information includes scheduled departure time, actual departure time, scheduled elapse time, departure delay, wheels-off time and taxi-out time by airport and airline. In this study the actual elapsed flight time is used, that is, the actual time between wheels-up to wheels-down. Since the reported flight times are only available for the O-D city pairs with nonstop scheduled-service flights, the flight times of other O-D city pairs are imputed using the GCD between the O-D. Connection time is also added to the trip time estimation for the O-D city pairs with connecting flights. An average connection time of 45 minutes is assumed.

Air travel cost are obtained from the BTS's Passenger Origin and Destination (O&D) Survey, a 10% sample of all airline tickets for U.S. carriers, excluding charter air travel. Average fares are based on domestic itinerary fares. Itinerary fares consist of round-trip fares unless the customer does not purchase a return trip. In that case, the one-way fare is included. Fares are based on the total ticket value which consists of the price charged by the airlines plus any additional taxes and fees levied by an outside entity at the time of purchase. Fares include only the price paid at the time of the ticket purchase and do not include other fees paid at the airport or onboard the aircraft. Averages do not include frequent-flyer or "zero fares" or a few abnormally high reported fares. The 10% sample tickets survey covers only some of the O-D city pairs of the 2001 NHTS long distance travel samples. Air fares do not have a clear statistical correlation with travel distances. Thus we cannot impute air fare based on distance or other available information and are able to attach an air fare for only a small subset of the 2001 NHTS records.

6.3 BINARY LOGIT MODEL

In this section, explanatory variables in the form of policy significant factors related to travel times and costs are incorporated in a binary logit choice mode. A subset of the 2001 NHTS long distance travel records, supplemented with trip time and monetary cost estimates, is used to calibrate the binary logit model capturing long distance travel modal choice between the personal vehicle and air modes (see Table 25).

Table 25. Discrete Choice Model Specification

Dependent Variable	**Type**	**Description**
Mode	Categorical	Auto, air
Alternative Specific Variables		
Access distance	Continuous	Car – 0 Air – distance between the household location and the nearest airport
Time	Continuous	Round trip travel time from origin to destination
Cost	Continuous	Monetary cost
Individual Specific Variables		
Income	Continuous	Total household income last 12 months (in thousand dollars).
Travel size	Continuous	Number of people on travel period trip (including household and non-household members)

The observed utility of the binary logit model is represented by the value function

$$V_{ij} = \alpha_j + \beta_1 \cdot d_{ij} + \beta_2 \cdot t_{ij} + \beta_3 \cdot c_{ij} + \gamma_{j1} \cdot inc_i + \gamma_{j2} \cdot s_i \tag{18}$$

where

α_j = alternative specific constant;

d_{ij} = mode specific access distance with a generic coefficient β_1;

t_{ij} = mode specific trip time with a generic coefficient β_2;

c_{ij} = mode specific cost with a generic coefficient β_3;

inc_i = income with an alternative specific coefficient γ_{j1}; and

s_i = travel party size with an alternative specific coefficient $\gamma_{j2.}$

6.4 RESULTS

The alternative (mode) specific access distance, trip time, and travel cost for the applicable long distance records in the 2001 NHTS dataset have been estimated, considering relevant trip characteristics such as travel distance and trip purpose. A subset of the 2001 NHTS long distance travel records, where values of the explanatory variables (i.e., income, travel party size, access distance to the airport, mode specific trip time and monetary cost) are available, is used to calibrate the discrete choice model. Table 26 lists the estimated coefficients and the corresponding statistics.

Table 26. Estimated Binary Logit Choice Model

	Estimate	Std. Error	t-value	Pr(>|t|)	Significance[1]
Constant (auto)	3.00735	0.168611	-17.836	< 2.2e-16	***
Access distance	-0.01855	0.003851	-4.8173	1.46E-06	***
Time	-0.02621	0.002368	-11.0697	< 2.2e-16	***
Cost	-0.00229	0.000258	-8.8794	< 2.2e-16	***
Income (auto)	-0.018929	0.001551	12.2072	< 2.2e-16	***
Travel party size (auto)	0.07539	0.020808	-3.6234	0.000291	***
Log-Likelihood			-1541.4		
Rho-square			0.3984		

[1]Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The effect of mode-specific level-of-service variables and household income on long distance travel modal choice is assessed and intended for mode shares forecasting and policy analysis. Table 27 lists the *aggregate* elasticities of all samples, which are computed by following Equations (10). For example, the direct elasticity of auto travel demand with respect to auto travel cost is -0.11, indicating about a 1.1% decrease in auto travel demand when the cost associated with driving increases by 10%. On the other hand, if the air fare increases by 10%, the demand for auto travel is expected to increase approximately by 0.6% according to the cross elasticity.

Table 27. Aggregate Direct and Cross-Elasticities of Auto Travel Demand

Variable	Elasticity Type	Aggregate Elasticity
Airport access distance	Cross	0.05
Air Time	Cross	0.02
Air Cost	Cross	0.06
Auto Time	Direct	-0.13
Auto Cost	Direct	-0.11
Income	Direct	-0.23
Travel party size	Direct	0.03

The entire sample set is divided by household income into five levels. The first grouping is below the poverty line income, which is set below $20,000. The second grouping is the income level between the national median and poverty line income, which is from $20,000 to $44,999. The third grouping for above national median income contains families with incomes greater than $45,000 and less than $75,000. The fourth group is families with $75,000 to

$100,000 annual income. The last group is $100,000 and above. Aggregate elasticities for each income groups are computed (Equation (13)) and listed in Table 28.

Table 28. Long Distance Auto Travel Demand Elasticities by Income Groups

Variable	All Samples	<20K	20-45K	45-75K	75-100K	>100K
Airport access distance	0.05	0.02	0.03	0.04	0.06	0.07
Air Time	0.02	0.01	0.01	0.01	0.02	0.02
Air Cost	0.06	0.03	0.04	0.05	0.08	0.10
Auto Time	-0.13	-0.09	-0.10	-0.12	-0.14	-0.18
Auto Cost	-0.11	-0.06	-0.07	-0.09	-0.13	-0.16
Income	-0.23	-0.02	-0.06	-0.14	-0.30	-0.54
Travel party size	0.03	0.01	0.02	0.03	0.04	0.05

Low income travelers tend to be inelastic with respect to cost changes because they cannot afford to switch to the generally faster air mode; while high income households are generally more elastic with respect to such costs. Households with very high income might be inelastic with the cost changes. This effect, however, cannot be derived from the NHTS dataset, as these households are grouped in the >100K annual income category.

7. CONCLUSIONS AND RECOMMENDATIONS

This project studies the effect of monetary costs on travel demand, including fuel cost and maintenance cost, as well as a set of socioeconomic characteristics. Note that any elasticity measure is based on an implied time frame over which changes in travel costs and volumes take place. Over the short run, usually defined as a single calendar year, most households will retain their current vehicles and must either reduce the number auto trips they make, or reduce the length of such trips in order to cut costs. The most effective options for doing so involve switching to other modes of transport (notably to public transit) and selecting closer destinations, coupled with better route planning and driving in a more fuel efficient manner. Given more time to adapt to higher travel costs, households have additional options available to them, including the replacement of current vehicles with more fuel efficient and less expensive ones. Significant VMT changes at the household level may also occur due to job or residence relocations, and to changes in the size and composition of the family unit (children are born, go to school, leave to live and work elsewhere, workers retire, etc.). Such socio-economic, demographic and locational changes are best captured in the form of long–run, multi-year elasticities, with the empirical literature consistently findings these elasticities to be 2 to 4 times larger than single year elasticities. As disaggregate, cross-sectional datasets have been used in this study, the reported elasticities are considered as long run estimates. A rough estimate of short run elasticities could be ¼ to ½ of the reported values in Table 9, Table 20, Table 27 and Table 28.

The following areas are suggested for future research:

- Examine the impact of parking costs and transit usage on vehicle travel demand, considering the recent changes in mass transit tax benefit and tax-free parking. Due to the difficulty of collecting parking costs on a wide geographic scale, existing studies on the effects of parking costs on auto use have so far been limited to city-specific analyses. The location and type of parking spaces offered both have a significant effect on demand elasticities. In addition, as transit usage could be affected by the changes in automobile operating costs and transit cost increases may lead to ridership losses where trips are of a more discretionary nature, it is suggested to take a closer look at the role of trip purpose, time of day (peak/off-peak) and household income levels in traveler responses to these modal shifting opportunities.
- The present study has shown the different effects in terms of the VMT and number of trips (or trip frequency) in response to changes in travel cost variables. The next step is to establish activity models so as to better understand and quantify the impact on trip aggregation and trip chaining.
- Capturing the effect of vehicle ownership choices more consistently and more directly in future VMT forecasting models is a worthwhile area for further exploration. The incorporation of vehicle ownership costs, including vehicle purchase costs, is not handled in a consistent manner across studies, but clearly needs to be

modeled in order to capture the effect of such costs on not only future vehicle miles of travel activity, but also future demand for motor fuels. Simultaneous equation or discrete/continuous modeling of the joint decisions to own vehicles of specific types and to make more or less use of each vehicle, in part as a function of travel costs, may be used for such analysis.

- There is limited up-to-date and statistically established empirical evidence on long-distance travel cost elasticities for the United States. More attention needs to be paid to these long distance travel cost options, especially in light of the growing interest in the high-speed rail options within U.S. intercity corridors, as well as the apparent growth in intercity bus travel in selected U.S. markets.

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