REFLECTING THE IMPACT OF FLUCTUATING FUEL PRICES ON TRAVEL BEHAVIOR IN THE CONTEXT OF REGIONAL MODEL IMPROVEMENTS AND DYNAMIC SIMULATIONS

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FINAL REPORT

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Disclaimer

This report has been prepared to provide technical information on reflecting the effects of fluctuating fuel prices on travel behavior in transportation planning models. It does not constitute a standard or a regulation. The author has made every effort to provide information that is true and accurate. However, the reader and user are solely responsible for any losses or damages that are incurred in the use of the report and the accompanying spreadsheet tool.

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1. INTRODUCTION

The year 2008 proved to be a defining moment in the history of transportation and is likely to be remembered as the year when the tide turned, particularly in the United States. Fuel prices rose to record levels shattering all previous records, including those set during the fuel crisis of the late 1970s and early 1980s. Transit agencies around the country reported record increases in ridership (APTA, 2008), and for the first time since the fuel crisis decades ago, total vehicle miles of travel (VMT) showed a decline between 2007 and 2008 in the United States (FHWA, 2008). This measure of travel demand declined by a little over two percent, with the nation traveling nearly 50 billion fewer vehicle miles in 2008 than in 2007 (FHWA, 2008). Fuel prices had been steadily rising since 2003, but it appears that the record set in 2008 at $4 per gallon proved to be a tipping point where travelers started making adjustments to their travel behavior, resulting in the drop in VMT. Media reports describing adjustments that people were making in consumption patterns and activity-travel behavior in response to higher gas prices were aplenty (MSNBC, 2008a, 2008b, 2008c, 2008d).

Travel demand forecasting models continue to serve as the primary tools for planning future infrastructure enhancements, analyzing traveler response to a wide array of policies and system conditions, and predicting changes in traveler behavior that might arise due to external forces. For many years, fuel prices did not tend to be a major focus of transportation planning models and policy analysis, primarily because fuel prices in the United States stayed at historical lows, evidence suggested that travel behavior is largely inelastic to small fluctuations in fuel price, and there were no concerns about the continuous flow of transportation financing and funding streams that were largely dependent on gas tax revenues.

In the recent past, however, there has been a shift in this traditional mindset. Not only have fuel prices fluctuated enough so as to impact economic activity, quality of life, and vitality of communities, but increasing emphasis on greenhouse gas (GHG) emissions reductions, energy sustainability, renewable energy development, and alternative energy sources has motivated transportation professionals to examine the implications of fluctuating fuel prices on travel demand and transportation finance streams. This particular project is more concerned with the first aspect, i.e., understanding how fluctuating fuel prices impact travel demand, although impacts on travel demand naturally translate into changes in transportation funding streams that are largely dependent on gas tax revenues. In particular, there are several factors that have contributed to an interest in better understanding how travelers respond to fluctuations in fuel prices:

a. Although fuel price fluctuations have largely been small perturbations for many decades that had little to no impact on travel demand, the fluctuations in the past few years (say, since 2004) have been anything but small. In 2008, gas prices topped $4 per gallon across the country, and later that same year, gas prices went back down to $2 per gallon. Gas prices in Spring/Summer 2009 were hovering around $2.60 per gallon, suggesting that price fluctuations continued to take place, particularly under volatile economic conditions. Trends and data analysis (presented later in the report) suggest that these price fluctuations are large and significant enough to trigger changes in travel behavior.

b. As fuel prices rise, or as the confidence level erodes among the public that fuel prices will remain steady for long periods, households are likely to transition their vehicular fleet towards more fuel efficient, smaller, and alternative fueled (hybrid fuel) vehicles. As a result of these shifts in the vehicular fleet mix, gas tax revenues will slide even if there is no other change in travel demand (vehicle miles of travel). As the gas tax revenue continues to be the primary source of funding for the highway trust fund, it is clear that the profession needs to identify alternative funding mechanisms and sources for transportation funding. Mileage-based fees and tolls are being considered as potential substitutes for the gas tax, but there are several issues that continue to make their widespread implementation (at least in the short term) rather challenging. There is a need to identify the fuel price fluctuation impacts on vehicular fleet mix, vehicle utilization and miles of travel, and gas tax revenues. Armed with such an understanding, policy makers will be able to devise acceptable alternative mechanisms that provide funding streams to offset the potential reduction in gas tax revenues.

c. Lower income groups and minorities are likely to be more substantially and adversely affected by large fluctuations in gas prices. They spend a higher proportion of their income on transportation costs and there is renewed interest in ensuring that viable alternative modes of transportation exist for such groups to access workplaces, activity destinations, and other opportunities. Social equity analysis of fuel price fluctuations, and the planning of multimodal transportation systems that offer transportation options to all, require the use of transportation planning models that are capable of accurately reflecting the impacts of fuel price fluctuations on all socio-economic strata of society. As fuel price issues were generally not a major focus area of transportation planning models in the past, it would be beneficial to examine the ability of models to incorporate the effects of fuel price fluctuations on travel behavior and vehicle miles of travel.

The analysis of the impacts of fluctuating fuel prices on travel demand is not straightforward (Goodwin et al, 2004). What makes the analysis of the impacts of fluctuating fuel prices on travel demand complex is that there are many confounding factors that make the isolation of fuel price impacts difficult, if not near impossible. Over the past three years, fuel prices have fluctuated appreciably, but these fluctuations have not happened in isolation of other economic phenomena. Fuel prices fluctuations have occurred during a time of economic recession (that most experts say started in December 2007) that has seen near-record drops in retail activity and sales, vehicle sales, stock market indices, and home values and sales. Unemployment rates have risen to levels not seen since the early 1980s. In the presence of these rather cataclysmic economic changes, it is difficult to isolate the impacts of fuel price fluctuations on vehicle miles of travel, fuel consumption, sales of vehicles, and other transportation activity. If annual vehicle miles of travel drop by a certain amount, how much of that is due to a rise in gas prices and how much of that is due to the drop in economic activity in the country or region? How can the impact of fuel price fluctuations be accurately isolated and quantified, and how (in turn) can these impacts be best reflected in travel demand modeling systems?

It is these interesting and critical questions that motivated this study. This study is not intended to serve as a comprehensive activity-travel demand model enhancement effort, but is rather aimed at providing some insights into how travel demand is impacted by changes in gas prices using real-world aggregate data as well as disaggregate choice models estimated on behavioral data sets. A related objective of the study is to develop a simple spreadsheet that uses elasticity measures derived from the disaggregate choice models to estimate aggregate vehicle ownership and utilization characteristics for the Maricopa County region, consistent with the aggregate traffic volume data that has been measured during the time that fuel prices fluctuated substantially. The study also aims to provide some information and ideas on how transportation planning models can be enhanced to better reflect the impact of fluctuating fuel prices on travel demand.

2. UNDERSTANDING BEHAVIORAL IMPACTS OF CHANGES IN FUEL PRICE

Changes in fuel prices can bring about a range of possible adjustments in human consumption patterns and activity-travel behavior. It is important to understand the types of adjustments that can be made and the spatio-temporal dimensions that are associated with these changes. Table 2.1 offers an overview of the types of changes that may occur as a result of changes in fuel prices.

Table 2.1. A Typology of Behavioral Changes in Response to Fluctuations in Fuel Prices

Space / Time	Local	Regional	National
Short-term	Activity participation Trip chaining Route Destination Mode	Activity participation Trip chaining Route Destination Mode	Long-distance travel
Medium-term	Activity participation Trip chaining Route Destination Mode Work Schedule	Activity participation Trip chaining Route Destination Mode Work Schedule Vehicle fleet	Long-distance travel Vehicle fleet
Long-term	Activity participation Trip chaining Route Destination Mode Residential Location Work Location Migration	Activity participation Trip chaining Route Destination Mode Vehicle fleet Residential location Work location Migration	Long-distance travel Vehicle fleet Migration

In the short term, individuals may make adjustments to their daily activity-travel engagement patterns in response to changes in fuel prices. The discussion here focuses on changes that may occur when fuel price rises, but the discussion can be easily reversed to consider the case in which fuel price falls as well, although one must recognize that behavioral adjustments made in response to a rise in fuel price may not be equal and opposite to those made in response to a fall in fuel price. Adjustments to daily activity-travel patterns may take a variety of forms. Individuals may drop an activity (most likely a discretionary or flexible activity) from the activity agenda or reduce the frequency of participation in an activity type. For example, instead of shopping three times a week, a household may choose to consolidate all shopping activities into a single trip once a week, thus making it necessary to consider the planning horizion of household activity and travel engagement when attempting to fully understand how fuel price fluctuations affect travel demand. Alternatively, individuals may retain the same (daily or weekly or monthly) activity agenda, but combine the activities more efficiently through the adoption of multi-stop trip chains. Thus, instead of pursuing a shopping activity and a personal business activity in two separate trip chains, one could potentially combine both activities into a single multi-stop trip chain. Such adjustments do not change the activity agenda per se, but result in changes in travel demand and characteristics. Changes to destination choice (travel to closer destinations) and route choice may also be made in the short term, as individuals attempt to reduce the amount of vehicular travel to control fuel costs. Shifts in mode (to walk, bike, car or vanpool, transit) are also possible in the short term. All of these shifts in behavior can impact activity-travel demand at the local level as well as at the regional level and hence these five items appear in the first two columns of the table. These adjustments may not have an impact at a national level as the activity-travel adjustments are primarily made in the local context. However, at the national level, it is possible that individuals will curtail long-distance recreational travel and businesses will cut back on official business travel to counter the effects of increased costs due to rising fuel prices. These adjustments can be made in the short term as a household can make a relatively short-term decision to alter vacation plans, or a business can implement business travel restrictions very rapidly.

All of these short term adjustments can also be made in the medium term and therefore, all of the activity-travel engagement modifications appear in the medium term row as well. Medium term adjustments generally take place over one to three years, as opposed to shorter term adjustments that can be made in a more instantaneous fashion. In the medium term, however, a couple of additional adjustments may be possible. Workers may negotiate with their employers to alter work arrangements. Rather than work traditional 5-day work weeks, employees may alter their work schedules such that they can work the requisite hours at the office in four days or telecommute one or two days a week. Such rearranging of work schedules would help eliminate the cost associated with commute travel on days of the week that the worker does not have to commute. As the commute trip generally tends to account for a sizeable portion of overall individual VMT (for workers), this adjustment can substantially impact local and regional travel demand. At the local scale, it is possible that workers who work or stay at home might undertake short home-based trips that would otherwise not be made when the worker commuted to the regular work place.

The other major adjustment that can be made in a medium-term time horizon is that of the vehicle fleet composition. It is entirely possible for a household to continue engaging in exactly the same activity-travel patterns as before the fuel price rise by simply adjusting its vehicle fleet composition so as to remain cost neutral. If fuel price doubles, and a household switches to a vehicle that is twice as fuel-efficient, the effective cost of driving remains unaltered and the household can undertake exactly the same activity-travel patterns as before without incurring additional expenditure (assuming that the transaction cost associated with switching to a different vehicle does not adversely impact money availability and consumer expenditure patterns). A potential change in fleet composition would have regional implications with respect to fuel consumption, gas tax revenues, emissions, and air quality. Similar implications would also result at a national level as the nation's fleet may fundamentally shift towards a more fuel-efficient and low emissions one.

In the long term, more fundamental changes in household and personal choices are conceivable. Households and individuals may continue to make changes in their daily, weekly, and monthly activity-travel patterns and choices that impact local and regional travel demand. Changes in work arrangements and vehicle fleet composition may take place in the long term as well. More unique to the long term adjustment horizon is the changes in spatial location choice that may result from fluctuations in fuel price. Households may choose to change residential location to reduce commuting costs (by moving closer to work locations) or housing costs (by moving to less expensive housing). Workers may choose to change jobs and find work opportunities close to the home location so as to cut back on commuting costs. Households that are struggling in one metropolitan area may choose to move to an entirely different urban area where commuting costs are lower, cost-of-living (e.g., housing) is more affordable, and taxes are lower. These decisions can affect migration patterns with implications on a local, regional, and national scale.

In the context of understanding and quantifying changes in behavior, one must pay adequate attention to scale. For example, from 2007 to 2008 the year-to-year increase in transit person miles of travel (PMT) across the country for the month of April was found to be 3.3 percent. This percent increase in transit ridership was associated with a 2.1 percent decrease in the nation's VMT, thus giving the potential mistaken perception that the lost VMT on the roads had been picked up by public transit systems around the country. However, if one examines the numbers more closely, as shown in Figure 2.1, the increase in PMT on transit accounts for just about one percent of the total reduction in VMT for the month of April. In other words, 99 percent of the reduction in VMT was accomplished by travelers through a variety of other adjustments including changes in destination choice, trip chaining patterns, activity generation and scheduling behavior, and route choice. Transportation planning models should be able to provide an adequate representation of scale so that errors are not made in the interpretation of demand data and model outputs.

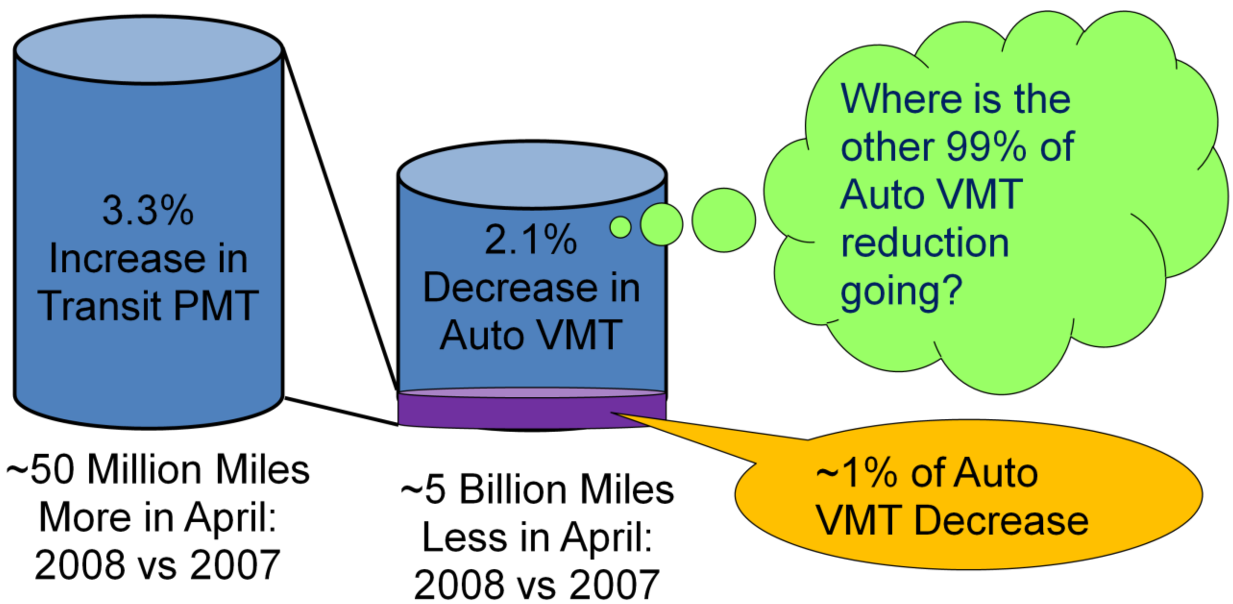

Figure 2.1. Understanding Scale in the Context of Mode Shifts

Overall, it can be seen that fuel price fluctuations can have impacts on activity-travel demand, vehicle fleet composition and utilization patterns, and spatial location choices – both at a local and national scale. While these shifts in behavior and choices can occur in response to both a rise or a fall in fuel price, it should be recognized that the changes in response to these two price signals are not necessarily equal and opposite to one another. Behavioral changes to fluctuations in price (or changes in system conditions at large) are not necessarily symmetric in nature. If a 50 percent hike in fuel price is associated with a two percent drop in travel demand, then it does not mean that a 50 percent drop in fuel price would be associated with an equal and opposite two percent increase in trip making. There are many factors that influence how people respond to price signals and these factors do not necessarily act in a symmetric fashion with respect to increases and decreases in prices. Similarly, behavior is often characterized by "hysteresis". This refers to the phenomenon where travel behavior does not revert to its original state when a system condition reverses itself to the original state. For example, when fuel price rises by 50 percent, a person may switch to public transit to save on transportation costs. When fuel price falls again by 50 percent, this person may not necessarily switch back to the auto mode. The person may have adapted to the use of transit and may be comfortable using the new mode of transportation and will not revert to the old behavior although the system conditions have been restored to their previous state. The concepts of behavioral asymmetry and hysteresis are not currently well represented in transportation planning models and as a result, predictions from travel models in response to price changes and pricing policies need to be viewed with caution.

While the preceding discussion has focused on the notion of "change" in behavior, one must also give due consideration to the possibility of the "do nothing" alternative. In response to fluctuations in fuel prices, it is entirely possible that a segment of the population will "do nothing" and make no change in behavior, activity-travel patterns, location choices, vehicle fleet composition, and vehicle miles of travel. These households may modify the household expenditure patterns so as to absorb the higher costs of transportation. By reallocating the household budget among various commodities and services, the household can absorb the higher transportation costs and continue activity-travel as usual. Unfortunately, the transportation profession has made little headway, if any, in understanding household consumer expenditure patterns and how transportation expenditures are traded-off against expenditures for other household expenditures such as utilities, food, child care, clothing, school, and s on. It will not be possible to fully understand behavioral response to fluctuations in fuel prices without a complete understanding of household consumer expenditure patterns. Some work is now being undertaken in this arena and the research shows promising directions to develop a more unifying theory and model system for transportation, household expenditures, and lifestyle choices.

How are the impacts of fluctuating fuel prices on travel demand captured in traditional zone-based travel model systems? If one were to consider the traditional four-step travel demand model, then each step of the process is capable of considering the effects of changes in fuel prices as follows:

a. *Trip Generation*: Trip generation is generally estimated using cross-classification methods of analysis or linear regression models. These models typically include an array of socio-economic and demographic variables as explanatory variables. Thus, in most trip generation models, fuel price impacts are not reflected. Some trip generation models include accessibility indices as explanatory variables. If the accessibility variables are formulated such that they incorporate the effects of "cost" (of which, fuel cost would be a component), then trip generation would be sensitive to fuel cost. In general, what is of interest here is to determine if there are trips that will be induced, or possibly foregone (suppressed), in the event of fuel price fluctuations. As mentioned earlier, behavior is not likely to be symmetric, i.e., the response to a fuel price drop is not likely to be equal and opposite to the response to a fuel price hike. Behavior is also likely to exhibit hysteresis, i.e., behavior does not revert to its original state even if fuel price comes back to its original state. Finally, although it may seemingly appear that trips are being induced or foregone, the actual out-of-home activities that are undertaken may actually remain the same. The pattern of trip chaining can be modified such that the number of trips increases (or decreases) even under a constant activity engagement pattern.

   This is where tour-based models and activity-based models can provide a much needed enhancement over current practice. These models are capable of reflecting changes in trip chaining patterns (tour formation) that might arise due to changes in "costs". Through the incorporation of log-sum terms that represent composite utility (disutility) values from destination choice and mode choice steps of the model system, tour generation and formation is sensitive to cost variables.

b. *Destination Choice (Trip Distribution)*: Trip distribution is typically implemented through the use of gravity models or destination choice models. In either case, composite impedance terms that represent the generalized cost of traveling from one zone to another are introduced as explanatory variables and influencing factors. These impedance terms often, but not always, include cost parameters that capture the effects of such things as fuel prices, parking costs, auto operating costs, transit fares, tolls, and so on. As a result of fluctuating fuel prices, it is entirely possible that travelers may alter their destinations for activities. They may choose to undertake activities at destinations closer to home or work locations (the traditional anchors of activity engagement), or destination locations may change simply due to a change in trip chaining patterns (tour formation). In any event, as long as the appropriate cost functions are included in the trip distribution or destination choice models, the impact of fluctuating fuel prices on destination choice (trip length) can be modeled. The question remains as to what the true impacts are, and how best they can be reflected in models of destination choice.

c. *Mode Choice*: The mode choice step is probably the clearest one in which fuel price effects are incorporated. Cost variables enter the utility function of virtually every modal alternative in a multinomial or nested logit model of mode choice. Auto operating costs change as a result of fluctuations in fuel price, and modal shifts result from changes in operating costs of the automobile. Empirical evidence suggests that there has been a small but noticeable shift from auto to transit as a result of rising fuel prices in 2008. It is entirely possible that some individuals who shifted to transit as a result of the fuel price spike *stayed with transit even after the fuel price reduced again.* This hysteresis effect is virtually impossible to reflect in traditional choice models of travel demand, which typically assume symmetry in behavior and absence of hysteresis. It would be useful to explore ways in which these behavioral phenomena can be incorporated into travel models. Nevertheless, the mode choice step is one in which fuel price fluctuations can be easily and effectively reflected with respect to their impacts on travel demand. What is of some difficulty, however, is to ensure that the cost variables included in the model accurately reflect the costs that are perceived by travelers. Many models therefore use “out-of-pocket” costs as the influencing variables to reflect the fact that people often perceive the cost of travel as only that involving actual out-of-pocket expenses paid on the trip. Such items as depreciation, insurance, vehicle maintenance, and vehicle registration often do not directly impact individual trip decisions.

   For example, an analysis of 2001 National Household Travel Survey (NHTS) data provides a trip length distribution for commuters on the journey to work (Figure 2.2). About 80 percent of commuters have one-way commute distances of just about 20 miles or less. If one were to assume the cost of gasoline to be $3 per gallon, fuel efficiency of 20 miles per gallon, and one-way transit fare to be $1.50, then commuters could essentially travel a distance of 10 miles and spend the same amount on gasoline or transit fare. In other words, for about 57 percent of the commuters, there is no perceived cost savings associated with taking transit under this scenario. Couple this with myriad other household and scheduling constraints, and the percent of commuters who can make a shift in mode in response to a gas price hike becomes quite small. This simple numerical example illustrates the challenge associated with bringing about change in mode choice, and the reason why mode choice is largely inelastic to fuel price fluctuations, except perhaps for the lowest income segments of society.

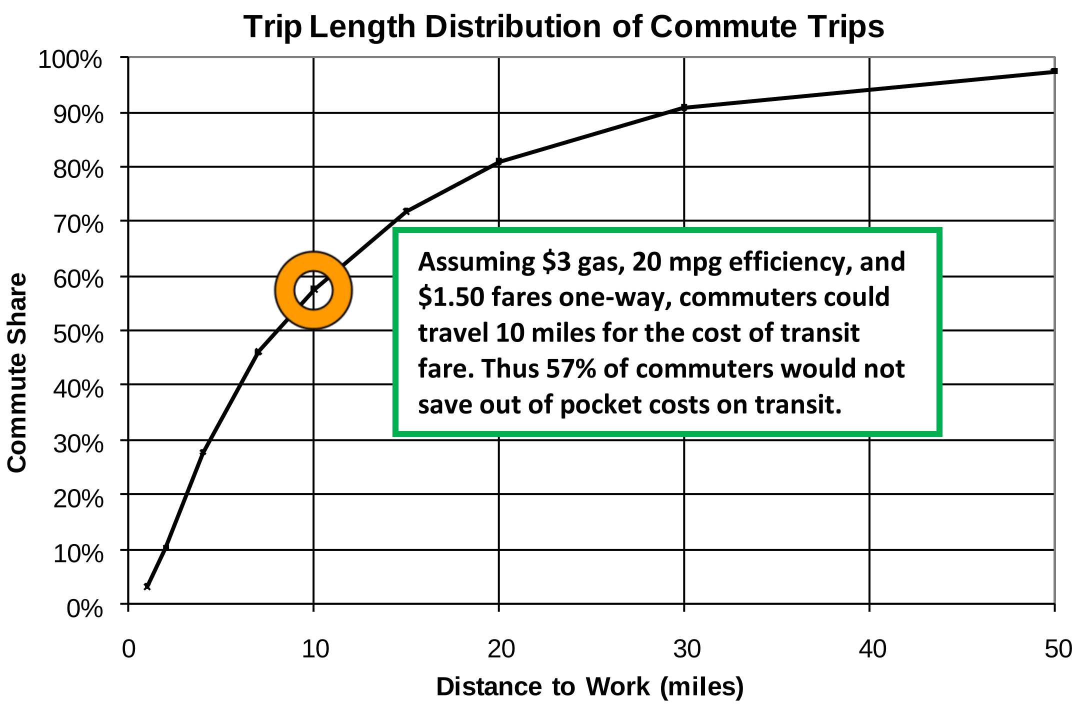

Figure 2.2 Comparison of Out-of-Pocket Fuel Costs and Transit Fares for Commuters

d. *Route Choice (Traffic Assignment)*: The route choice or traffic assignment step of the travel forecasting process is another area where the effect of cost can be effectively incorporated. Some changes in route choice will naturally occur due to shifts in destination choice and trip chaining patterns. However, even if an origin-destination travel episode were to stay the same, it is entirely possible that an individual will now choose a shorter-distance route, even if it is less desirable from other perspectives. Another possibility is that an individual will choose the non-toll route in order to compensate for the increased expenditure on fuel costs. Through the use of generalized cost functions that incorporate an array of cost variables, including fuel costs, one can potentially reflect the impacts of fuel price fluctuations on route choice. Traffic assignment models that have traditionally utilized only travel time measures as impedance values would have to be enhanced to incorporate cost variables, including fuel costs.

Activity-travel demand models are thus capable of potentially capturing the rather short-term effects of fuel price fluctuations on behavior. These models are not, however, well-equipped to handle the medium-term and long term impacts of price fluctuations. In the medium and long term, households may alter their vehicle fleets, change work schedules and locations, or move to a different residential location. These changes in behavior and longer term location choices are not captured within the domain of an activity-travel demand model. To effectively capture the medium and long term impacts, it is necessary to have robust vehicle ownership and land use model systems that are sensitive to price signals. A vehicle ownership model should not be limited to estimating the number of vehicles in a household (although that is, in and of itself, useful), but should be extended to estimating the number of vehicles in a household by vintage, body type, and fuel type. By doing so, the model system will be able to capture the changes in fleet composition that may result due to changes in fuel prices.

Consistent with the movement towards microsimulation of individual activity-travel patterns in the travel demand modeling arena, land use and location choice models are also moving towards disaggregate microsimulation of spatial location choices and socio-economic attributes of individuals. Residential location and workplace location choice models should be specified such that longer term location choices are sensitive to accessibility measures that incorporate cost components in the definition of accessibility. Multimodal accessibility measures that incorporate fuel cost would prove effective in simulating how longer term location choices may change in response to changes in fuel costs. Similarly, microsimulation model systems will need to incorporate modules that simulate work schedules as a function of cost (accessibility) variables (among other influencing factors). Model enhancements that can help provide policy sensitivity in the fuel price arena are further discussed in the concluding section of this project final report.

A final note that is due here is that regarding the recognition of heterogeneity in the population. Human behavior varies considerably across the population and models need to be specified to recognize this heterogeneity. Not everybody is sensitive to fuel price in the same way; some individuals may be more sensitive than others. While variations in sensitivity may occur across socio-economic market segments (such as those defined by income, car ownership, employment status, availability of alternative modes) defined by observed variables, variations may also occur due to unobserved attributes (such as lifestyle factors, attitudes and perceptions, values and beliefs, constraints and opportunities). While accounting for heterogeneity due to observed factors is rather straightforward, accounting for heterogeneity that arises from unobserved attributes is more challenging and warrants further attention, particularly in the context of recent developments in choice modeling methods that account for such attributes.

3. REVIEW OF EVIDENCE REGARDING FUEL PRICE IMPACTS ON TRAVEL

The interest in understanding the impacts of fuel prices was originally spurred by the oil crisis in the mid-to-late 1970's when gasoline prices soared. During that period, the price of gasoline went up by 20 percent, and Americans in turn consumed nearly six percent less fuel. The decrease in fuel consumption at that time was brought about by a number of changes including purchase of more fuel-efficient vehicles, switching to an alternate mode of transportation including public transit, moving closer to their place of work among other reasons (TMIP, 2007). Following the rise in gasoline prices during the oil crisis, prices fell in the early 1980's and following a relatively stable period during the 1990s, fuel prices once again increased dramatically from about 2004 through 2008, with a spike in the summer months of 2008. The average price of gasoline in the United States rose from $1.84 per gallon in 2004 to over $4.00 per gallon in June and July of 2008 (EIA, 2009). During this period, the average price for a gallon of gasoline in Arizona generally mirrored the national trends for gasoline prices (AAA, 2009). During the summer of 2008 when the gas prices were on the rise, people in Maricopa County saw average fuel prices reach over $4.00 a gallon at the pump (EIA, 2009). After the spike in the summer of 2008, fuel prices dropped in the following months as the economic downturn became more deep-rooted and severe. In early 2009, from January to April, the average price of gasoline was rising again with prices per gallon in the US rising from $1.92 to $2.54 (EIA, 2009). Despite the lower average fuel prices in the recent past in comparison to the high point reached in the summer of 2008, it is conceivable that fuel prices will increase in the near future, particularly as the economy recovers and rapidly developing economies of the world (e.g., China, India, Brazil) become larger consumers of the world's petroleum resources (Mouawad and Werdigier, 2007).

The increase in gasoline prices has not only impacted motorists but also the transit industry. The impact on the transit industry has been rather mixed. While the transit industry has experienced increased levels of transit ridership, the industry has also suffered from increased operating costs due to rising gasoline prices. In response to rising fuel costs, motorists are now considering the use of public transit options as opposed to driving their personal vehicle. Many transit properties around the country have reported increases in ridership, although it is difficult to isolate the impacts of fuel price changes on transit ridership increases from other socio-economic and system service changes.

3.1 Fuel Price Impacts on Travel Demand and Vehicle Miles of Travel

According to the Brookings Institute (Puentes and Tomer, 2008), which annually publishes reports on driving patterns in the US using measures like vehicles miles traveled (VMT), the total VMT for the nation has risen every year since 1956 until recent years. Between 1991 and 2004, VMT had risen by 38.4 percent, with a nearly 2.4 percent increase every year for over a decade. However, starting December 2004, the rate of increase in VMT has dropped; the percent change in VMT compared to the immediately preceding year for 2005, 2006, and 2007 was 0.8, 0.6, and -0.3 percent respectively. Puentes and Tomer (2008) noted that the figure for 2007 was significant because, "for the first time since 1980, and only the fourth time since the end of World War II, the annual change in national VMT was actually negative." This negative VMT trend continued into much of 2008. Per capita VMT also followed a similar negative trend during this period. In December 2008, average VMT per capita in the US was 9,564 miles, a figure that was about 40 miles less than the same measure in 1998. The intriguing part of the decline in VMT was that it did not always coincide with a surge in gasoline prices. Although there are periods of clear overlap wherein VMT declined at the same time that fuel prices rose, there are periods of VMT decline that are not necessarily associated with any substantial increases in fuel costs. Indeed, the authors argue that fuel prices alone are unlikely to contribute to decreases in VMT, although they do play an important role. They find that declines in VMT numbers started to show up before the price spike in 2008, and even though prices dropped after the summer months of 2008, data shows that miles traveled remained at its lowest level since 1999. This suggests that there are other factors (beyond the price of fuel) which are affecting the amount people drive (Puentes and Tomer, 2008). They note that the economic downturn, which began in late 2007 or early 2008, became more deep-rooted and severe in the latter months of 2008, thus contributing to reduced levels of economic activity, travel, and interestingly enough, lower fuel prices as global demand for oil decreased.

According to the literature analyzing the impact of gasoline prices on trends in VMT, the elasticity of VMT to gasoline prices in the long run (-0.30) is twice that of the elasticity in the short run (-0.15) (Litman, 2008). Johansson and Schipper (1997) noted that these elasticity estimates coincide with those found in other nations. This means that an increase of fuel price by 10 percent would result in an approximately one and a half percent decrease in VMT in the short run, and a three percent decrease in the long run. There are a few studies that have reported larger long run elasticity values (for example, Puller and Greening, 1999, report a long-run elasticity of -0.69), but the general range reported in the literature tends to suggest that VMT is inelastic to changes in fuel prices with elasticity values tending closer to -0.1 and -0.2. In developed countries, travel demand (measured in terms of VMT) is highly inelastic to fuel prices (Nicol, 2003; Hughes et al, 2006; Gicheva et al, 2007). Even with the recent decrease in VMT in the United States between 2007 and 2008, the fuel price elasticity of VMT appears to be just about -0.1. Between April 2007 and April 2008, a 21 percent increase in gas price was accompanied by a 2.1 percent decrease in VMT, suggesting that fuel price elasticity of demand (at least for that change in fuel price) was just about -0.1. From a per capita standpoint, this represents a drop of just about five vehicle miles of travel per week, from about 250 miles per capita in April 2007 to about

245 miles per capita in 2008. Prior to 2007, VMT continued to rise (albeit at a slower rate) despite increases in fuel prices, suggesting that individuals just absorbed the higher energy costs with virtually no impact on activity-travel demand.

An aspect that merits due consideration in the specification of travel demand models is the representation of population heterogeneity. A study conducted by Wadud et al (2009) showed that considerable variation in price and income elasticities exists across different income and demographic groups. In another study, Wadud et al (2010) found that income was one of the most significant determinants of elasticity with respect to fuel price. As expected, it was found that the lowest income quintile had the largest price elasticity. On the other hand, gasoline fuel price elasticities for the highest income quintiles were found to be extremely small. In addition to income, travel needs and constraints, location of residence, and level of vehicle ownership were identified as additional socioeconomic factors influencing fuel price elasticity. Urban households, who presumably have a wider range of modal options, were found to have higher price elasticity values than households in more rural areas. Consideration should be given to segmentation along these dimensions to accurately reflect the impact of fuel prices on travel by different socio-economic and demographic groups.

3.2 Fuel Price Impacts on Public Transportation Use

Over the past several years, public transportation systems across the country have experienced an increase in ridership. Valley Metro which operates public transportation in the greater Phoenix metropolitan area has also experienced an increase in ridership from less than five million average transit trips per month in 2007 to almost five and a half million rides per month in 2008. Following the introduction of the new light rail system, Valley Metro has experienced ridership numbers of over six million riders per month in the first quarter of 2009 (Valley Metro, 2009). The increase in ridership has been observed across all forms of public transportation. The increase in transit ridership has prompted many observers to link this with increasing fuel prices, indicating that some motorists are choosing to take public transportation rather than drive their personal vehicle. While it appears that the rising demand for public transport is correlated to the increase in gasoline prices, most studies have shown that the relationship is relatively inelastic (e.g., Mattson, 2008). Although gasoline prices are likely to play some role in influencing public transit ridership, it is likely that there are numerous other factors including the state of the economy and changes in service levels that influence ridership, possibly more so than does fuel cost.

Previous studies document considerable variation in the elasticities of the demand for public transportation. The majority of estimates of the elasticity of public transit ridership with respect to fuel prices range between 0.05 and 0.40 (Litman, 2008; Luk and Hepburn, 1993; Storchmann, 2001; TRACE, 1999), implying that if gas prices increased by one percent, public transit ridership would increase anywhere between 0.05 and 0.40 percent. Mattson (2008) studied the short run and long run elasticities in demand for public transportation due to changes in fuel prices using data from small urban and rural transit systems in the upper Midwest and mountain states. The author estimated a polynomial distributed lag model of bus ridership using aggregate data for transit systems in large, medium-large, medium-small, and small urban areas. The results for the large and medium-large cities showed that the response to changes in gas price was relatively fast, with the majority of changes to transit demand occurring in either the same month or the following month in which the change is gas price occurred. Interestingly, the medium-small cities showed an immediate increase in ridership following the increase in gas prices as well. For small cities, on the other hand, there was no substantial change until after five months, and the impact waned after about seven months. The long-run elasticities were computed to be 0.12, 0.13, 0.16, and 0.08 for the large, medium-large, medium-small, and small cities, respectively. An explanation offered by the study for the quick response to changes in fuel prices in the larger cities was that people living in urban areas tend to be more aware of public transit alternatives compared to those living in small cities and rural areas. Another explanation for the higher elasticity values in larger cities is that the number of public transit alternatives is greater, frequency of service is better, route coverage is superior, and network accessibility is more robust when compared with smaller cities or rural areas. Therefore, a person living in a large city would be more attracted to a public transit alternative during a period of high fuel prices compared to an individual living in a smaller city or rural area. Indeed, the lowest elasticity value was found for small cities. However, the highest rate of elasticity was not observed for large cities, but rather for medium-small cities (Mattson, 2008). However, the difference in elasticity values across the first three city size categories is small.

The increase in public transit ridership during the periods of increased gasoline prices is often associated with higher revenues for the transit agencies, but for many transit authorities, the increase in ticket revenues is offset by the decrease in public funding due to a reduction in gas tax revenues, and the increase in operational costs because of higher fuel prices. As a result, transit agencies often cut back on frequency of service, reduce the hours of service, eliminate routes, or even increase ticket fares. Often the financial impacts of increased ridership, reduced revenues, and additional operating costs are not felt immediately. This is partly because many transit agencies buy their gasoline in advance at a fixed price, a practice known as hedging, to cover several months if not the entire year of service. One study noted that, in the coming years even transit systems that have been able to escape the worst impacts of fluctuating fuel prices would be put to the test as fuel prices continue to rise or fluctuate unpredictably (KFH Group, 2008).

These kinds of financial impacts are not just limited to surface public transportation alternatives. The airline industry has experienced similar impacts due to rising fuel costs. From 2004 to 2008, the price of jet fuel nearly doubled from $1.03 per gallon to $2.23 per gallon. As a result, fuel costs accounted for a substantively larger portion of airline operating costs, accounting for about a quarter of their operational costs (Steinberg, 2007). Airline fuel prices remained largely unchanged through 2007, but experienced a drastic increase in 2008. It is estimated that a one-cent increase in the price of jet fuel would increase the operating costs of the airline industry by nearly $195 million each year (Inflation Data, 2009). In the months of June and July of 2008, when the price of oil exceeded $125 per barrel, it was projected that the airline industry's fuel costs went up by about nearly $9 billion (FAA, 2009). The first response by many airline companies was to reduce fuel consumption. With many operational and technological changes in the industry in the last few years, airline companies have been able to curb fuel consumption to reduce operating costs, but it has not been enough to curb or offset rising operating costs due to recent fuel price hikes (Steinberg, 2007). In an attempt to further recover operating costs due to rising fuel prices, airline companies have started charging higher fares, and fees for services that were previously provided to patrons at no charge. It is believed that if oil prices remain at $100 or more a barrel for a long period of time, airlines would eventually have to raise their fares and charge higher service fees, as well as reduce the number of flights and the number of destinations they serve in an effort to cut costs. This could lead to airlines ceasing operations and/or merging together, which could in turn reduce competition, increase fares, and lessen airline travel demand (FAA, 2009).

3.3 Fuel Price Impacts on Auto Ownership and Fleet Composition

Vehicle fleet composition and auto ownership are critical aspects of travel demand, and important determinants of energy consumption and greenhouse gas (GHG) emissions. Between 1990 and 2003, while emissions from passenger cars increased by just about two percent, GHG emissions from light duty trucks (LDTs) increased by about 50 percent (EPA, 2006). The increase in GHG emissions from automobiles and LDTs reflects the overall growth in travel demand (measured by vehicle miles of travel or VMT) and the substantial shift in household vehicle fleet composition towards larger, less fuel-efficient vehicles. The sport utility vehicle (SUV) market share, in particular, increased from just about one percent in 1976 to over 25 percent in 2003, whereas passenger cars experienced a decrease in share from over 80 percent to just about 47 percent during this period (EPA, 2006).

The higher fuel prices have had a dramatic impact on the automotive industry in the past several months. The big three automakers in the United States, who have relied heavily on the sales of large vehicles such as SUVs and trucks, have reported record losses of staggering figures in the past year (Austin, 2008). Toyota, which sells more fuel-efficient vehicles including the popular Prius gas-electric hybrid car in the United States, sold more vehicles than General Motors in the past year for which sales figures are available (Krisher, 2008). Households are clearly migrating to smaller and more fuel-efficient hybrid vehicles as they turnover their vehicle fleet in the household in response to the possibility that high fuel prices are here to stay (Buss, 2008). In the United States, the rise in fuel prices has been simultaneously met with a slumping housing market and record housing foreclosure rates, resulting in households losing the equity that they thought they had built up in their homes. These economic forces have created the perfect storm requiring households to adjust their consumption patterns, activity-travel behavior, and expenditures for various commodities and goods. At the same time, however, auto manufacturers are moving forward with the development of alternative fuel vehicles of various kinds that are clean and fuel efficient. The shifts in consumer demand (largely in response to higher fuel costs, but also in response to increased environmental awareness and sensitivity), coupled with new automotive technologies hitting markets around the world, may actually facilitate growth in vehicular travel demand (or at least maintaining levels of VMT seen during low fuel price years) as consumers are able to extract increasing amounts of VMT per fuel dollar of expenditure from their new vehicles.

Although there is evidence in the vehicle market to suggest that people are adjusting their vehicle type choices in response to rising fuel prices, there is at least one study that suggests that consumer vehicle purchase decisions are not impacted by fuel cost considerations. Turrentine et al (2007) conducted a study which focused on how consumers' knowledge, beliefs, and behaviors with respect to purchase price and fuel consumption influence their decision about which vehicle to purchase. The main focus of the study was to determine what role, if any, fuel economy played in consumers' choice of the vehicle type. Data for the study was gathered by interviewing 57 households in Northern California who had recently purchased or were about to purchase a vehicle. Respondents were stratified into nine "lifestyle sectors" based on their attitudes towards fuel consumption. The results indicated that a large gap exists in people's knowledge about fuel costs associated with a vehicle and its fuel consumption. It was found that even households with high income struggled to accurately estimate fuel costs for a vehicle and the potential recovery in costs associated with purchasing a fuel efficient vehicle. Furthermore, the study revealed that most motorists chose to purchase a fuel-efficient vehicle out of personal interest or to simply impress their peers rather than for any economic or financial reasons. Hybrid vehicle owners typically chose to purchase a fuel-efficient vehicle in order to satisfy short-term economic motivations instead of long-term savings. This study indicated that people are not necessarily able to perceive or measure fuel costs accurately in their travel decision-making processes. In other words, consideration needs to be given to the use of "perceived" costs in travel demand models as opposed to "actual" or "true" costs of operating an automobile.

The Congressional Budget Office (CBO, 2008) conducted a study aimed at understanding the impact of fuel prices on vehicle markets and driving behavior. In particular the study was aimed at understanding the impact of gasoline prices on traffic volumes, market shares for different vehicle types, traffic flow, transit ridership, and speed of traffic. The data for the study was largely obtained from the State of California. The report notes that most previous studies on short-run responsiveness have only shown negligible changes in travel demand relative to fuel price increases. However, if prices remained high, or even go higher, the long-run responsiveness can be expected to result in significant changes in driving behavior and vehicle markets (CBO, 2008*;* DOE, 1996).

The study utilized data collected at a dozen metropolitan highway locations, together with fuel price data for California. The study showed that, during weekdays, every 50 cent increase in gas price was accompanied by a 0.7 percent decline in the number of freeway trips. The observations were made in a metro area that offered public transportation alternatives including rail transit. It was observed that during the same period, transit ridership in the area increased by an almost commensurate amount. Median freeway speeds also declined, by about three quarters of a mile per hour for every 50 cent increase in gas price since 2003 – possibly reflecting increased congestion due to population growth, but also the effects of individuals driving more slowly to enhance fuel economy.

In terms of vehicle fleet composition, it was observed in the study that buyers were not choosing to purchase light trucks (pick-ups), sport-utility vehicles (SUVs), and minivans as much as they did in the past. It was estimated that consumers are only about one-fifth as responsive to short-run gas price changes today, when compared with consumers from several decades ago. The study attributed the decline in sensitivity to several factors. One of the main reasons mentioned in the study is that there has been a substantial increase in real income, which makes gasoline purchases a significantly smaller part of consumers' disposable income (CBO, 2008).

The study also projected that a 10 percent increase in the retail price of gasoline would reduce consumption by about 0.6 percent in the short run. In the long run, however, consumers would be more responsive to a sustained increase in fuel price. This is because they would have more time and more need to make changes that would affect their fuel consumption. Such changes would include the switch to a more fuel-efficient vehicle, or moving to a location that is closer to work. It was estimated that a sustained increase in gasoline price would decrease gasoline consumption by four percent in the long run due to a combination of such long term changes. While there would be a reduction in gasoline consumption, this does not necessarily imply that there is a corresponding reduction in VMT. Individuals may be able to sustain the level of VMT production seen in pre-fuel price hike days by virtue of driving a different fleet of vehicles that is more fuel efficient and economical. Thus, fuel consumption reductions can be realized without necessarily realizing reductions in VMT. Once again, it is important to reflect these types of phenomena in travel demand models which are often used to build long term 20 year forecasts for urban areas in the nation. The report by the Congressional Budget Office (CBO, 2008) estimated that it would take about 15 years (less than the planning horizon of a long range transportation plan) for the effects of a sustained increase in fuel prices to be fully realized.

4. TRENDS AND CHANGES IN TRAVEL AND SOCIO-ECONOMIC CHARACTERISTICS

This section of the report presents trends and changes in socio-economic and travel demand measures over the past several years with a view to understand how various transportation and economic indices have tracked in relation to changes in fuel prices.

4.1 Socio-economic Characteristics

Over the past decade, the State of Arizona, and Maricopa County in particular, has been one of the fastest growing regions in the state. This growth has been strongly associated with growth in population, employment, economic activity, building and construction, and travel demand and associated congestion. The effects of a fuel price increase on traffic and travel demand cannot be viewed in isolation of the other socio-economic and demographic characteristics and their dynamics over time. This section presents some selected descriptions of socio-economic characteristics of the region over the past several years.

Figure 4.1 shows the number of vehicle registrations and total population for the State of Arizona and Maricopa County over the past decade. It is clear that the state and the county experienced rapid growth particularly in the middle of the last decade, but that growth has considerably slowed in the past year. In fact, the number of registered vehicles in the state and the county appear to be showing a very slight decline in the past year, suggesting a slowdown in economic activity and population growth in the region.

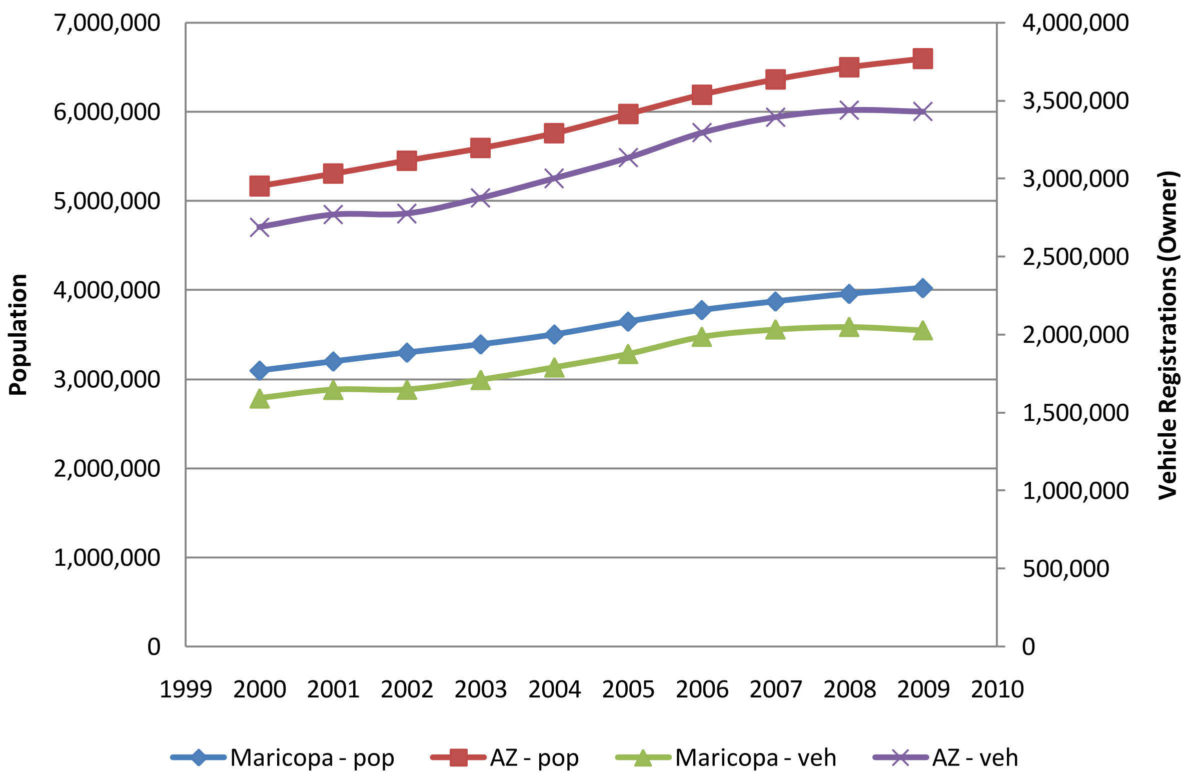

Figure 4.1. Arizona and Maricopa Population and Vehicle Registrations
Source: http://factfinder.census.gov/ for population
http://www.azdot.gov/mvd/statistics/registeredVehicles.asp for vehicle registrations

Figure 4.2 shows the Maricopa County unemployment rate in relation to the statewide VMT per capita. It is somewhat difficult to get reliable VMT statistics at the county level and hence the statewide VMT estimates are used as a surrogate for the county VMT trend. It is not unreasonable to expect county

VMT trends to track closely with state trends as Maricopa county accounts for about two-thirds of the state population. It is seen that the unemployment rate steadily dropped through 2007 and reached a low point of less than four percent unemployment in 2007. However, after 2007, the unemployment rate has been steadily rising. In 2008, during the period of the highest fuel price levels, the unemployment rate was not particularly high. The statewide rate was just about six percent, while the Maricopa county unemployment rate was just hovering around five percent. As such, the full effects of the economic recession had not yet been felt at the time that the fuel prices spiked to over $4 per gallon. In 2009, the unemployment rate continued to rise as the economic recession became more deep-rooted and severe. Unemployment rates now hover over nine percent for the state and over eight percent for the county. When one examines the VMT per capita, there is a rather noticeable drop after 2006, when fuel prices started to consistently rise to levels not experienced previously. In other words, VMT per capita started to drop off even before the full effects of the recession affected the unemployment rate. It may be argued that individuals made short-run adjustments in travel patterns in response to the fuel price spike, although it is more likely that the adjustments were made in response to the slowing economy and reduced consumer confidence on the future state of the economy.

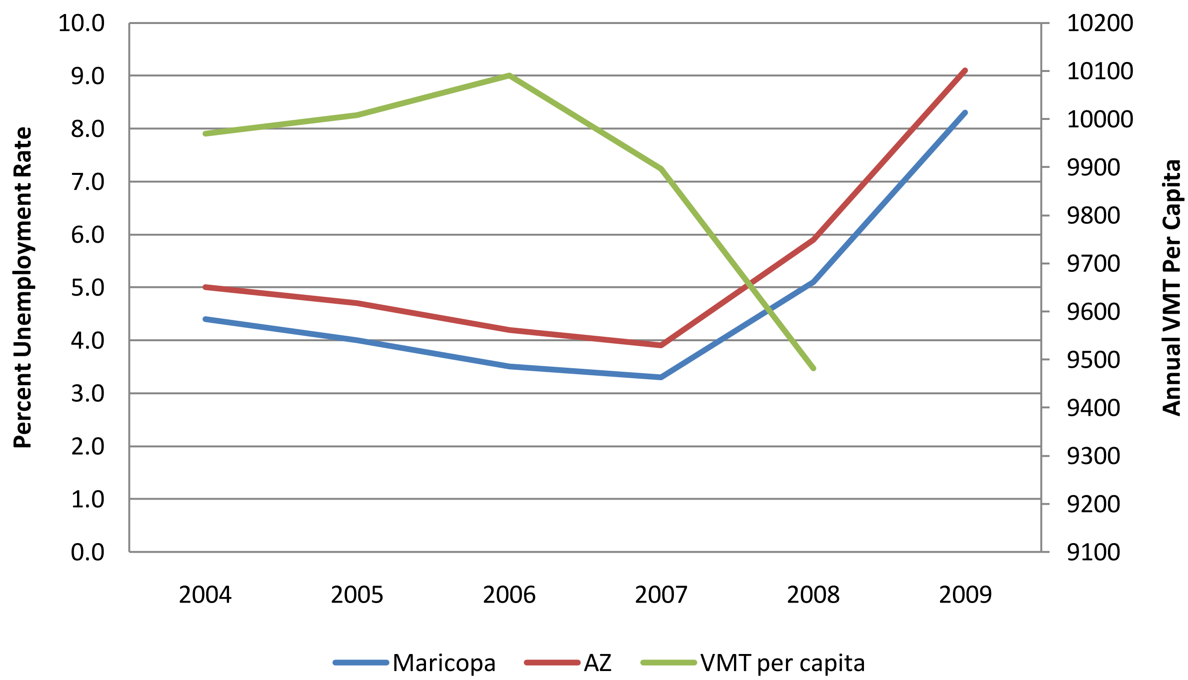

Figure 4.2. Maricopa Unemployment Rate in relation to Arizona VMT per capita
Source: http://www.bls.gov/data/#unemployment

Figure 4.3 shows the trends in income and fuel price per gallon for Maricopa County, with annual averages presented for the past decade. Emphasis should be placed on the real income and price levels as these values are corrected for inflation and reflect values that may be compared over time. It is interesting to note that real income did not change or increase considerably over the past decade. In fact, there was a slight dip in the middle of the decade, possibly due to the surge in lower-paying service and construction jobs during that period. What has clearly contributed to the decrease in VMT, at least in part, is the decreasing gap or distance between the income curve and the fuel price curve. If one were to compare the real income and real fuel price levels over the decade, the gap between the two curves becomes increasingly small, thus contributing to the slower growth in VMT and eventual downturn in VMT in the past few years. However, it is unlikely that a decrease in VMT is caused by fuel price escalation alone. Vehicle miles of travel continued to increase through the middle of the decade despite increases in fuel price, and it is only after an economic recession started to take root that VMT began to fall. Thus, it appears that a combination of an economic recession and downturn, and higher fuel prices, contributed to the decrease in VMT per capita.

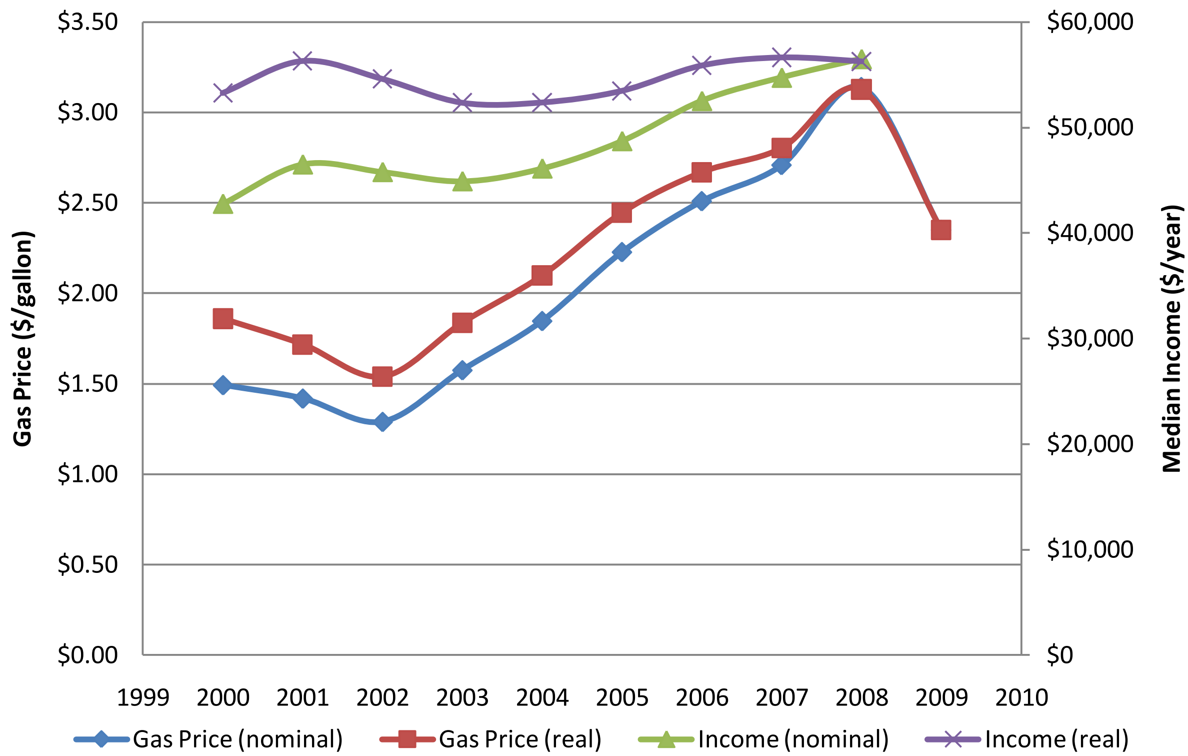

Figure 4.3. Real (adjusted to 2009 dollars) and Nominal Income and Fuel Price Levels
Source: http://www.eia.doe.gov/

Another major consideration in this regard is that of the notion of a "threshold" effect. While it is certainly plausible that a combination of factors contribute to the reduction in VMT, another possible reason for the noticeable reduction in vehicle miles of travel in 2007 and beyond maybe that fuel price levels finally reached a certain threshold value that trigger a change in travel behavior. In other words, response to fuel price escalation is not a continuous function, but more of a step or discontinuous function. In such a case, demand or behavior remains essentially unchanged for a range of fuel price hikes, but then begins to show noticeable changes when the price reaches a certain value. The notion of thresholds is being increasingly recognized in the travel demand modeling literature and more data needs to be collected to fully understand if and when threshold effects are present and how such values may be computed using models that capture discontinuous behavioral phenomena. In this report, while the possible presence of threshold effects is duly acknowledged, the analysis (presented later) does imply a more continuous response function. However, as more data becomes available and analytical methods continue to advance, alternative response function forms need to be tested and evaluated for their ability to capture behavioral changes.

To further understand how travel demand has changed in relation to economic indicators in the region, Figures 4.4 and 4.5 depict trends in statewide sales tax revenues and county/city median housing values in relation to statewide VMT per capita. It is interesting to note that VMT per capita tracks very closely with both of these indicators of economic health and activity. It appears that individuals cut back on spending (and hence the fall in sales tax revenues) in the latter part of the decade and this cutback in spending is associated with a concomitant decline in VMT per capita. A similar trend is seen in the figure depicting trends in median housing value. In general, the VMT per capita trend closely mirrors the trend in median housing value suggesting that consumer confidence, the state of the economy, and perception of equity built up in the home all impact travel demand.

The graphs in this section clearly show that VMT is closely associated with the state of the economy. It is best to see how VMT changed in relation to the fuel price during a period of economic stability, as opposed to a downturn that has been witnessed in the past few years. If one were to consider the period from 2006 to 2007 when fuel prices did escalate somewhat, and the economy had not yet entered a recession (although signs of a housing market meltdown were beginning to manifest themselves), the VMT per capita did decrease. Vehicle miles of travel did not increase in proportion to the population increase, thus contributing a decrease in VMT per capita between those two years. Since 2007, while fuel prices escalated and then came back down, VMT per capita has consistently decreased presumably because of the economic recession taking root. It is therefore difficult to isolate effects of fuel price fluctuations from effects of changes in economic indicators. However, the phenomenon observed between 2006 and 2007, coupled with evidence in the literature, suggests that individuals do respond to fuel price escalations, albeit in a modest or inelastic fashion.

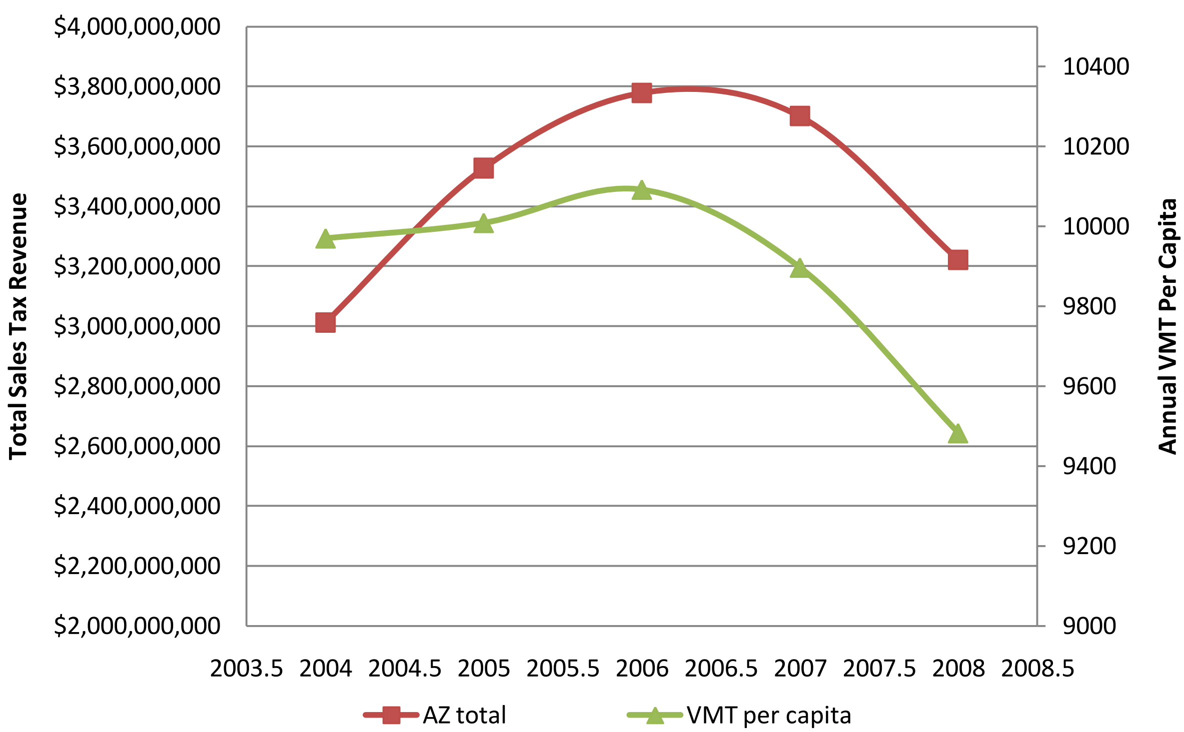

Figure 4.4. State Sales Tax Revenues in relation to Arizona VMT per capita
Source: http://www.azdor.gov/

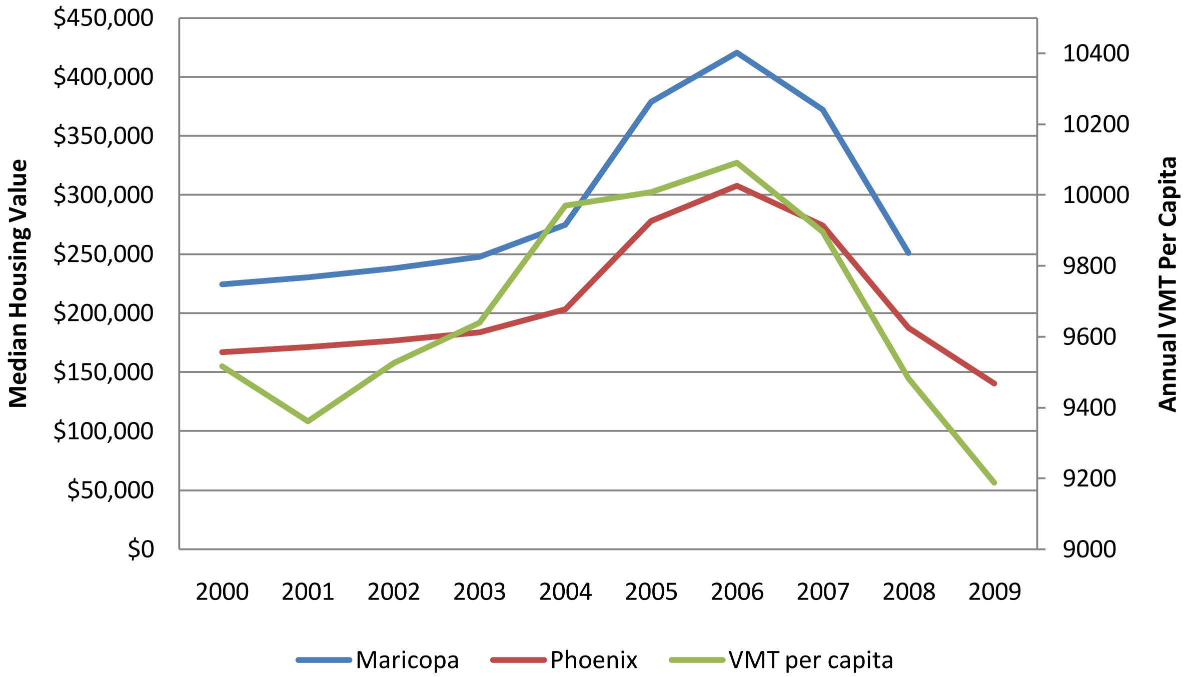

Figure 4.5. Median Housing values for Maricopa County and Phoenix Metro Area in relation to Arizona VMT per capita

Source: http://mysite.verizon.net/vzeqrguz/housingbubble/phoenix.html
http://factfinder.census.gov/

4.2 Transportation Trends

In this section, an examination of some transportation trends is done to see how aggregate travel demand tracks in relation to changes in fuel price. Figure 4.6 shows annual fuel consumption in the state and for Maricopa County over the past decade. While total fuel consumption steadily rose during the earlier part of the decade, it has clearly leveled off in the past few years despite continued growth in population (although growth in population has slowed). More notably, fuel consumption per capita has decreased quite substantially, both at the state level and for the county. The fuel consumption per capita, which was well over 450 gallons per year in the earlier part of the decade fell to just about 400 gallons towards the latter part of the decade. Even between 2006 and 2007, fuel consumption per capita decreased despite no serious effects of the economic recession being felt; at least some of this decrease in fuel consumption may be attributed to the rise in fuel prices during that time.

Figure 4.7 shows trends in VMT in the state over the past decade. Exact VMT figures are not available for Maricopa County, but given that Maricopa County accounts for about two-thirds of the population of the state, it can reasonably be expected that Maricopa County VMT trends mirror those of the state. Once again, total VMT appears to be leveling off at about 2006 or 2007, just about when real fuel prices were hovering well over $2.50 per gallon (in 2008 dollars). As noted earlier, VMT per capita shows a decrease between 2006 and 2007 despite no serious effects of the economic recession at that time, although some signs of a slowdown in the economy were evident. Since 2007, VMT per capita drops quite dramatically, but it is clear that this drop can be tied closely to the economic recession becoming more severe and deep-rooted.

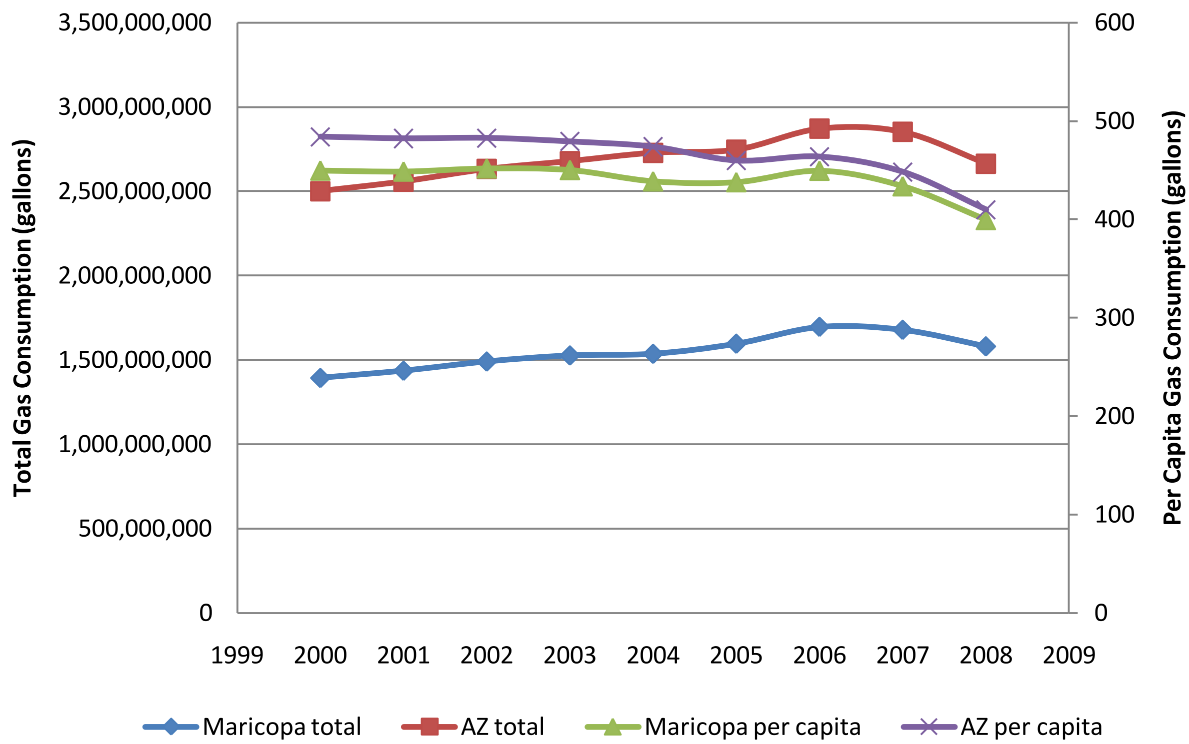

Figure 4.6. Annual Fuel Consumption

Source: http://www.azdot.gov/Inside_ADOT/fms/gallon2.asp

In order to better understand and visualize the trend in VMT in relation to the fuel price, an indexed version of the plot was generated; this plot is shown in Figure 4.8. In this figure, only data from 2007 and 2008 is shown by indexing monthly averages, setting figures at January 2007 equal to one. It can be seen that the fuel price in 2008 is consistently higher than that in 2007, with the exception towards the end of 2008 when fuel prices fell in response to a deep economic recession settling in. In the summer months of 2008, one notices the largest difference between 2007 and 2008 fuel price values. If one were to examine the monthly VMT trends, it is seen that the 2008 VMT trend is consistently below that for 2007 signifying that VMT has gone down on a month-to-month comparison between those two years. The difficult question to answer, however, is the extent to which this decrease is due to the economic recession versus the fuel price increase. Even if some of that difference were attributed to the increase in fuel price, what is interesting to note is that the difference in VMT trend lines between 2007 and 2008 is quite small in relation to the difference in fuel price trend lines. In addition, the difference between the 2007 and 2008 VMT lines is more striking in the middle of the year and in the Fall season months, when the effect of the fuel price escalation may have been felt most. It is also possible that there is a lagged effect in response to fuel price increases with travel demand changes occurring in months that follow a substantial fuel price increase. Nevertheless, as fuel price in 2008 came back down to 2007 levels (and became even lower than 2007 levels towards the end of the year), the gap between the 2007 and 2008 VMT lines becomes narrower again (see the month of December), suggesting that there may have been some rebound in travel as gas prices plummeted in the end of 2008.

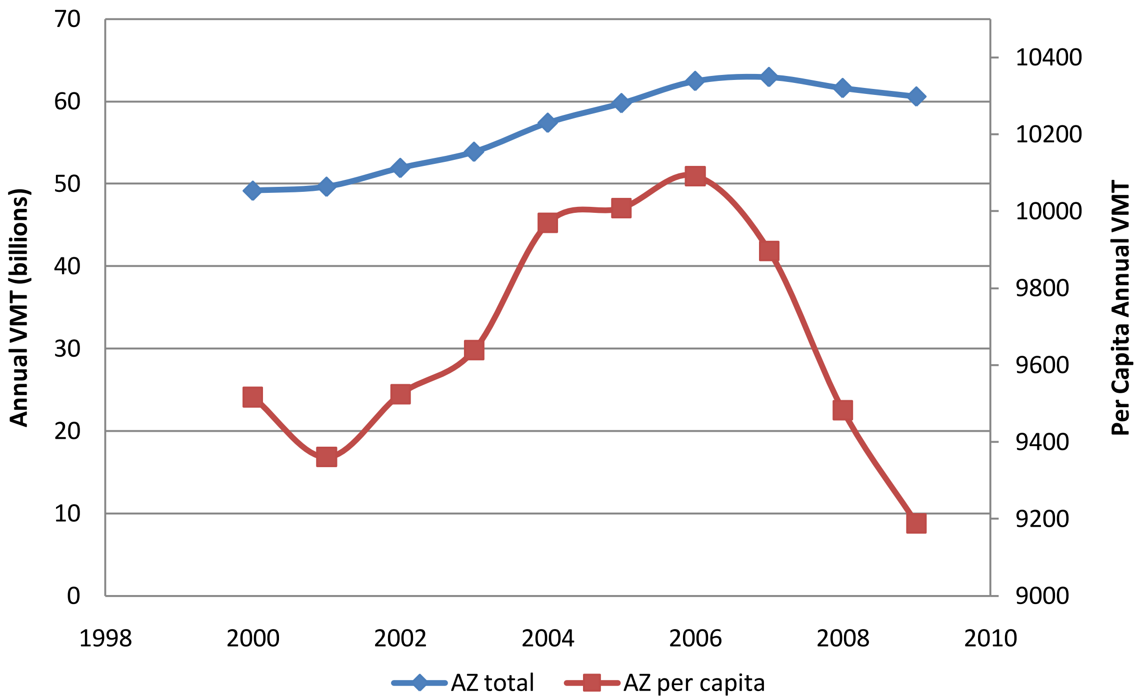

Figure 4.7. Annual Total Vehicle Miles of Travel (VMT)
Source: http://www.azdot.gov/mpd/data/hpms.asp

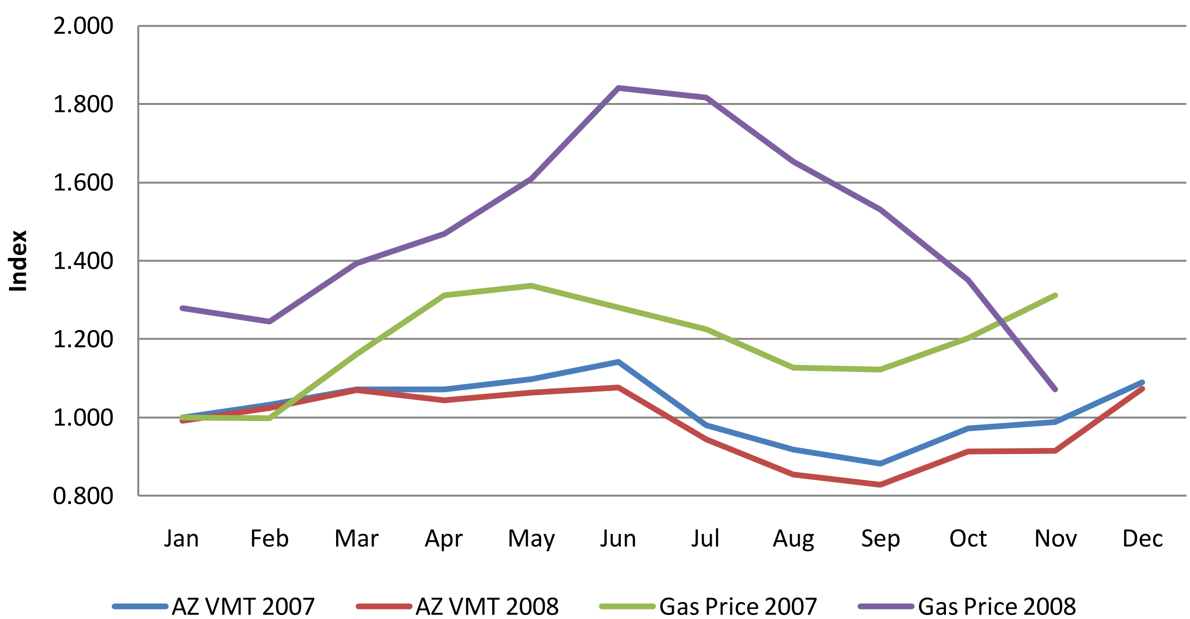

Figure 4.8. Monthly VMT and Fuel Price Trends (January 2007=1)
Source: Fuel price data provided by Maricopa Association of Governments
http://www.azdot.gov/mpd/data/hpms.asp

Average Daily Traffic (ADT) data from freeway monitoring stations was compiled and provided to the research team by the Maricopa Association of Governments, for potential use in this project. This data was also normalized and plotted to compare monthly trends in 2007 and 2008. As some data was missing in January 2007, the month of February 2007 was chosen as the reference month for this plot. Once again, it is seen that the 2008 ADT line consistently falls below the 2007 ADT trend line, suggesting that there is a clear reduction in traffic volumes in response to the higher fuel price and weaker economic conditions that prevailed in 2008 in comparison to 2007. What is interesting to note, however, is that the difference between the 2007 ADT trend line and 2008 ADT trend line is rather uniform throughout the months of the year. This is in sharp contrast to the varying difference in fuel price between 2007 and 2008. If traffic demand were truly sensitive to fuel price, one should have seen at least some variation in the difference between monthly 2007 traffic and monthly 2008 traffic, consistent with the variation in difference in fuel price trend lines. However, there is virtually no such variation at all, potentially indicating that the difference in traffic volume is largely due to the economic recession that took root as opposed to the fluctuations in fuel price.

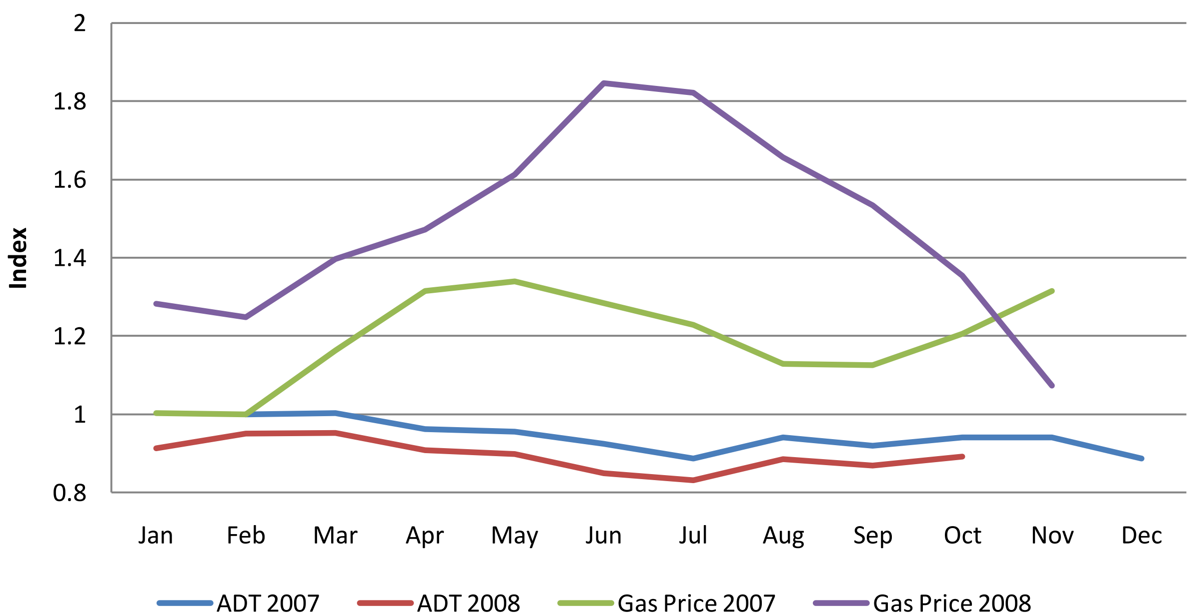

Figure 4.9. Average Daily Traffic (ADT) and Fuel Price Trends (February 2007=1)
Source: Data provided by Maricopa Association of Governments

Annual transit ridership in the county, as reported by Valley Metro, has steadily increased over the years. Interestingly, if one were to plot the ridership per capita, this too shows an increasing trend, with a slight drop in the middle of the decade. This plot is shown in Figure 4.10. It can be seen that transit ridership took a sharp upturn in 2007, and even recorded an increase between 2006 and 2007. While it is certainly plausible that this sharp increase in public transit ridership per capita occurred at least in part due to the economic downturn, it is difficult to fully explain an increase in transit ridership in that way. One would certainly expect overall travel demand to decrease in response to a recession, but an increase in transit ridership during a time of recession must, at least in part, be due to other factors influencing behavioral choice decision-making processes of individuals. In this case, it may indeed be the case that at least some segments of society, more adversely impacted by the rising fuel price (low income groups, for example, who tend to be disproportionately higher users of public transit systems) shifted to public transit in response to higher fuel prices.

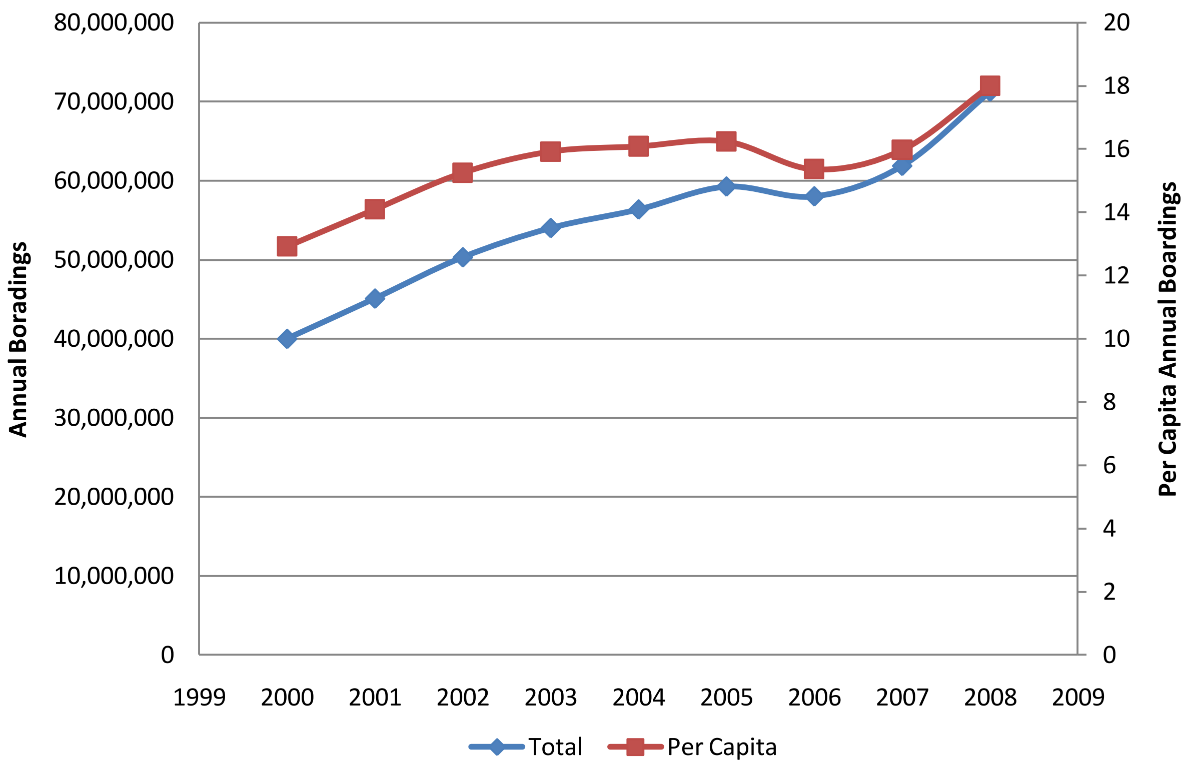

Figure 4.10. Annual Transit Ridership in Maricopa County

Source: http://www.valleymetro.org/valley_metro/publications/ridership_reports/

Indeed, if one were to examine the indexed trend lines depicted in Figure 4.11, monthly ridership in 2008 is consistently higher than that in 2007. Unlike the ADT trend lines, however, it is seen that there is some variation in the difference between the 2007 and 2008 trend lines over the course of the year. However, this variation does not show any clear pattern in relation to the magnitude of difference between 2007 and 2008 in monthly fuel prices. It is plausible that there is inherently more variation in transit ridership (whose numbers tend to be much smaller in magnitude in comparison to ADT figures), thus contributing to the varying differences across the months of the year. In any event, the increased transit ridership, while partially attributable to service enhancements, may be due to increased fuel price levels in 2008 compared to 2007. As transit riders tend to be lower income segments of society, who are more adversely impacted by higher fuel prices, there may have been a real shift in mode choice for those on the margin – and the fuel price hike may have been just enough to tip them over to using transit modes.

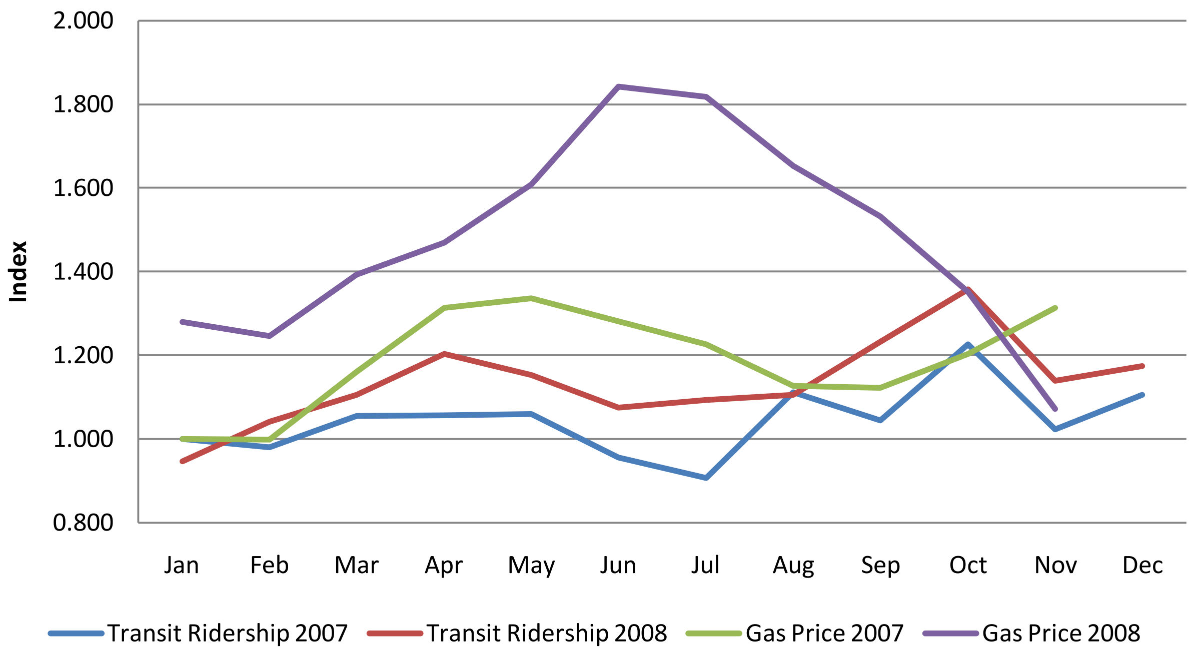

Figure 4.11. Monthly Transit Ridership and Fuel Price Trends (January 2007=1)
Source: Data provided by Maricopa Association of Governments

The Average Daily Traffic (ADT) data tabulated and provided by the Maricopa Association of Governments was used to compute elasticities of demand based on changes that took place between 2007 and 2008. Average Daily Traffic (ADT) data is available both weekdays and weekends for each month of the year in 2007 and 2008. Table 4.1 shows a summary of the data, including average monthly fuel price in each month, weekday and weekend ADT values, and the elasticity computed for each month of the year. The elasticity is computed by simply dividing the percent change in ADT by the percent change in fuel price for that month.

Table 4.1. Fuel Price Elasticity of Average Daily Traffic at Select Monitoring Locations

Month	Fuel Price		ADT				Elasticity	
	2007	2008	2007		2008			
			Wkday	Wkend	Wkday	Wkend	Wkday	Wkend
January	2.24	2.87	374,875	271,008	363,643	267,521	-0.107	-0.046
February	2.24	2.79	722,771	572,762	699,154	523,162	-0.132	-0.349
March	2.60	3.12	556,782	446,097	517,205	406,050	-0.355	-0.449
April	2.94	3.29	712,237	536,777	678,243	497,152	-0.401	-0.620
May	2.99	3.60	698,479	570,754	670,149	496,340	-0.199	-0.640
June	2.87	4.13	866,767	646,306	804,735	555,399	-0.164	-0.322
July	2.75	4.07	844,587	589,666	788,395	532,529	-0.138	-0.201
August	2.52	3.70	357,918	275,124	345,865	248,757	-0.072	-0.205
September	2.52	3.43	768,573	550,416	711,809	497,076	-0.203	-0.266
October	2.69	3.03	853,433	649,201	803,339	592,682	-0.474	-0.703

Source: Data provided by Maricopa Association of Governments

In general, all elasticities are negative indicating that demand decreased during the period of fuel price escalation for each month of the two years. As mentioned earlier, it is not likely that the decrease in demand is purely due to the fuel price escalation, but if one were to compute elasticities under such a major assumption, the elasticity values are still very small, suggesting that travel demand (ADT) is largely inelastic in response to fluctuations in price signals. One interesting finding, however, is that the elasticity values are consistently larger for weekend days than for weekdays, suggesting that discretionary weekend travel may be more responsive (elastic) to price fluctuations (or economic downturns) than weekday travel that tends to be characterized by a greater degree of mandatory work, work-related, school, and serve-child trips. The summer months did not necessarily show higher elasticity values compared to other months of the year, signifying that the high fuel prices seen in the summer of 2008 did not necessarily witness an associated disproportionately high decrease in travel demand.

4.3 Travel Demand Characteristics

The recent availability of the 2008 National Household Travel Survey data offers an excellent opportunity to compare travel demand characteristics over time. At the last instance that the National Household Travel Survey was conducted, fuel prices were at near record lows and it would therefore be of much interest to see how travel demand characteristics have changed between the two years, while attempting to simultaneously control for seasonality effects. In addition, since the summer of 2008 had an especially high surge in fuel prices, a comparison of travel demand between the summer and other months of 2008 can provide some insights into whether there is a rapid noticeable response by consumers in reaction to a rather dramatic change in fuel prices.

Table 4.2 presents daily trip rates per person for 2001 and 2008. The analysis presented in this section has been performed for the subsample of Arizona respondents in both survey years. The analysis is weighted to correct for any non-response or other biases that might affect the analysis of unweighted data sets. Further, only respondents 16 years or above who provided travel information on regular weekdays (Monday through Thursday) were included in the analysis subsample. The first two columns of the table present trip rates by purpose for the winter months of 2001 and 2008.

Table 4.2. Arizona NHTS Daily Trip Rates by Purpose (Weighted)

Purpose	2001 Winter	2008 Winter	% Change	2001 Summer	2008 Summer	% Change	% Diff (winter - summer 2008)
HBW	0.64	0.61	-4.71%	0.69	0.64	-6.92%	-4.05%
HBShop	0.90	0.82	-8.66%	0.91	0.84	-8.22%	-1.65%
HBSocRec	0.51	0.44	-14.24%	0.59	0.35	-40.74%	25.46%
HBO	0.73	1.00	36.83%	0.69	0.87	25.43%	14.53%
NHB	1.43	1.17	-18.30%	1.45	1.26	-13.39%	-7.07%
Total	4.22	4.04	-4.16%	4.34	3.96	-8.81%	2.20%

The percent difference shows that there is a consistent decrease in trip rates across all trip purposes, except for home-based other trips which show a small increase between the two years. The subsequent columns show trip rates by purpose for the summer months, and once again it is seen that there is a consistent decrease in trip rates with the exception of home-based other trips which exhibits an increase. What is particularly noteworthy is that the social-recreation trip rate shows the greatest percent drop in the summer comparison, and a rather large percent drop in the winter comparison as well, suggesting that individuals were clearly cutting back on social-recreational (discretionary) activities and travel outside home. To what extent this decrease can be attributed to the fuel price increase, however, remains an open question.

If one were to compare winter 2008 trip rates against summer 2008 trip rates, it is found that the winter 2008 trip rates are slightly lower than the summer 2008 trip rates (when fuel prices surged), with the exception of two key categories – home-based social-recreation trips and home-based other trips. There is a clear reduction in trip rates for these two trip purposes, suggesting that individuals cut back on these discretionary activities and travel during the summer months when fuel prices spiked, but then recovered somewhat in the winter months of 2008 on both of these types of trips. It may be argued that the Arizona summer temperatures make people stay at home more in the summer months, but a comparison of 2001 summer and winter trip rates shows that there does not appear to be a summer temperature effect. The 2001 summer rate for social-recreational travel is higher than that in the 2001 winter months, and the 2001 summer rate for home-based other trips is only slightly lower than that in the 2001 winter months. What is even more interesting to see is that the overall trip rate actually increases in the summer of 2001 when compared with the winter of 2001. In other words, one would expect summer trip rates to be a bit higher than trip rates in other months. However, the exact opposite is seen in 2008. The trip rate in the summer is lower than that in the winter months of 2008, suggesting that a combination of the fuel price surge and economic downturn affected travel and activity engagement in the summer months.

If one were to examine annual person miles traveled for the two survey years, the findings are not very inconsistent with those seen in Table 4.2 in conjunction with a comparison of trip rates. Between the winter of 2001 and winter of 2008, person miles of travel decreased overall, although increases were observed for shopping, work, and other trips. However, dramatic decreases in social-recreation and non-home based trips contributed to a net decrease in person miles of travel. Similarly, between the summer of 2001 and summer of 2008, a decrease in person miles of travel is observed, with decreases in virtually every category except shopping. In comparing the winter of 2008 with the summer of 2008, it is found that person miles of travel is higher in the summer, a finding that is inconsistent with the findings of Table 4.2. It appears that the person miles of travel table may be impacted by the presence of long distance trips in the summer and further analysis should be undertaken to isolate urban area trips from the longer distance travel episodes.

Table 4.3. Arizona NHTS Annual Person Miles Traveled (PMT) by Purpose (Weighted)

Purpose	2001 Winter	2008 Winter	% Change	2001 Summer	2008 Summer	% Change	% Diff (winter - summer 2008)
HBW	2,636	2,997	13.68%	3,141	2,860	-8.96%	4.79%
HBShop	1,637	2,028	23.89%	1,749	1,915	9.48%	5.91%
HBSocRec	1,265	1,091	-13.78%	1,176	1,114	-5.21%	-2.12%
HBO	1,790	3,232	80.57%	3,036	2,156	-28.98%	49.88%
NHB	8,825	3,779	-57.17%	7,445	7,219	-3.03%	-47.65%
Total	16,152	13,127	-18.73%	16,547	15,264	-7.75%	-14.01%

A comparison of mode splits between 2001 and 2008 is furnished in Table 4.4. It is interesting to note that there is a decrease in the SOV share of trips between 2001 and 2008 in both seasons. The decrease is more dramatic in the summer months of 2008, suggesting that the surge in fuel prices in 2008 may have had a differential impact on mode splits in comparison to other months of the year. However, one could argue that the economic recession had an impact on mode choice with individuals in certain market segments adversely impacted by the recession choosing to switch out of the SOV mode. However, if there is no appreciable difference in the effects of the recession between the winter and summer months, then it appears that the fuel price surge in the summer is indeed a major contributing factor to SOV mode splits falling more substantively during this period. The other primary auto mode, HOV, also experienced a slight decrease, although the decrease is quite considerably smaller than that seen for SOV. What is interesting to note is that, between summer of 2008 and winter of 2008, the auto mode as a whole (combining SOV and HOV) held steady at about 86.6 percent share, but with some internal re-allocation between the SOV and HOV modes. Bus, bike, and school bus gained share, suggesting that there was some mode shifting that took place in 2008 relative to 2001. In comparing the mode shares between the summer and winter of 2008, there is a rise in SOV share, a fall in HOV share, and modest changes in other mode shares, but nothing that would suggest that individuals made changes in mode choice in the summer of 2008 when fuel prices surged. In other words, it appears that person trip rates and miles of travel may undergo adjustments first (as seen by the larger percentage changes in Tables 4.2 and 4.3), prior to more significant changes that involve mode of travel.

Table 4.4. Arizona NHTS Mode Splits (Weighted)

Mode	2001 Winter	2008 Winter	% Change	2001 Summer	2008 Summer	% Change	% Diff (winter - summer 2008)
SOV	49.30%	48.60%	-0.70%	57.70%	53.20%	-4.50%	-4.60%
HOV	38.40%	38.00%	-0.40%	33.80%	33.40%	-0.40%	4.60%
Bus	0.50%	1.80%	1.30%	0.00%	1.70%	1.70%	0.10%
Rail	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Walk	9.10%	8.80%	-0.30%	7.70%	8.30%	0.60%	0.50%
Bike	0.50%	0.90%	0.40%	0.10%	1.10%	1.00%	-0.20%
Taxi	0.20%	0.10%	-0.10%	0.00%	0.20%	0.20%	-0.10%
School Bus	0.40%	0.60%	0.20%	0.00%	0.60%	0.60%	0.00%
Other	1.60%	1.20%	-0.40%	0.80%	1.50%	0.70%	-0.30%

Finally, with respect to auto ownership, it is seen that the higher fuel prices of 2008 relative to 2001 did little to make any changes in the trend towards owning larger gas-guzzling vehicles. This is not surprising as the earlier part of the decade saw a surge in demand for larger vehicles and it is likely that individuals had already acquired these vehicles by the time the recession hit and fuel prices surged in 2007-2008 and later. Between 2001 and 2008, there is an increase in overall auto ownership, with a clear increase in the share of larger vehicles. Thus, it is clear that any adjustments in auto ownership patterns in response to fuel price changes or fluctuations in the economy would constitute lagged responses in which changes would be observed only some months or years after the events.

Table 4.5. Arizona NHTS Vehicle Ownership (Weighted)

Vehicle Type	2001		2008		Change	
	Average per HH	Percent	Average per HH	Percent	Average	Percent
Car	0.93	51.22%	0.89	45.79%	-4.02%	-5.43%
Van	0.14	7.94%	0.15	7.47%	1.06%	-0.47%
SUV	0.30	16.35%	0.37	19.14%	25.69%	2.79%
Pickup Truck	0.37	20.68%	0.42	21.45%	11.33%	0.77%
Other	0.07	3.82%	0.12	6.16%	73.20%	2.34%
Total	1.81	100.00%	1.94	100.00%	7.36%	0.00%

4.4 Closing Thoughts on Aggregate Trend Data

This section has attempted to summarize a set of aggregate statistics, measured over time, to explore the potential relationship that exists between changes in travel demand vis-à-vis changes in fuel prices. The aggregate trend data show that there has been a consistent decrease in travel demand since about 2006, a period during which fuel prices escalated considerably before dropping again in late 2008. However, this period was also characterized by a deep recession that increasingly took root over the past two years, thus masking the ability to isolate fuel price impacts on travel demand. In the presence of conflicting economic forces – rising fuel prices and degenerating state of the economy – it is difficult to decipher the extent to which fuel price fluctuations truly contributed to changes in travel demand. In fact, a look at the trend data suggests that fuel price fluctuations did very little to change travel demand, and that changes in travel demand may have been largely due to the economic downturn that took place in the last few years. Nevertheless, a few indications – notably the decrease in travel demand between 2006 and 2007 when the recession had not yet settled in and the increase in transit ridership suggesting that lower income groups may have modified their behavior – prompt one to surmise that rising fuel prices does have an impact on travel demand, even if the effect is modest as noted previously in the literature. Elasticity values computed based on monthly volume data between 2007 and 2008 show that, even if one were to assume that all changes in demand are due to fuel price signals, demand is very inelastic and largely insensitive to fuel prices. Similarly, analysis performed using the 2001 and 2008 National Household Travel Survey (NHTS) data shows that there is no appreciable drop in travel the months of the highest fuel prices relative to other months covered by the survey. However, there is a somewhat consistent drop in discretionary travel rates between 2001 and 2008, suggesting once again that a combination of the economic downturn and fuel price escalation led to a reduction in travel demand. However, longer term adjustments in travel choices, such as those involving mode choice and vehicle ownership, did not manifest themselves in the 2008 NHTS data analysis.

Given the lack of conclusiveness that one can derive from the aggregate trends and statistics, it is clear that a more disaggregate econometric modeling approach needs to be adopted to better understand how individuals modify behavior in response to changes in fuel prices. The next two sections present such disaggregate model estimation efforts.

5. MODELING VEHICLE FLEET COMPOSITION AND UTILIZATION

In this project report, an in-depth analysis of a few key transportation choices is conducted with a view to better understand how vehicle miles of travel may be impacted by changes in fuel prices. The analysis does not intend to address all aspects of activity-travel behavior as such a comprehensive analysis and model development effort would be beyond the scope of this project. Two key aspects of behavior are modeled as they potentially capture the medium and short-term responses to fuel price fluctuations. These two aspects are vehicle ownership by type of vehicle and vehicle miles of travel. The first choice dimension may be viewed as one that is adjusted over the medium-term in response to changes in fuel prices, while the second dimension may be viewed as capturing a combination of the short-term responses that individuals might make in response to fuel price changes. For example, people may consolidate trips, chain trips together, change destination choice, shift mode, and shift route – all of these changes would result in changes in VMT and hence this dimension is explicitly modeled in the in-depth analysis. This section offers a joint model of vehicle fleet composition and utilization with a view to obtain elasticities that can then be incorporated into a spreadsheet tool capable of serving as a quick-response device for computing changes in vehicle fleet composition and VMT in response to changes in fuel prices. In the next section, the analysis will be taken a step further to consider these choices in the context of consumer expenditure patterns to start addressing the economic drivers that need to be tackled if one desires to truly understand how people and households make adjustments in response to changes in price signals.

There is undoubtedly close interplay between vehicle type choice (vehicle fleet composition in households) and usage (vehicle miles of travel) in the transport energy and emission arena. Households adjust to cost structures, socio-economic dynamics, the built environment, and environmental sensitivity by making conscious decisions or choices on the types of vehicles that they will acquire *and* the amount of miles that the vehicles will be driven (Bhat and Sen, 2006). These choice dimensions (i.e., type of vehicle and miles of travel) together determine the amount of fuel consumed (and therefore fuel cost borne by the household) and the amount of GHG emissions that the household will produce from its travel. At one extreme, a fuel efficient vehicle driven low miles will result in low energy consumption and fewer emissions. At the other extreme, a large fuel-inefficient vehicle driven lots of miles will result in high energy consumption and high emissions. It is therefore of interest to model these two choice dimensions *jointly* in an integrated modeling framework.

For this purpose, a joint model of household vehicle type choice and usage is formulated and estimated on a data set derived from the 2000 San Francisco Bay Area Travel Survey (BATS). This data set has been used because the travel survey data set has been integrated with numerous secondary data sources to offer a rich set of environmental and contextual variables describing the built environment and network level of service measures. The joint model system recognizes that the choice of type of vehicle is not an exogenous factor in determining household vehicle miles of travel. On the contrary, vehicle type choice is an endogenous variable in its own right and there may be common unobserved factors that simultaneously influence vehicle type choice and miles of travel. The simultaneous equations model system takes the form of a joint discrete-continuous model to reflect the discrete nature of the vehicle type choice and the continuous nature of the miles of travel.

The maximum likelihood estimation of joint discrete-continuous model systems has largely been done through distributional transformations to facilitate a closed form expression or through simulation approaches to evaluate the log-likelihood function. These approaches have their limitations and one of the major features of the model estimation effort here is that a Copula-based methodology was applied for estimating the model system. The Copula-based methodology offers a closed-form expression for evaluating the log-likelihood function in the estimation of model parameters.

5.1 On Modeling Vehicle Type Choice and Usage

The analysis and modeling of vehicle type choice and usage has been much of interest to the profession for many years. Several early studies (e.g., Mannering and Winston, 1985; Train, 1986) examined vehicle type choice in terms of the number of vehicles and vintage. More recent studies, however, have examined vehicle choice in terms of the number of vehicles by type (e.g., Feng et al, 2005; Fang, 2008) or vintage and type (Goldberg, 1998; Bhat et al, 2009; West, 2004). Thus, the focus of research in the vehicle holdings arena has clearly shifted to understanding the type of vehicles possessed by households and this has been largely motivated by energy and environmental concerns, and facilitated by the availability of detailed data about household vehicle holdings (e.g., NHTS data). In all studies, vehicle miles of travel (VMT) serves as the measure of usage.

Virtually all of the studies cited previously employ discrete-continuous model specifications of vehicle ownership (discrete) and utilization (continuous) choices. Typically, except for Bhat et al. (2009), the jointness is modeled by capturing the statistical correlation between unobserved variables affecting vehicle type choice and utilization. Many of these studies adopt sequential estimation techniques proposed by Dubin and McFadden (1984) that involve the use of conditional expectation correction terms (West, 2004) or instrumental variables (Train, 1986; Mannering and Winston, 1985; Goldberg, 1998).

Studies of vehicle type choice have included a range of household and personal socio-economic and demographic characteristics as explanatory factors of household vehicle holdings. However, recent work in this arena has attempted to expand the set of explanatory variables to include vehicle attributes such as purchase price, operating cost, fuel efficiency, and vehicle performance (Mohammadian and Miller, 2003). Kockelman and Zhao (2000) account for the impact of trip type or purpose in their model of vehicle holdings while Choo and Mokhtarian (2004) consider the impact of driver's personality and travel preferences or perceptions. Environmental concerns are considered by Ewing and Sarigollu (2000) and built environment effects are included in the work by Potoglou (2008). Brownstone and Golob (2009), in an attempt to analyze the impact of residential density on vehicle usage and energy consumption, utilize structural equations modeling methods to account for self-selection effects; however, their work does not consider vehicle type choice or holdings in a discrete choice framework due to the limitations of structural equations methods in modeling multinomial choice variables.

Considerable advances have been made recently in the modeling of vehicle holdings and usage with the development of the multiple discrete-continuous extreme value (MDCEV) model (Bhat and Sen, 2006). In that paper, the authors estimate a MDCEV model of household vehicle type choice and usage; the model system explicitly recognizes that households own a mix of vehicle types at any given point in time, thus leading to the exercise of multiple discrete choices (as opposed to single discrete choices). Vehicle usage is measured by VMT for each vehicle in the household fleet. More recently, Bhat et al (2009) adopt a joint nested MDCEV-MNL model structure to capture additional dimensions of vehicle holdings. In addition to vehicle type choice and usage, this study also models vintage (age) of vehicle and make and model of the vehicle within each body type. The joint MDCEV-MNL model is used to analyze the impacts of fuel prices, built environment variables, household and personal characteristics, and vehicle attributes on the multitude of dimensions that describe household vehicle holdings.

In contrast to these recent studies, the analysis presented in this report reverts to the treatment of household vehicle type choice as a simple multinomial choice variable by considering the most recent vehicle purchased by a household. The MDCEV model structure, although extremely useful to capture the mix of vehicle holdings at any given point in time, fails to capture the dynamics associated with vehicle acquisition. By considering the type of vehicle purchased most recently by a household, one can examine the choice of vehicle type in the context of the other vehicles already owned by the household. Thus, the unit of analysis is no longer a household as such, but the actual vehicle purchase itself. As in the earlier studies, vehicle miles of travel (VMT) is used as the measure of vehicle usage. This leads to the formulation of a more classic joint multinomial logit (MNL) – continuous regression model of vehicle type choice and usage. This formulation constitutes a discrete-continuous model system with the ability to account for endogeneity or self-selection effects (Mannering and Hensher, 1987). These effects are captured through error correlations that account for unobserved factors that affect both vehicle type choice and usage. For example, an individual who "likes to drive" may choose to purchase a certain premium type of car (e.g., high performance car, luxury vehicle) and put many VMT on it. This unobserved personal attribute or preference will then lead to self-selection or error correlation effects. In this way, this paper provides a unique perspective on the dynamics of vehicle purchase decisions as opposed to a snapshot of household vehicle holdings.

In past research, joint discrete-continuous model systems have been estimated using either two-step sequential estimation approaches or simulation-based approaches that approximate multidimensional integrals to evaluate the log-likelihood function over its domain space. These approaches have been necessitated by the lack of closed form expressions for the joint choice distributions that characterize the log-likelihood function. To overcome these challenges, the analysis presented here adopts a Copula-based methodology. The Copula approach to sample selection models is based on the concept of a "copula" which is a multivariate functional form for the joint distribution of random variables derived purely from pre-specified parametric marginal distributions of each random variable (Bhat and Eluru, 2009). This approach is particularly suited to estimate potential error correlation effects in the joint vehicle type and usage choice model system. The approach allows one to test different dependency forms for the joint distribution of the error terms in the two choice processes. In other words, the vehicle type and mileage decisions may be impacted by different unobserved factors, while also recognizing the potential interdependence among these unobserved factors using a host of different dependency surfaces (as opposed to the usual joint normal distribution used de facto in earlier studies). On the other hand, the MDCEV approach ties the discrete and continuous choices in a more restrictive framework by having a single stochastic utility function (and therefore, a single error term) that underlies both the discrete and continuous choices. In short, the model system estimated for this project is capable of determining the extent to which differences in the VMT between different vehicle types are due to "true" effects of vehicle type attributes and policy variables (such as fuel prices), or due to individuals self-selecting to choose vehicle types based on their attitudes, preferences, needs, and desires; and this is done using a novel methodology that obviates the need for adopting less flexible model specifications that must be estimated by simulation-based or limited information maximum likelihood (LIML) methods.

There is one other important advantage of the copula approach over the MDCEV approach, which is that the MDCEV approach needs to have an exogenous total mileage budget of households for implementation. Bhat et al (2009) develop this budget by aggregating the mileage across all vehicles held by a household and adding non-motorized mode mileage. However, the non-motorized mileage is a relatively negligible fraction of total mileage, effectively imposing the constraint that total motorized vehicle utilization is exogenous, and does not change in response to policies or fuel cost increases (though the MDCEV model allows substitution in vehicle mileage across different vehicle types). There is no such restriction imposed in the approach adopted in this project.

5.2 Modeling Methodology

In this study, a copula-based joint multinomial logit – switching regression modeling framework is proposed to jointly model vehicle type choice and usage. Specifically, copula-based methods are used to capture the jointness between the multinomial discrete choice model of vehicle type choice and the regression models of annual vehicle mileage (i.e., vehicle usage). This is a unique application of the copula approach in the field of transportation to model self-selection with polychotomous endogenous variables (vehicle type choice, in this context). This section offers a very brief overview of the modeling methodology and form. For the sake of brevity, the entire modeling methodology and econometric formulations are not presented in this report. Detailed presentations of the model formulations may be found in Spissu et al (2009).

5.2.1 The Vehicle Type Choice Model Component

Let $q(q=1,\ 2,\ ...,\ Q)$ and $i(i=1,2,...I)$ be the indices to represent households and vehicle types, respectively. The vehicle type choice model component takes the familiar discrete choice formulation. Consider the following equation that represents the utility structure of the vehicle type choice model:

$$u_{qi}^{*}=\beta_i^{'}x_{qi}+\varepsilon_{qi} \tag{1}$$

In the equation above, u_{qi}^{*} is the latent utility that the q^{th} household derives from acquiring a vehicle of type i, x_{qi} is a column vector of household attributes (including a constant, demographics, and activity-travel environment characteristics) affecting the utility, β_i is the corresponding coefficient (column)vector, and ε_{qi} is the error term capturing the effects of unobserved factors on the utility associated with vehicle type i. With this utility specification, as with any discrete choice model, a household(*q*) is assumed to choose a vehicle of type i if it is associated with the maximum utility among all I vehicle types; that is, if

$$u_{qi}^{*}>\max_{j=1,2,...,I,\ j\neq i} u_{qj}^{*} \tag{2}$$

Next, following Lee (1983), the polychotomous discrete choice model is recast in the form of a series of binary choice formulations, one for each vehicle type. To do so, let R_{qi} be a dichotomous variable that takes the values 0 and 1, with $R_{qi}=1$ if the i^{th} alternative is chosen by the q^{th} household and $R_{qi}=0$ otherwise. Subsequently, substituting $\beta_i^{'}x_{qi}+\varepsilon_{qi}$ for u_{qi}^{*} [from Equation (1)] in Equation (2), one can represent the discrete choice model formulation equivalently as:

$$R_{qi}=1 \ \text{ iff } \ \beta_i^{'}x_{qi}>\nu_{qi},\quad (i=1,2,...I) \tag{3}$$

$$\text{where } \ \nu_{qi}=\{\max_{j=1,2,...,I,\ j\neq i} u_{qj}^{*}\}-\varepsilon_{qi} \tag{4}$$

Equation (3) represents a series of binary choice formulations, which is equivalent to the multinomial discrete choice model of vehicle type. Further, in Equation (4), the distribution of ν_{qi} depends on the distributional assumptions of the ε_{qi} terms. For example, type-1 extreme value distributed ε_{qi} terms that are independent (across i) and identically distributed imply a logistic distribution for the ν_{qi} terms. The distribution of the ν_{qi} terms, in turn, will determine the form of vehicle type choice probability expressions.

5.2.2 The Vehicle Mileage Model Component

The vehicle mileage model component takes the form of the classic log-linear regression, as shown below:

$$m^*_{qi} = \alpha'_i z_{qi} + \eta_{qi}, \qquad m_{qi} = 1[R_{qi} = 1]\, m^*_{qi} \tag{5}$$

In the equation above, m^*_{qi} is a latent variable representing the logarithm of household(*q*)'s annual mileage on the vehicle of type i if the household were to choose that type of vehicle in its recent vehicle acquisition. This latent vehicle usage variable is mapped to observed household attributes and the corresponding attribute effects in the form of column vectors z_{qi} and α'_i, respectively, as well as to unobserved factors through a η_{qi} term. On the right hand side of this equation, the notation $1[R_{qi} = 1]$ represents an indicator function taking the value 1 if household q chooses vehicle type i, and 0 otherwise. That is, m^*_{qi} is observed (in the form of m_{qi}) only if household q is observed to hold a vehicle of type i.

5.2.3 The Joint Model: A Copula-based Approach

The specifications of the individual model components discussed in the previous two sections may be brought together in the following equation system:

$$\begin{aligned} &R_{qi} = 1 \ \text{ iff } \ \beta'_i x_{qi} > \nu_{qi}, \ \ (i = 1, 2, ... I) \\ &m^*_{qi} = \alpha'_i z_{qi} + \eta_{qi}, \ \ m_{qi} = 1[R_{qi} = 1]\, m^*_{qi} \end{aligned} \tag{6}$$

The linkage between the two equations above, for each vehicle type $i (i = 1, 2, ... I)$, depends on the type and the extent of the dependency between the stochastic terms ν_{qi} and η_{qi}. As indicated earlier, in this paper, copula-based methods are used to capture and explore these dependencies (or correlations/linkages/couplings). More specifically, copulas are used to describe the joint distribution of the ν_{qi} and η_{qi} terms. In this approach, first, the ν_{qi} and η_{qi} terms are transformed into uniform distributions using their inverse cumulative distribution functions. Subsequently, copulas are applied to "couple" the uniformly distributed inverse cumulative distributions into multivariate joint distributions. Complete details and formulations of these transformations may be found in Spissu et al (2009).

The joint model has the following log-likelihood expression for a random sample of Q households $(q = 1,\ 2,\ ...,\ Q)$:

$$L = \prod_{q=1}^{Q} \left[\prod_{i=1}^{I} P\left(m_{qi} | \beta_i' x_{qi} > \nu_{qi} \right) \times P\left(\beta_i' x_{qi} > \nu_{qi} \right)^{R_{qi}} \right]. \tag{7}$$

This log-likelihood function can be written in a form that incorporates copulas as described in detail in Spissu et al (2009). To complete the model specification, it is assumed that the ε_{qi} terms $(\text{for}\, i = 1, 2, ...I)$ associated with the vehicle type choice model component are independent and identically distributed (IID) type-1 extreme value distributed, and that the η_{qi} terms associated with the switching regressions of the logarithm of vehicle mileage follow a normal distribution centered at zero (and, as indicated earlier, with variance $\sigma_{\eta i}^2$). Given these marginal distributions, the log-likelihood expression that incorporates copulas to characterize the dependency across the choice dimensions of interest has a closed form expression (for most of the copulas available in the literature) and hence obviates the need for numerical/simulation-based estimation.

5.3 Data Description

In order to fully understand and model vehicle type choice and utilization patterns, it is important to have a comprehensive behavioral survey data set that includes a host of environmental and contextual variables that describe built environment attributes and network level of service. Unfortunately, such a comprehensive data set could not be compiled for the Phoenix metropolitan area within the scope of this project. Hence a readily available disaggregate data set that included a rich set of contextual variables was identified and used for model estimation. Given that the model is an econometrically advanced and rigorous disaggregate choice model system, it is likely that the relationships identified in the model will be applicable to other areas, although it is recognized that such transferability of parameters must be done with due caution. Nevertheless, for purposes of understanding behavior and deriving useful measures of sensitivity and elasticity, it was felt that the use of an alternate location data set would be acceptable.

The primary data set used for this study is derived from the 2000 San Francisco Bay Area Travel Survey (BATS). The survey collected information on vehicle fleet composition for over 15,000 households in the San Francisco Bay Area. The survey also collected detailed activity and travel information for all household members over a two-day period along with their socio-economic and demographic characteristics. Information collected on household vehicle holdings included the make/model/year of all vehicles owned by the household, the year of possession of the vehicles, odometer reading on the day of possession, and the odometer reading on the two days of the activity-travel diary survey.

Several secondary data items had been merged into the survey data set to provide a more comprehensive database suitable for the type of study undertaken in this project. The Consumer Guide (2005) and EPA Fuel Economy Guide (EPA, 2005) were used to associate a host of vehicle attributes (e.g., costs, internal dimensions, performance characteristics, fuel emissions, fuel type) to each make/model/year. Residential location variables and built environment attributes were constructed and extracted from land use/demographic coverage data, Census 2000 data, and GIS layers of bicycle and transportation network facilities. Bhat et al (2009) provide a detailed description of the extraction of secondary data and the compilation of the comprehensive database with all secondary attributes merged into the vehicle file.

Based on information from the activity-travel diary, each vehicle was assigned a primary driver. The primary driver was the person in the household who drove the vehicle the most miles over the two-day diary period. In this study, the log of annual vehicle miles traveled (for each vehicle) serves as the continuous dependent variable. Annual vehicle mileage was computed for each vehicle using the odometer readings recorded at the end of the diary period, reported mileage at the time of vehicle possession, the survey year, and the year of possession. The annual vehicle mileage is then:

$$\text{Annual Mileage} = \frac{\text{Mileage recorded at end of survey - Miles on possession}}{\text{Survey year} - \text{Year of possession}} \tag{8}$$

A log-sum variable was computed from the multinomial logit (MNL) model results presented in Bhat et al (2009) for the choice of vehicle make/model for each vehicle type. This log-sum variable contains information on the vehicle attributes, fuel price, and household characteristics (i.e., household size and income) that affected the choice of vehicle make/model within each vehicle type category.

In order to capture the dynamics of vehicle type choice and usage, this study focuses on modeling recent vehicle acquisitions by households in the sample. All of the vehicles that were acquired within the preceding five year period of the survey were selected for inclusion in the modeling effort. A total of 3770 households acquired at least one vehicle in the preceding five year period. Of these 3770 households, 2919 households purchased only one vehicle, 403 households purchased two vehicles, and 15 households purchased three vehicles within the five year span. Thus the unit of analysis in this study is the "recently purchased vehicle". The study is attempting to model the type of vehicle chosen in the purchase and the annual mileage accumulated on the vehicle. Vehicles that were purchased prior to the five year span were deliberately excluded from the analysis to avoid the data consistency problem; all attribute data is for the year 2000 and hence it was considered prudent to ensure that only those vehicle acquisitions reasonably close to the year 2000 were included in the analysis. Sample size considerations motivated the use of five years worth of vehicle acquisition data (as opposed to a period shorter than five years).

Descriptive statistics for each vehicle type are shown in Table 5.1. The table also furnishes mean VMT and log (VMT) for each vehicle type. The vehicles were aggregated into six types based on sample size considerations and to be consistent with past research on household vehicle holdings by type. About one-quarter of the vehicles acquired were compact sedans while 30 percent were larger sedans. The SUV, pickup truck, and van categories are associated with smaller, but still substantial, percentages in terms of share of all acquisitions. More importantly, they are associated with higher vehicle miles of travel, all in excess of 15,000 miles per year. On the other hand, all of the car categories (sedans and coupe) are associated with mileage that is less than 14,500 miles per year. Thus, it appears that larger vehicles are driven more miles, on average, than smaller vehicles – with subsequent implications for energy consumption and emissions. The last column shows the percent of transactions in each vehicle type where the household already had the same vehicle type when making the particular purchase in question. For example, in 10 percent of the 908 compact sedan purchases, the household already had a compact sedan in its fleet. In general, these percentages are all quite low, suggesting that there is considerable dynamics and history dependency in vehicle purchases – if a household owns a certain vehicle type, then the likelihood of purchasing the same vehicle type again is rather small. Additional detailed descriptive statistics of the survey sample may be found in Spissu et al (2009).

Table 5.1 Descriptive Statistics of the Recently Purchased Vehicle Type

Vehicle category	N	%	VMT[miles]	LogVMT	Presence of an old vehicle of that type in the Household
Compact Sedan	908	24.08	13471	9.33	10%
Large Sedan	1164	30.88	14462	9.35	17%
Coupe	309	8.20	13221	9.23	7%
SUV	553	14.67	15550	9.45	5%
Pick-up Truck	439	11.64	16146	9.40	10%
Van	397	10.53	16163	9.48	4%
Total Sample	*3770*	*100.00*			

5.4 Model Estimation Results

This section presents a detailed description of model estimation results for the copula-based joint model of vehicle type choice and vehicle miles of travel. The empirical analysis involved estimating the joint model with several different copula-based dependency structures as well as the independent structure (i.e., independent models). Six different copulas were explored to estimate the jointness between the vehicle choice component and the usage component for each vehicle type. The six types are Gaussian (same as the Lee, 1983 specification), FGM, Frank, Gumbel, Clayton, and Joe (see Bhat and Eluru, 2009, for a complete description of these alternate copulas).

The maximum likelihood estimation of the sample selection model with different copulas leads to a case of non-nested models. Thus, the traditional likelihood ratio test for comparing alternative model specifications is not applicable in this context. An approach to select among the competing copula-based models is the Bayesian Information Criterion (BIC), which collapses to a comparison of the log-likelihood values across different models if all of the competing models have the same exogenous variables and a single copula dependence parameter ϑ (see Bhat and Eluru, 2009) as in this model estimation effort.

It was found that the best model fit was obtained when the Frank copula was used for the continuous regression model associated with all six vehicle types. The log-likelihood value at convergence for the Frank copula-based model is found to be -9403.47. The likelihood value at convergence for the independent model structure is -9774.668, clearly rejecting the hypothesis of independence between the vehicle type choice and vehicle usage equations in favor of the model structure that recognizes error correlations.

Estimation results obtained using the Frank copula are presented in Table 5.2. The copula dependency parameters show highly significant positive dependency (or correlation) between the vehicle type choice and the VMT. This indicates that unobserved factors that make a household/individual more inclined to acquire a certain vehicle type also make the individual more inclined to put more miles on that vehicle.

Table 5.2. Estimation Results of the Joint Vehicle Type Choice – VMT Model with Frank Copulas

Variable	MNL						Regression (Dependent variable = LogVMT)					
	Compact Sedan	Large Sedan	Coupe	SUV	Pickup Truck	Van	Compact Sedan	Large Sedan	Coupe	SUV	Pickup Truck	Van
Constant	-	-0.501 (-2.93)	-0.535 (-3.21)	0.122 (0.74)	-0.433 (-2.30)	-2.396 (-9.91)	8.467 (127.99)	8.610 (183.36)	8.241 (61.47)	8.569 (104.90)	8.437 (76.09)	8.755 (126.34)
Age (age >= 56 yrs is base)												
Age between 16 and 35 yrs	-	-0.362 (-4.52)	-0.362 (-4.52)	-0.362 (-4.52)	-0.362 (-4.52)	-0.362 (-4.52)	0.161 (6.45)	0.161 (6.45)	-	0.161 (6.45)	0.161 (6.45)	0.161 (6.45)
Age between 36 and 55 years	-	-	0.368 (4.23)	-	-	0.368 (4.23)	-	-	-	-	-	-
Male	-	0.142 (1.91)	0.142 (1.91)	0.142 (1.91)	1.564 (11.76)	-0.157 (-1.28)	0.040 (1.92)	0.040 (1.92)	-0.136 (-1.68)	0.040 (1.92)	-	0.040 (1.92)
Ethnicity (Caucasian is base)												
African-American	-	-	-	-	-0.731 (-2.26)	-0.731 (-2.26)	0.261 (3.58)	0.261 (3.58)	0.261 (3.58)	-	-	-
Hispanic		-0.310 (-1.98)	-0.310 (-1.98)	-	-	-	-	-	-	-	-	-
Asian	-	-	-0.346 (-2.54)	-0.346 (-2.54)	-1.508 (-5.02)	-	-0.104 (-2.74)	-0.104 (-2.74)	-	-	-	-0.104 (-2.74)
Other	-	-	-	-0.582 (-1.91)	-0.582 (-1.91)	-	-	-	-	-	-	-
Annual household income												
Annual income (35K-90K)	-	0.350 (2.76)	0.350 (2.76)	0.350 (2.76)	-	0.350 (2.76)	0.084 (3.23)	0.084 (3.23)	-	-	-	-
Annual income (>90K)	-	0.649 (4.57)	0.649 (4.57)	0.649 (4.57)	-0.205 (-1.68)	0.649 (4.57)	-	-	0.145 (3.41)	0.145 (3.41)	-	-
No. of children in the household												
No. of children < = 4 yrs	-	-	-0.311 (-2.64)	0.246 (3.34)	-0.311 (-2.64)	0.246 (3.34)	-0.053 (-1.75)	-	-	-	0.252 (2.31)	-0.053 (-1.75)
No. of children 5 - 10 yrs	-	0.300 (3.87)	-	0.300 (3.87)	0.300 (3.87)	0.300 (3.87)	-	-	0.117 (1.74)	-	0.117 (1.74)	-
No. of children 11 - 15 yrs	-	-	-0.591 (-3.11)	-	-	-	-	0.102 (3.51)	-	0.102 (3.51)	-	-
No. of children 16 and 17 yrs	-	-	-	-	-	-	-	0.081 (1.21)	-	-	-	-

Table 5.2. Estimation Results of the Joint Model with Frank Copulas (*continued*)

Variable	MNL						Regression (Dependent variable = LogVMT)					
	Compact Sedan	**Large Sedan**	**Coupe**	**SUV**	**Pickup Truck**	**Van**	**Compact Sedan**	**Large Sedan**	**Coupe**	**SUV**	**Pickup Truck**	**Van**
Number of senior adults (> 65 years) in the household	-	0.331 (4.88)	-	-0.453 (-3.33)	-	0.331 (4.88)	-0.141 (-6.75)	-0.141 (-6.75)	-0.141 (-6.75)	-0.141 (-6.75)	-0.141 (-6.75)	-0.141 (-6.75)
Household size	-	-	-	-	-	0.495 (11.12)	-	-	-0.069 (-2.21)	-	-0.069 (-2.21)	-
Number of employed individuals in the household	-	-0.163 (-3.67)	-0.163 (-3.67)	-0.163 (-3.67)	-	-0.163 (-3.67)	0.070 (4.45)	0.070 (4.45)	-	-	0.070 (4.45)	-
Land Use Structure Variables												
Population Density	-	-	-	-	-	-	-0.004 (-2.50)	-	-	-0.002 (-1.28)	-	-
Employment Density	-	-	-0.002 (-1.99)	-	-0.002 (-1.99)	-	-	-	-	-	-	-
Land use mix (range 0 - 1)	-	-	-0.544 (-2.70)	-	-0.544 (-2.70)	-	-	-	-	-	-	-
Presence of 4+ physical activity centers	-	-	-	-	-	-	-0.050 (-1.26)	-	-0.050 (-1.26)	-0.050 (-1.26)	-	-
Commercial / Industrial Acres within 1 mile radius	-	-	-	-0.001 (-2.31)	-	-0.001 (-1.98)	-	-	-	-	-	-
Local Transportation Network Measures												
Walk access time to in-zone transit stop	-	0.012 (2.04)	-	-	0.012 (2.04)	0.012 (2.04)	-	-	-	-	-	-
No. of zones accessible by bike within 6 miles	-	-	-	-	-0.010 (-4.58)	-	-	-	-	-	-0.006 (-3.88)	-
Presence of old vehicles (same type)	-	0.110 (1.40)	0.110 (1.40)	-	-0.404 (-2.66)	-0.404 (-2.66)	-	-	-	-	-	-
Logsum	1.000	1.000	1.000	1.000	1.000	1.000	-	-	-	-	-	-
Copula dependency parameter (θ)	-	-	-	-	-	-	-6.730 (-12.47)	-6.405 (-12.78)	-6.967 (-8.07)	-6.209 (-9.42)	-7.352 (-10.54)	-6.605 (-8.96)
Scale parameter	-	-	-	-	-	-	0.848 (30.99)	0.743 (33.13)	1.047 (19.37)	0.803 (22.99)	1.114 (24.40)	0.765 (22.46)
Log-likelihood at convergence	-9403.47											

The magnitudes of the correlation are slightly higher for the coupe and pick-up truck vehicle types, suggesting that there is a higher level of loyalty associated with these vehicle types. These individuals are likely to be those who enjoy driving and enjoy high-performance vehicles; those who are drawn towards these vehicle types are likely to be those who drive and accumulate more miles more than others.

The first six columns of Table 3 present the results of the discrete choice component of the model while the latter six columns present the linear regressions corresponding to usage. The baseline preference constants do not have a straightforward interpretation, given the presence of several continuous exogenous variables in the model. Nevertheless, the constants appear to suggest that in the five year period prior to 2000, households tended to acquire SUVs in preference to other vehicle types and had the lowest preference for the acquisition of vans. Consistent with the descriptive statistics, younger age groups tended to acquire compact sedans in comparison to all other vehicle types while the middle age group tended to acquire coupes and vans. Males are more likely to acquire large sedans, coupes, SUVs, and pick-up trucks, and least likely to acquire vans. Differences are also found across ethnic groups. African-Americans are less likely to acquire pick-up trucks and vans, Hispanics are less likely to acquire large sedans and coupes, and Asians are more prone to acquiring sedans and vans.

Households with high income (greater than $90,000 per year) are more likely to acquire large sedans, coupes, SUVs, and vans and least likely to acquire pick-up trucks. In general, higher income households show a greater propensity to acquire a vehicle (for all vehicle types except pick-up truck) in comparison to lower income households as evidenced by the larger positive coefficients associated with the higher income group. The presence of children is generally associated with a propensity to acquire large sedans, SUVs, and vans. The presence of seniors in the household is associated with the purchase of large sedans and vans. These households show a lower propensity to acquire SUVs. Larger household sizes are associated with the purchase of vans. All of these findings are consistent with expectations and with the large body of literature that speaks to the types of vehicles that households acquire in the context of their socio-economic and demographic characteristics.

It is interesting to note that the variable representing the number of workers was associated with a negative coefficient on four of the six vehicle types. It is likely that these households have already acquired the vehicles that they need and simply did not need to purchase vehicles (other than specialty vehicles such as compact sedan or pick-up truck) in the five year period covered by this data set. Households residing in high employment density areas were less likely to acquire coupes and pick-up trucks. It is likely that pick-up trucks are more suitable to the rugged terrains of suburban/rural areas or the occupational and family needs of households residing in such areas. The land use mix variable provides a rather similar indication. However, it is not immediately clear why the coupe vehicle type also has a negative coefficient associated with its acquisition. The built environment influences may need to be investigated more closely, particularly because the built environment may be endogenous, at least in the long term. As the commercial and industrial acreage within a one mile radius increases, the probability of purchasing a SUV or van decreases. This is consistent with the notion that SUVs and vans tend to be vehicles acquired by suburban/rural households that are likely to be farther away from commercial and industrial property. Those who reside in shorter walk access to transit stops are less likely to acquire larger vehicles (large sedans, pick-up trucks, and vans). It is possible that households who have such access are residing in higher density areas with limited parking space and maneuverability. Hence there is a lower likelihood of acquiring large vehicles. This is further confirmed with the finding that, as the number of zones accessible by bicycle within six miles increases (i.e., as density increases), the probability of purchasing pick-up trucks decreases.

There is clear history dependency in vehicle acquisition. If a household already owns a pick-up truck or a van in its fleet, then it is less likely that the household will acquire another one of these vehicle types. On the other hand, if a household already owns a large sedan or a coupe, then the household is more likely to acquire the same vehicle type again. It is conceivable that pick-up trucks and vans are specialty vehicles (large vehicles) and most households do not need more than one of these types of vehicles. Therefore, if one of these vehicle types already exists in the fleet, then the household is unlikely to acquire another one of these. On the other hand, sedans and coupes constitute general purpose automobiles and households may have multiple vehicles of these types for various members of the household. The log-sum parameter is set to one, indicating independence among alternatives in the choice set. This variable captures the utility derived from the different make/model combinations within each vehicle type.

The second set of six columns includes the linear regressions for the vehicle usage variable. There is one equation for each vehicle type. It is found that young individuals are more likely to drive more than other age groups. Males drive more miles on most vehicle types, except for coupes and pick-up trucks. These findings are rather surprising as one would expect males to put more miles on coupes and pick-up trucks. However, the fact that males are more likely to purchase one of these vehicle types does not necessarily mean that they are going to put more miles on it. Asians are associated with lower mileage on compact and large sedans and vans. African-Americans put more miles on all of the car types – compact and large sedans, and coupes.

Those in the middle income range put more miles on cars, while those in the higher income group accumulate more miles on coupes and SUVs. Those with young children (less than or equal to four years of age) put less miles on compact sedans and vans, presumably because of the constraints associated with traveling with very young children. However, as the number of older children increases, households accumulate more miles across a range of vehicle types (as evidenced by the positive coefficients associated with variables representing number of children by age group). Seniors accumulate fewer miles across all vehicle types, larger households put fewer miles on coupes and pick-up trucks, and households with more workers accumulate more miles on three of the six vehicle types. Virtually of these findings are consistent with expectations.

Higher population density and the greater presence of physical activity centers in the vicinity of the residential area contribute negatively to the accumulation of miles, particularly for small cars and SUVs. This finding is consistent with the notion that higher densities are associated with lower vehicular miles of travel. Zonal density is also negatively associated with miles accumulated on pick-up trucks. Finally, as mentioned earlier, the copula dependency parameter estimates show that there is significant error correlation between vehicle type choice and usage for all vehicle types. In addition, the significant scale parameter suggests that there are considerable unobserved factors affecting usage patterns for all vehicle types. These findings clearly support the adoption of a joint simultaneous equations framework for modeling vehicle type choice and utilization.

5.5 A Policy Simulation Example

The model system estimated in this study can be used to determine the impact of changes in socio-economic, built environment, or vehicle attributes on vehicle type choice and utilization. In this project, changes in vehicle type choice and utilization due to an increase in the fuel price from about \$2.55 (the fuel price per gallon in the year 2000, converted to current dollars) to \$5.00 per gallon. This constitutes a 96 percent increase in fuel price. The changes are applied to each vehicle type in the model through the recalculation of the vehicle make/model log-sum variable according to the specification in Bhat et al (2009). This log-sum variable is used as an explanatory variable in the vehicle type choice model component.

The policy simulation results presented here should be viewed as more long-run or medium-term shifts in behavior as opposed to short-term adjustments in behavior in response to a fuel price hike. It should be recognized that it is generally difficult for households to change fleet composition in the immediate short-term; rather, they may change activity-travel patterns in response to a fuel price hike or absorb the additional transportation cost and adjust other household expenditures (the subject of the next section), thus keeping activity-travel demand relatively stable in the short term. In the longer term, the vehicle fleet may be changed and usage patterns adjusted further in light of the new household vehicle fleet. It is these longer term adjustments that the policy simulation example purports to capture.

The effect of the fuel price change on aggregate vehicle holdings and usage patterns is measured along two dimensions, i.e., the percent change in acquisition of various vehicle types, and the percent change in the annual vehicle usage (VMT) for each vehicle type. Results of the shifts brought about by the 96 percent change in fuel costs considered in this study are tabulated in Table 5.3. Policy simulations offered by the Frank copula-based model are furnished in the table. The results show a shift from larger vehicles to smaller vehicles as one would expect; however, the magnitude of shift in vehicle usage is smaller than the magnitude of shift in vehicle type choice behavior. In other words, the Frank copula-based model is suggesting that people will shift vehicle type choices more than they will shift or change vehicle miles of travel (amount of travel undertaken).

The policy simulation results provided by the Frank copula-based model appear to be consistent with expectations. Households have generally proven to be more responsive with respect to their vehicle type choice than with vehicle usage (miles of travel). Over the past few years, fuel prices have increased dramatically (doubled) and reached record levels averaging $4 per gallon in the United States in the year 2008. Throughout the period of increase in fuel prices, vehicle miles of travel continued to grow (albeit at a rather slower rate than in the past) until the record high fuel prices set in summer of 2008 (FHWA, 2008). Even after record high fuel prices were reached, total VMT reduced a mere two percent, clearly suggesting that the amount of travel people undertake is quite inelastic to increases in fuel prices.

Table 5.3. Impact of Increase in Fuel Price from $2.55 to $5.00 per Gallon (96% Increase in Fuel Cost)

Vehicle Type	% change in holdings of vehicle type	% change in overall use of vehicle type
Compact Sedan	1.25	0.98
Large Sedan	0.28	0.23
Coupe	0.30	0.26
SUV	-1.57	-1.33
Pickup Truck	-1.04	-0.82
Van	-0.88	-0.80
Total	-	-0.13

On the other hand, there is plenty of evidence to suggest that people are changing their vehicle acquisition and type choice patterns. The big three automakers in the USA, General Motors, Ford, and Chrysler, that have relied heavily on sales of large vehicles (SUVs, vans, and crossover vehicles) in the past, are all reporting record losses of staggering proportions (Vlasic and Bunkley, 2008). Several models of minivans have been discontinued (Durbin, 2008). Consumers are migrating away from large vehicles and shifting to smaller, more fuel-efficient, and gas-electric hybrid vehicles in droves (Buss, 2008). Toyota, which sells more fuel-efficient and gas-electric hybrid vehicles, has reported sales figures exceeding that of General Motors for the first time in the history of the automotive industry (CNN, 2008). Ford Motor Company, which reported losses of $8.7 billion in the second quarter of 2008, is considering shipping smaller models that it sells in Europe to the United States to meet consumer demand for smaller and more fuel-efficient vehicles (Smith, 2008). In other words, vehicle type choice appears to be shifting in response to rising fuel prices. But vehicle usage patterns (VMT) have shown very small shifts. All of these real-world shifts are consistent with the policy simulation results offered by the Frank copula-based model, suggesting that this model specification offers more behaviorally realistic simulations in the vehicle type choice – utilization modeling context. It is these sensitivities that are reflected in the spreadsheet model that accompanies this report.

6. MODELING TRANSPORTATION CHOICES FROM A CONSUMER EXPENDITURE PERSPECTIVE

There is no question that recent increases in fuel prices has heightened interest in examining the impact of rising vehicle operating expenses on household transportation expenditures, in relation to expenditures on other categories of consumption. Previous research has generally examined transportation-related expenditures in isolation or in relation to just one or two other categories of consumption due to complexities associated with attempting to analyze all categories of consumption simultaneously. Important questions of interest arise in the context of trying to understand household adjustments in response to transportation cost increases (that may be brought about by a fuel price increase, new toll, parking costs, value pricing, transit fare hike, and so on). How do households respond when the price of fuel increases? How do household adapt their consumption patterns, in terms of the monetary expenditures allocated to various categories of goods and services? Household activity-travel patterns are closely related to household consumption patterns and monetary expenditures. When households engage in more consumption of goods and services outside the home (such as eating out, going to the movies, shopping), then this directly leads to more activities and travel consistent with the behavioral paradigm that travel demand is a derived demand. Unfortunately, there has been very little work examining household expenditure patterns across the entire range of goods and services consumed by households and how these patterns change in response to price increases in the transportation sector. There is very little understanding of the types of trade-offs or adjustments that households would make in their consumption patterns. What are the short-term and long-term elasticities of consumption patterns in response to fuel price increases? In addition, there has been little work (other than some recent work by Anas, 2007) in the area of integrating activity-travel demand and monetary expenditures or consumption patterns in a unified framework. Given that dimensions of travel, consumption, and monetary expenditures are all closely inter-related, and major advances have been made in modeling complex inter-related phenomena, the time is ripe to move in the direction of developing integrated models of activity-travel demand and monetary expenditures of consumption. Before such integrated models can be developed, however, human consumption patterns and monetary expenditures for various goods and services need to be understood and modeled.

This section presents a comprehensive analysis of consumer expenditures in the United States using disaggregate consumption data from the 2002 Consumer Expenditure Survey conducted by the Bureau of Labor Statistics (BLS). While it is certainly desirable to use more current consumer expenditure data, disaggregate consumer expenditure survey data must be purchased for a fee from the Bureau of Labor Statistics. As the research team had the 2002 data readily available from a prior purchase several years ago, this data set was used for the study merely for the sake of convenience. As the modeling methodology is econometrically rigorous and disaggregate, many of the relationships and trade-offs identified in this project are likely to hold true regardless of the year of the dataset used for model development. However, due caution should be exercised in interpreting the results of the formulation.

A multiple discrete continuous nested extreme value (MDCNEV) modeling methodology is employed in to explicitly recognize that people choose to consume various goods and commodities in differing amounts. The methodology accommodates the possibility of zero consumption of certain commodities and the nesting structure in the model accounts for correlations between the stochastic terms of the utilities of different expenditure categories. The paper also provides estimates of short-term and long-term elasticities in response to increases in fuel prices to show how the modeling methodology is suited to answering the types of questions raised earlier. The MDCNEV model estimates are used to simulate how households adjust to increases in fuel expenditures. By considering a comprehensive set of expenditure categories, the model is able to provide a full picture of household adjustment patterns.

6.1 On Modeling Consumer Expenditure Patterns

The field of travel behavior has long recognized that travel demand is a derived demand, derived from the human desire and need to participate in activities and consume goods and services distributed in time and space (Jones, 1979; Jones et al, 1993; Bhat and Koppelman, 1999; Pendyala and Goulias, 2002). However, most travel demand models recognize the activity-based nature of travel demand, but ignore the consumption side of the enterprise, possibly due to the lack of data about and/or the inherent difficulty with modeling consumption patterns and the monetary expenditures associated with such patterns. A recent attempt by Anas (2007) to develop a unifying model of activities and travel and monetary expenditures is an exception and provides a framework for considering the integration of these concepts. As mentioned previously, the rise in fuel prices has provided a major impetus to move in the direction of comprehensive modeling of activity-travel demand and human consumption and monetary expenditure patterns.

It is possible that much attention has not been paid to the expenditure side of the enterprise because the cost of transportation in many developed countries has been rather stable or even decreasing (on a per-mile basis) for many years. This has certainly been the case in the United States for nearly 30 years, since about the late 1970s. There is considerable research that has documented the relative inelasticity of demand to fuel price increases (Puller and Greening, 1999; Nicol, 2003; Hughes et al, 2006). This has been true in several other developed countries as well. For example, Moriarty (2002) analyzes data for Australia and several OECD countries and finds that the transport expenses share of household income has been fairly constant in recent decades at the aggregate level, although substantial variations do exist across demographic groups defined by income and regional location. However, the trend of a constant transport expenditure share may not hold any longer. In fact, recent studies using Consumer Expenditure Survey data in the United States (Gicheva et al, 2007; Cooper, 2005) has reiterated the notion of fuel price inelasticity by showing that household-level fuel expenditures increase in proportion to the increase in fuel prices. Based on this evidence, the recent sharp increase in fuel prices, coupled with the relative price inelasticity of behavior/demand, is likely to result in an increase in household fuel expenditures for transportation. For example, the Bureau of Labor Statistics in the United States reports that, between 2004 and 2005, household fuel expenditures for transportation increased by 26 percent, an amount that roughly coincides with the increase in fuel prices themselves. Such increases in fuel expenditures are likely to significantly decrease the disposable income available to households, which in turn may impact overall consumption patterns for various goods and services as cost of living rises (Fetters and Writer, 2008). Any changes in consumption patterns are likely to have an impact on activity-travel demand as well. For example, a household may cut back on eat-out trips or social-recreational activities as disposable income available to afford/undertake these types of activities decreases in the face of rising transportation fuel costs.

Given that transportation expenditures account for nearly 20 percent of total household expenses and 12-15 percent of total household income, it is no surprise that the study of transportation expenditures has been of much interest. Several early household expenditure studies did focus on transportation-related expenses to assess the proportion of income and total household expenditures that are related to transportation (e.g., Prais and Houthakker, 1955; Oi and Shuldiner, 1962). Nicholson and Lim (1987) offer a review of several early studies of household transportation-related expenditures. More recently, there has been a surge in studies examining household transportation expenditures, at least partly motivated by the rising fuel prices around the world and the growing concern about modal access to destinations for poorer segments of society that may not have access to a personal automobile.

Recent work by Thakuriah and Liao (2005, 2006) has examined household transportation expenditures using 1999 and 2000 Consumer Expenditure Survey data in the United States. The first piece of work explores the impact of several factors on household vehicle ownership expenditures including socio-economic characteristics and geographic region of residence in the country. They note that households with one or more vehicles spend, on average, 18 cents of every additional dollar on vehicles. In their second piece of work, they estimate Tobit models to understand the relationship between transportation expenditures (termed mobility investments) and ability to pay (measured by income). They find that there is a cyclical relationship between transportation expenditures and income. As income increases, transportation expenditures increase; as transportation expenditures increase, so does income – presumably because transportation expenditures facilitate access to distant jobs that offer higher income.

There has been some work examining transportation expenditures in relation to expenditures on another commodity or service. For example, Choo et al (2007) examine whether transportation and telecommunications tend to be substitutes, complements, or neither. For this analysis, they examine consumer expenditures for transportation and telecommunications using 1984-2002 consumer expenditure survey data in the United States. They find that all income elasticities are positive, indicating that demand for both transportation and telecommunications increases with increasing income. Vehicle operating expenses (fuel, maintenance, and insurance) are relatively less elastic than entertainment travel and other transportation expenses to income fluctuations. Another study, by Sanchez et al (2006), examines transportation expenditures in relation to housing expenditures. Noting that housing and transportation constitute the two largest shares of total household expenditures, they argued that these two commodities should be considered together as there is a potential trade-off between these expenditures. Indeed, there is a vast body of literature devoted to the traditional theory that households trade-off housing costs with transportation costs in choosing a residential location. Using cluster analysis techniques, they find that such a trade-off relationship does indeed exist and that these expenditures cannot be treated in isolation of one another.

In another study, Gicheva et al (2007) examine the relationship between fuel prices, fuel-related expenditures, and grocery purchases by households. Using detailed Consumer Expenditure Survey data and scanner data from a large grocery chain on the west coast of the United States, they perform a statistical analysis to determine the extent to which rising fuel prices are affecting food purchasing and expenditures. They find that household fuel expenditures have gone up directly with rising fuel prices, and that households have adjusted food consumption patterns to compensate for this. They find that expenditure on food-away-from-home (eat-out) reduces by about 45-50 percent for a 100 percent increase in fuel price. However, the savings on eating out are partially offset by increased grocery purchases for eating in-home. Within grocery purchases, they also find that consumers substitute regular shelf-priced products with special promotional items to take advantage of savings.

The three studies reviewed in the previous paragraph clearly indicate that transportation expenditures ought not to be studied in isolation as there are relationships in consumer expenditures across commodity categories. Unfortunately, there has been virtually no work that considers transportation expenditures in the context of consumer expenditures for the full range of commodities, goods, and services that households consume. In the present context of rising fuel prices, it is absolutely imperative that the profession adopt a holistic approach that considers transportation expenditures in the context of all other expenditures and household savings. To help fill this gap, a multiple discrete continuous nested extreme value (MDCNEV) model of household expenditures is developed and estimated in this project. The model can be used to understand the trade-offs that households make in response to rising fuel prices and quantify the short- and long-term price elasticities of demand.

6.2 Modeling Methodology

The modeling methodology uses a resource allocation modeling framework, in which the household income is apportioned among an extensive set of annual household expenditures, including housing, utilities, food, alcohol and tobacco products, clothing and apparel, personal care, household maintenance, entertainment, education, health care, business services, and a variety of transportation expenditures including vehicle purchases, vehicle insurance, fuel and motor oil, vehicle operating expenses, air travel, and public transportation. Along with these expenditure categories, the methodology accounts for household savings as well.

The MDCNEV model, formulated by Pinjari and Bhat (2010), is analogous to the nested logit extension of the multinomial logit model. In this case, the MDCNEV model is an extension of the original non-nested version called the multiple discrete continuous extreme value (MDCEV) model formulated by Bhat (2005, 2008). The MDCEV framework is a utility maximization-based resource allocation model that considers the possibility that households spend on different types of goods and services to satisfy needs and desires. This is achieved by incorporating diminishing marginal returns with increasing expenditure in each good/service to represent satiation effects. The model also allows for corner solutions in that households may choose not to spend on certain categories (e.g., alcohol and tobacco products). The MDCNEV model extends the original MDCEV modeling framework to incorporate unobserved interdependencies among various categories of goods and services. More specifically, the nested extreme value extension of the MDCEV model captures correlations between the stochastic terms of the utilities of different expenditure categories. The MDCNEV model estimation results can be used to simulate how households adjust to increases in fuel prices and transportation related expenditures. This section presents the model formulation in brief; detailed formulations of the MDCEV model may be found in Bhat (2005, 2008) and of the MDCNEV model in Pinjari and Bhat (2010).

Consider the following additive non-linear functional form for utility (Bhat, 2008):

$$U(\boldsymbol{t}) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\}; \ \psi_k > 0, \alpha_k \le 1, \gamma_k > 0 \qquad (9)$$

In the above utility function, the total utility derived from the allocation process is assumed to be the sum of subutilities derived from the proportions allocated to each alternative *k*. Specifically, *U*(***t***) is the total utility derived from allocating a non-negative amount t_k of the total budget to each consumption (or expenditure) category (or alternative) *k*, including savings; and ψ_k, α_k and γ_k are the parameters associated with alternative *k*, each of which is discussed below.

The term ψ_k in the above utility function corresponds to the marginal random utility of one unit of consumption of alternative k at the point of zero consumption for the alternative (as can be observed from computing $\partial U(\boldsymbol{t}) / \partial t_k \,|_{t_k=0}$, which is equal to ψ_k). ψ_k controls the discrete choice consumption (or not) decision for alternative *k*. Thus, this term is referred to as the baseline preference parameter for alternative *k*. It should be noted that along with the discrete choice decision, ψ_k also controls the continuous choice decision (how much to consume) for alternative *k* (as can be observed from the presence of ψ_k in the expression for the marginal utility of consumption for non-zero consumption: $\partial U(\boldsymbol{t}) / \partial t_k \,|_{t_k>0}$).

To complete the baseline parameter specification, the baseline parameters are expressed as functions of observed and unobserved attributes of alternatives and decision-makers as below:

$$\psi(\mathrm{z}_k, \varepsilon_k) = \exp(\beta' \mathrm{z}_k + \varepsilon_k) \qquad (10)$$

In the above expression, the observed attributes are specified through the vector z_k of attributes characterizing alternative *k* and the decision-maker. The unobserved attributes are (or the stochasticity is) introduced through a multiplicative random term ε_k that captures unobserved (to the analyst) characteristics affecting ψ_k.

The role of α_k is to reduce the marginal utility with increasing consumption of alternative *k*; that is, it represents a satiation (or non-linearity) parameter. When α_k = 1 for all *k*, this represents the case of absence of satiation effects or, equivalently, the case of constant marginal utility. As α_k moves downward from the value of 1, the satiation effect (or the diminishing marginal utility effect) for alternative *k* increases. When $\alpha_k \to 0$, the subutility function for alternative *k* collapses to $U_k = \gamma_k \psi_k \ln\left(\frac{x_k}{\gamma_k} + 1 \right)$. α_k can also take negative values and, when $\alpha_k \to -\infty$, this implies immediate and full satiation (i.e., infinite decrease in the marginal utility).

The term γ_k (γ_k >0) is a translation parameter that serves to allow corner solutions (zero consumption) for alternative *k*. However, it also serves as a satiation (or non-linearity) parameter capturing diminishing marginal utility with increasing consumption. Values of γ_k closer to zero imply higher rate of diminishing marginal utility (or lower consumption) for a given level of baseline preference. For alternatives that are always consumed by all decision-makers in the data (such as, housing, utilities, and food) there is no discrete choice. Thus γ_k is not applicable for such alternatives and the sub-utility for such alternatives becomes $U_k = \frac{1}{\alpha_k}\psi_k t_k^{\alpha_k}$.

Having discussed the functional form of the utility structure and the role of each parameter in the utility function, the budget allocation problem may now be formulated. From the analyst's perspective, the household maximizes the random utility subject to a linear budget constraint and non-negativity constraints on t_k:

$$\sum_{k=1}^{K} t_k = T \text{ (where } T \text{ is the total budget) and } t_k \geq 0 \;\forall\; k \;(k = 1, 2, ..., K) \tag{11}$$

The analyst can solve for the optimal consumption pattern by forming the following Lagrangian and applying the Kuhn-Tucker (KT) conditions:

$$L = \sum_k \frac{\gamma_k}{\alpha_k} \exp(\beta' z_k + \varepsilon_k) \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} - \lambda \left[\sum_{k=1}^{K} t_k - T \right], \tag{12}$$

where λ is the Lagrangian multiplier associated with the budget constraint. The KT first-order conditions for the optimal consumptions $(t_k^*; k = 1, 2, ..., K)$ are given by:

$$\exp(\beta' z_k + \varepsilon_k) \left(\frac{t_k^*}{\gamma_k} + 1 \right)^{\alpha_k - 1} - \lambda = 0, \text{ if } t_k^* > 0, \; (k = 1, 2, ..., K) \tag{13}$$

$$\exp(\beta' z_k + \varepsilon_k) \left(\frac{t_k^*}{\gamma_k} + 1 \right)^{\alpha_k - 1} - \lambda < 0, \text{ if } t_k^* = 0, \; (k = 1, 2, ..., K)$$

For the sake of brevity, the remainder of the derivation of the probability expressions is not furnished here. Additional details of the formulations may be found in Pinjari and Bhat (2010). As indicated in their paper, the general probability expression that they derive represents the MDCNEV consumption probability for any consumption pattern with a two-level nested extreme value error structure. The probability expression can be used in the log-likelihood formation and subsequent maximum likelihood estimation of the parameters for any dataset with mutually exclusive groups (or nests) of interdependent alternatives (i.e., mutually exclusive groups of alternatives with correlated utilities) and multiple discrete-continuous choice outcomes. Further, they have shown that the MDCNEV probability expression simplifies to Bhat's (2008) MDCEV probability expression when each of the utility functions are independent of one another.

6.3 Data Description

The source of data used for this analysis is the 2002 Consumer Expenditure (CEX) Survey (BLS, 2004). The CEX survey is a national level survey conducted by the US Census Bureau for the Bureau of Labor Statistics (BLS, 2003). This survey has been carried out regularly since 1980 and is designed to collect information on incomes and expenditures/buying habits of consumers in the United States. In addition, information on individual and household socio-economic, demographic, employment, and vehicle characteristics is also collected. The survey program consists of two different surveys – the Interview Survey and the Diary Survey (BLS, 2001). The Diary Survey is a self-administered instrument that captures information on all purchases made by a consumer over a two-week period. The Diary allows respondents to record all frequently made small-scale purchases. The Interview Survey is conducted on a rotating panel basis administered over five quarters and collects data on quarterly expenditures on larger-cost items, in addition to all expenditures that occur on a regular basis. Each component of the CEX survey queries an independent sample of consumer units which is representative of the US population. For this analysis, the 2002 Interview Survey data available at the National Bureau of Economic Research (NBER, 2003) archive of Consumer Expenditure Survey microdata extracts was used.

NBER processes the original CEX survey data of BLS to consolidate hundreds of expenditure, income, and wealth items into 109 distinct categories (Harris and Sabelhaus, 2000). These microdata extracts are provided at the NBER website in two different files – a family file that contains household level income, expenditure, and basic household demographics, and a member file that contains additional demographic information on each household member. In order to facilitate the analysis and modeling effort for this project, the data was further processed in the following manner:

a. Different family files containing the annual expenditures were merged to form an annual expenditures file for the year 2002.
b. The annual family file was integrated with the member file to form a single file including both individual and household level information.
c. Only households with complete information on all four quarters were extracted and selected for analysis. Other screening and consistency checks were applied as well.
d. The 109 categories of expenditure and income were further consolidated. Appropriate groups were aggregated to calculate net household annual income (after taxes), and form 17 broad categories of annual expenditure. The first column of Table 6.1 provides the list of all aggregate expenditure categories, and the subcategories within these expenditure categories.
e. An annual household savings variable was computed by subtracting total annual expenditure from the total net annual income. If savings were negative (which is possible when households go into debt on their credit cards, for example), then the savings variable was recoded to zero.
f. A budget variable was created by adding expenditures across all 17 expenditure categories and savings. If the income is greater than the sum of expenditures and savings, then the budget is equal to the income; otherwise, the budget is equal to the sum of expenditures (as there is no savings).
g. All expenditures and savings were converted into proportions (or percentages) of the budget variable.

The final sample for analysis includes 4084 households with the information identified above. Descriptive statistics for expenditures on the 17 categories are furnished in Table 6.1 for this sample of households.

It is found that all households incurred expenditures for housing, utilities, and food. Housing expenditures account for about 19 percent of income while food accounts for about 13 percent. For all other categories, at least some households did not allocate any expenditure at all. More than 90 percent of households incur expenditures for clothing, personal care, household maintenance, health care, business services, and entertainment and recreation. About three-quarters of the households incurred expenditures for alcohol and tobacco products while a lower 65 percent of households spent resources on education.

Table 6.1. Descriptive Statistics of Household Expenditures and Savings

Expenditure Category	Number (%) of Households (HHs) Spending In	Average Household Expenditure ($/yr) for all HHs	Average Household Expenditure ($/yr) for HHs spending in this category	Number of Households Who Spent ONLY in This Category and Housing/Food /Utilities
Housing (rent, property taxes, payments on mortgage principal, interest payments on property loan)	4084 (100%)	8691 (19.0%)	8691	0
Utilities (electricity, gas, water, sanitary services, fuel oil, coal, telephone and telegraph bills)	4084 (100%)	2866 (7.5%)	2866	0
Food (food and non-alcoholic product purchases at grocery stores and at restaurants)	4084 (100%)	5297 (13.2%)	5297	0
Alcohol and Tobacco Products (all alcohol and tobacco products purchased for home use as well as at restaurants)	2966 (74.6%)	623 (1.6%)	858	0
Clothing and Apparel (clothing, shoes, dry cleaning bills, watches, jewelry etc.)	3912 (95.8%)	1252 (2.6%)	1307	0
Personal Care (services such as barber shops, beauty parlors, health clubs)	3766 (92.2%)	257 (0.6%)	279	0
Household Maintenance (household furniture/supplies/ equipment, gardening and other household operation)	3777 (92.5%)	1482 (3.0%)	1602	0
Entertainment and Recreation (club/gym memberships, movies etc, recreational trips, recreational/sports equipment)	4016 (98.3%)	2372 (4.9%)	2412	0
Education (cost of books, nursery/ elementary/ secondary education, higher education and other education services.)	2595 (63.5%)	867 (1.4%)	1364	0
Health Care (hospital expenses, prescription drugs and medicines, health insurance and other health care expenses)	3899 (95.5%)	3026 (7.6%)	3170	0
Business Services and Welfare Activities (financial/legal/ professional services, political/religious contributions)	3669 (89.8%)	1392 (3.0%)	1549	0
New/Used Vehicle Purchase (Net outlay of vehicle acquisition excluding trade in allowance, if any)	1074 (26.3%)	3499 (6.0%)	13306	0
Gasoline and Motor Oil	3833 (93.9%)	1299 (2.9%)	1384	0
Vehicle Insurance	3289 (80.5%)	955 (2.2%)	1186	0
Vehicle Operating and Maintenance (repair, greasing, tires, tubes, washing, parking, storage, tolls, interest, rental, etc.)	3679 (90.1%)	1433 (2.9%)	1591	0
Air Travel	1289 (31.6%)	256 (0.5%)	812	0
Public Transportation (fares on mass transit, taxicab, railway, bus etc.)	1443 (35.5%)	125 (0.3%)	354	0
Savings (Income after taxes – total expenditure in above categories, or zero if the difference is negative)	2566 (62.8%)	14215 (20.9%)	22625	0

With regard to transportation-related expenses, the categories are maintained at a detailed disaggregate level to facilitate an understanding of relative expenditures for transportation related items. About one-quarter of the sample reports expenditures on vehicle acquisition. More than 90 percent of sample incurs expenditures on fuel and motor oil and vehicle operating and maintenance expenses. About 80 percent of the sample has vehicle-insurance related expenses, suggesting that a sizeable number of households operate motor vehicles with no insurance or have insurance costs paid for them (possibly by an employer or self-employed business). About one-third of the sample reports spending money on public transportation and air travel. All together, expenditures on transportation-related items account for about 15 percent of household income, a figure that is quite consistent with reported national figures.

Only about 63 percent of the households report savings of greater than zero. All other households report savings of zero or less; all negative values were recoded to zero. It is possible that some households have assets that are not sources of regular income and therefore not captured in this survey. Some households may have large lump-sum payments in a given year, for example, in the context of a large down payment for a housing purchase or a car purchase. In such years, savings may be less than or equal to zero for these households. Finally, households in the lower income brackets may not be able to save as they live paycheck-to-paycheck. A more detailed analysis of the data showed that many households in the zero savings category did indeed fall into the lower income brackets. By recoding the savings as zero and retaining these households in the sample, issues of sample selection bias are avoided in this paper.

The MDCNEV formulation adopted in this analysis is supported by the information in the last column of the table where it is found that no household consumes just one single category beyond housing/food/utilities. All households consume at least two additional categories beyond these three essential items, which are consumed by every household. The MDCNEV model is able to account for such multiple category consumption patterns, where households spend resources on several categories and no resources on others. The MDCNEV model is able to do this without having to deal with sample selection or zero-inflated data issues. Moreover, the MDCNEV model is based on the theory of random utility maximization, which is a theoretical framework embodying much of discrete choice modeling in the field of transportation and consumer demand.

6.4 Model Estimation Results

Model estimation was performed on two different versions of data sets – the version in which all expenditures are retained as actual dollar values and another version in which all expenditures were treated as proportions of the total budget variable. Based on considerations of statistical fit, intuitiveness and interpretation of the model coefficients, and ability to conduct sensitivity analysis, the model based on proportions data was found to be better. Therefore, only estimation results for the proportions-based model are presented in this final report. For the proportions data, the budget is set to 100. Explanatory variables in the model included household socio-economics, personal demographics, and residential and regional location variables. Non-linear effects of vehicle ownership were captured, either by introducing dummy variables for different car ownership levels or by using a spline specification for multi-car households. These variables will be described later in the context of the discussion of the model estimation results.

Model estimation results are presented in Table 6.2.

Table 6.2. Estimation Results of the MDCNEV Model of Household Consumer Expenditures

Variable	Housing	Utilities	Food	Alcohol and Tobacco Products	Clothing and Apparel	Personal Care	HH Maint-enance	Enter-tainment and Recrea-tion	Educa-tion	Health Care	Business Services and Welfare Activities	New/ Used Vehicle Purchase	Gasoline and Motor Oil	Vehicle Insurance	Vehicle Opera-tion Mainten-ance	Air Travel	Public Trans-portation	Saving
Baseline constants		-0.096 (-1.51)	0.451 (4.97)	-1.870 (-23.83)	-0.362 (-4.54)	-0.754 (-11.75)	-1.189 (-19.92)	-0.163 (-2.14)	-3.345 (-33.68)	-0.146 (-1.85)	-1.228 (-19.20)	-3.909 (-44.27)	-0.812 (-12.80)	-2.501 (-28.42)	-2.034 (-24.95)	-3.689 (-37.29)	-2.586 (-17.66)	-2.305 (-29.79)
Satiation parameters	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)
Translation parameters	NA	NA	NA	0.638 (24.63)	0.295 (20.88)	0.116 (24.33)	0.504 (24.57)	0.373 (16.16)	0.206 (26.32)	0.676 (20.37)	0.488 (25.13)	39.472 (12.63)	0.386 (15.82)	0.947 (21.46)	0.619 (19.84)	0.633 (14.95)	0.214 (19.01)	24.656 (16.75)
Impact of household socio-demographic variables on baseline utility																		
Household size	-0.057 (-4.01)	0.097 (6.01)	0.139 (8.13)															
Children present (≤18yr)	0.206 (5.21)			-0.194 (-4.72)	0.395 (10.38)				0.724 (13.78)			0.149 (3.43)						-0.180 (-3.54)
Number of workers in the HH				0.147 (7.61)	0.124 (6.16)				0.235 (10.12)			0.235 (8.28)	0.286 (11.35)	0.215 (8.99)	0.290 (13.12)			0.313 (12.32)
Income 30-70k (base: income ≤30k)		-0.664 (-13.54)	-0.613 (-12.10)			-0.175 (-5.09)				-0.353 (-7.93)		0.294 (5.82)	-0.303 (-7.16)	-0.184 (-5.20)		0.668 (7.52)		
Income > 70k	-0.158 (-4.33)	-1.273 (-15.62)	-0.999 (-13.63)			-0.196 (-3.85)				-0.809 (-12.23)	-0.171 (-3.12)		-0.923 (-12.60)	-0.628 (-9.65)	-0.341 (-5.91)	1.120 (10.84)		
HH w/ 2 cars (base: 1 car)												0.176 (3.10)	0.473 (10.37)					
HH ≥ 3 cars												0.531 (8.63)	0.568 (9.65)					
No. of vehicles														0.813 (14.17)	0.624 (12.26)		-0.608 (-12.43)	
NCar2														-0.510 (-7.45)	-0.564 (-10.95)	-0.239 (-3.00)		-0.108 (-6.11)
NCar3														-0.281 (-6.93)		0.232 (2.40)	0.684 (10.45)	
Home owner (base: renter)	-0.856 (-23.22)	0.101 (1.97)	-0.279 (-4.90)	-0.357 (-8.28)	-0.423 (-11.45)		0.474 (11.16)										-0.378 (-5.65)	-0.197 (-3.64)
Impact of the attributes of household head on baseline utility																		
Non-Caucasian (base: Caucasian)				-0.150 (-3.15)				-0.140 (-2.93)									0.313 (4.41)	

Variable	Housing	Utilities	Food	Alcohol and Tobacco Products	Clothing and Apparel	Personal Care	HH Maint-enance	Enter-tainment and Recrea-tion	Educa-tion	Health Care	Business Services and Welfare Activities	New/ Used Vehicle Purchase	Gasoline and Motor Oil	Vehicle Insurance	Vehicle Opera-tion Mainten-ance	Air Travel	Public Trans-portation	Saving
Male (base: female)				0.191 (5.72)	-0.096 (-2.91)				-0.198 (-4.70)									
Age≤50yr (base: age>50yr)	0.425 (13.97)			0.319 (7.62)				0.176 (4.45)	0.147 (2.77)	-0.735 (-18.12)	-0.287 (-8.34)							
Education < bachelors (base: < high school)									0.612 (7.98)		0.272 (6.62)							
Education ≥ bachelors									1.217 (14.96)		0.411 (8.27)							
Married (base: unmarried)				-0.146 (-3.74)						0.651 (11.28)	0.165 (4.90)							
Widowed /divorced/ separated					-0.079 (-2.09)					0.463 (7.94)								
Impact of spatial and regional location variables on baseline utility																		
Urban (base: rural)	0.578 (18.02)																0.465 (3.95)	
Northeast (base: South)	0.382 (10.02)				0.113 (2.55)			0.151 (2.89)									0.624 (8.92)	
Midwest	0.190 (6.04)						0.108 (2.62)	0.165 (3.68)	0.161 (3.068)									
West	0.315 (9.30)	-0.209 (-3.94)			0.077 (1.90)		0.072 (1.65)	0.125 (2.74)	0.317 (6.02)							0.478 (6.58)	0.559 (7.77)	-0.174 (-3.17)

Nesting parameters (θ)

θ_1 for the nest containing housing, utilities, household maintenance, and business services and welfare activities is 0.771, t-statistic for θ_1 =1 is 29.09.

θ_2 for the nest containing food, alcohol and tobacco products, and entertainment and recreation is 0.707, t-statistic for θ_2 =1 is 22.19.

θ_3 for the nest containing clothing and apparel and personal care is 0.651, t-statistic for θ_3 =1 is 26.96.

θ_4 for the nest containing new/ used vehicle purchase, gasoline and motor oil, vehicle insurance, and vehicle operation maintenance is 0.596, t-statistic for θ_4 =1 is 41.29.

Goodness of fit

Log-likelihood at constants = -150,620; Log-likelihood at convergence (MDCEV model) = -146552.7; Log-likelihood at convergence (MDCNEV model) = -142,821.6

Adjusted $\overline{\rho^2}$ = 0.052; Likelihood ratio between the MDCNEV and MDCEV models = 7462.3 >> 9.49 (χ^2 at 95% confidence level and 4 restrictions)

The baseline preference constants in the first row show the overall proclivity of households toward spending in each category relative to housing (the baseline category). Virtually all constants are negative indicating that housing accounts for the largest share of expenditure among all categories. The only exception is food, which has a significant positive baseline constant. All households spend on food, but it is not clear why this constant is positive when households spend significantly less on food than housing (on average). Like many choice model situations, the presence of continuous explanatory variables in the specification may be clouding the interpretation of these constants.

All satiation parameters (α_k) are fixed to zero in this model estimation effort to facilitate the estimation process (Bhat, 2008). Several different model specifications were tried and the specification where all satiation parameters were set to zero yielded the most intuitive results with the best goodness-of-fit. This does not imply that the model does not account for satiation effects. The translation parameters (γ_k) presented in the third row capture the variation in the extent of non-linearity (or the extent of decrease in marginal utility) across different expenditure categories. Thus, these parameters account for diminishing marginal returns or satiation effects in consumption of various categories. These parameters also facilitate zero consumption on multiple categories (corner solutions). There are no translation parameters for the housing, utilities, and food categories because these items are consumed by all households. For all other expenditure categories, as the magnitude of γ_k increases, the rate of decrease in the marginal utility (i.e., satiation effects) decreases and the proportion of spending increases. All of the parameters are statistically significant, indicating that there are zero consumption patterns and satiation effects for all categories. The value is highest for vehicle purchase, indicating that households are likely to allocate a large proportion of their budget to acquiring a vehicle. This is consistent with expectations. The second highest value is for savings, suggesting that households who save, attempt to save as much of their money as possible. The lowest value is for personal care, suggesting that the lowest proportion of money is allocated to this category and satiation is reached very quickly for most households on this category. These findings are all consistent with the descriptive statistics in Table 6.1.

Coefficients associated with an array of explanatory variables are provided in the next several rows of the table. A positive coefficient means that an increase in the explanatory variable increases the proportion of budget allocated to a category of expenditure and vice versa. For example, household size contributes to higher proportion of resource allocation to utilities and food, but a lower percent allocation to housing. It is possible that, as household size increases, income increases as well; as such, even though households do not allocate less absolute dollar amounts to housing, the proportion of income accounted for by housing decreases, thus contributing to this negative coefficient. The presence of children contributes to higher proportions of income allocated to housing, clothing, education, and vehicle purchases, but lower proportions allocated to alcohol/tobacco and savings. As the number of workers increases, so does the proportion allocated to numerous categories including alcohol/tobacco, clothing, education, vehicle purchases, other transportation expenses, and savings.

All of these findings are consistent with expectations as higher proportions of resources need to be allocated to several categories to raise children or support multi-worker households. Higher income groups tend to spend a lower proportion of their resources on numerous expenditure categories including, for example, utilities, food, personal care, health care, and transportation. Indeed, as the budget available goes up, one would expect the proportions allocated to these items to go down, and this is corroborated by the negative coefficients. The exception is air travel, where the proportion allocated to air travel goes up with income. Also, the middle income group spends a higher proportion on vehicle purchases, possibly due to the cost of a vehicle constituting a large proportion of their income.

Multicar households tend to allocate a greater proportion of their income to vehicle purchases, presumably to add more vehicles or replace existing ones, as evidenced by the positive coefficients associated with two- and three-car households. As expected, these households also allocate higher proportions of income to fuel and motor oil. The continuous variable representing the number of vehicles positively impacts the proportion of expenditure for vehicle insurance and vehicle operation and maintenance, and reduces the proportion allocated to public transportation. However, there are non-linear effects of car ownership on proportions allocated to these expenditure categories. Non-linear effects of car ownership were captured by introducing two variables defined as follows:

For households with two or more vehicles,

NCar2 = Max {0, number of vehicles in household – 1}.

For households with three or more vehicles,

NCar3 = Max {0, number of vehicles in household – 2}.

These variables are found to have negative coefficients associated with them for vehicle insurance and vehicle operation and maintenance. This means that the rate of increase in proportion of income allocated to these categories (as vehicle ownership increases) decreases as the number of vehicles owned by a household goes beyond two. Also, as the number of vehicles goes beyond two, household savings appear to constitute a smaller percentage of income.

Home owners tend to spend a smaller proportion on housing, food, alcohol/tobacco, clothing, and public transportation, but a higher proportion for utilities and household maintenance. These findings are consistent with the notion that home owners are, on average, higher income than home renters, but home maintenance can prove expensive. Similarly, the negative coefficient on the savings variable does not necessarily mean that home owners save less; it simply means that the proportion of their income (which is higher than that for renters) allocated to savings is lower.

Virtually all of the other findings are consistent with expectations. Also, the remaining variables do not have a significant impact on vehicle acquisition or maintenance/operation related expenditure percentages. As such, the remaining findings are noted only briefly. In comparison to Caucasians, other ethnic groups spend a lower proportion on alcohol/tobacco and entertainment and recreation, but spend a higher proportion for public transportation. These findings suggest that there are differences across ethnic groups with respect to income, transportation expenditures, and use of transportation modes. Males allocate a larger proportion to alcohol/tobacco, but less to clothing and education. Those who are younger allocate higher proportions to housing, alcohol/tobacco, entertainment, and education, but lower proportions to health care and business services and welfare activities. Higher education is associated with greater allocation of resources to education and business services. Those who are married allocate higher proportions to health care and business services, but lower proportions to alcohol and tobacco (presumably due to family influence). Those who are widowed/ separated/divorced allocate lower proportion to clothing, but higher proportion to health care, presumably because these individuals are either elderly or seek counseling.

Those in urban areas allocate higher proportion of income to housing, reflecting the higher prices of housing in urban areas. They also spend higher proportions on public transportation, once again reflecting the urban area effect. Several regional differences are also noted with those in the Northeast spending higher proportions of income on housing, clothing, entertainment, and public transportation (relative to those in the South). Midwesterners spend higher proportions for household maintenance and education as well. Those in the West not only spend higher proportions for all of these aforementioned categories, but also for air travel. On the other hand, they spend smaller proportion for utilities and for savings. In general, these findings reflect regional differences in housing prices, income levels, and prices of goods and services (BLS, 1998).

Several configurations for nests among different alternatives were considered and estimated, and later refined based on intuitive and statistical considerations. The final specification includes four nests:

a. Housing, utilities, household maintenance, and business services and welfare activities
b. Food, alcohol/tobacco products, and entertainment and recreation
c. Clothing and apparel, and personal care
d. New/used vehicle purchase, fuel and motor oil, vehicle insurance, and vehicle operation and maintenance.

The nesting parameters are shown in Table 2; all of the parameters are significantly greater than zero and less than one, suggesting that the nesting structure adopted here is appropriate for modeling household consumption patterns for multiple categories. This means that there is a high degree of correlation among alternatives within individual nests. This is quite reasonable as there may be several common unobserved factors that could affect all alternatives within a nest. Households that are "home-oriented" may allocate higher proportions of income to all categories in the first nest, those that are "out-of-home oriented" may allocate higher proportions to all categories in the second nest, those that are "personal appearance oriented" may allocate higher proportions to all categories in the third nest, and those that are "driving-oriented" may allocate higher proportions to the fourth nest categories. These personal and household orientations or proclivities/attitudes may constitute unobserved factors that simultaneously impact household percent expenditures on categories within individual nests.

The log-likelihood value for the MDCEV model with only the constants and satiation/translation parameters is -150620. The corresponding value at convergence for the fully specified MDCEV model is -146552.7 and that for the fully specified MDCNEV model is -142821.6 (for four additional parameters corresponding to the four nests). The likelihood ratio test statistic comparing the MDCEV and MDCNEV is 7462.3, which is much higher than the critical χ^2 value with four restrictions at any level of significance. This suggests that the MDCEV model form may be rejected in favor of the MDCNEV model adopted in this study.

6.5 Sample Sensitivity Analysis

The model presented in this section of the report can be used to analyze how households adjust their consumption patterns in response to increases in expenditures in one or more of the 17 expenditure categories considered. In the context of the current study which is concerned with fuel price fluctuation effects, such sensitivity analysis can shed light on how households respond and adjust to rising expenditures on fuel and motor oil.

Between 2003 and 2008, fuel prices in the United States have more than doubled. In order to test the impact of such a fuel price increase on consumption patterns, it is assumed that household fuel and motor oil expenditures double while household incomes remain constant. This is a reasonable assumption in light of findings reported in several studies in the literature (reviewed earlier in this report) suggesting that fuel demand is highly price inelastic. Such an increase in fuel and motor oil expenditures is likely to significantly decrease the disposable income available to households, which in turn may impact overall consumption and savings patterns. Results of the sensitivity analysis conducted in this study are consistent with this conjecture and offer quantitative estimates of the adjustments that would occur as a result of the change in proportion of income allocated to the fuel and motor oil category of expenditure.

Policy simulations were carried out in this study for two different scenarios, a short-term scenario and a long-term scenario. For both scenarios, the total budget (or total annual income) was assumed constant and to remain the same, while the fuel expenditures were assumed to double. For example, if a household's expenditure on fuel was 5 percent of its total budget (or income) in the base case, it was increased to 10 percent in the policy scenario. Subsequently, the model estimates were used to apportion the remaining 90 percent of available budget among the remaining expenditure categories and savings. For the short-term scenario, however, several fixed or long-term expenditures were assumed to remain constant and unaffected by rising fuel prices. These categories included housing, utilities, education, health care, and vehicle insurance. Expenditure allocations could change only for the other categories. For the long-term scenario, no expenditure category was assumed to be fixed in value.

Policy scenario simulation results are shown in Table 6.3. The percent values shown in the table are average percent values predicted by the model for both the base case and policy scenario (where fuel prices double). As expected, adjustments are made across the board, even in the short-term. The two largest adjustments are made in savings and food expenditures. Savings take a hit as households have to spend more resources for fuel. Next food consumption takes a hit as households tend to eat-out less often and purchase less expensive or promotional items from the grocery store for their meals at home. These findings are consistent with several reports (Peterson, 2006; Gicheva et al, 2007) and anecdotal evidence and poll data reported recently in the media (Linn, 2008a; Linn, 2008b; MSNBC, 2008b, 2008d). The next category most affected is that of vehicle purchases, another finding that is consistent with recent reports of lagging sales of vehicles for virtually all automobile manufacturers (MSNBC, 2008a). It is very possible that households who are in the market for a vehicle are postponing vehicle purchases or buying a cheaper/smaller car in response to rising fuel prices, even in the short term. Other categories that take a hit include discretionary spending items such as entertainment and recreation, clothing and apparel, and household maintenance. It is interesting to note that vehicle operating and maintenance expense category also shows an adjustment. This may be due to households choosing to use regular grade fuel (as opposed to premium fuels), traveling fewer vehicle miles, and servicing their vehicle less frequently (e.g., having an oil change done every 5000 miles instead of 3000 miles). Finally, household maintenance projects also seem to be potentially postponed as households grapple with the increase in fuel price. Many of these shifts in expenditure patterns are potentially directly correlated with adjustments/changes in daily and weekly activity-travel demand.

The long-term shifts in expenditure patterns generally mirror the patterns seen in the short term, except that one can clearly see the longer-term dynamics that may occur. Besides savings, food, and vehicle purchases (which experienced the largest shifts in the short-term as well), housing and utilities show major adjustments in percent expenditures. The drop in percentage points allocated to housing is 0.50 while that for utilities is 0.28. These findings suggest that, in the longer term, households may shift to less expensive housing, smaller housing (where utility costs would be lower), and potentially, housing that is closer to destination and job opportunities. The lower percent for vehicle operating and maintenance costs is also indicative of this.

Table 6.3. Short-Term and Long Term Impacts of a 100% Fuel Price Increase: A Simulation Exercise

Expenditure Category	Short-Term Impact			Long-Term Impact		
	Percentage of Total Budget		Drop in the Percentage Points	Percentage of Total Budget		Drop in the Percentage Points
	Base Case	Policy Case		Base Case	Policy Case	
Housing	-	-	-	18.68	18.18	-0.50
Utilities	-	-	-	9.85	9.57	-0.28
Food	16.22	15.54	-0.68	15.40	15.00	-0.40
Alcohol and Tobacco Products	2.59	2.46	-0.13	2.48	2.41	-0.06
Clothing and Apparel	3.88	3.72	-0.16	3.84	3.72	-0.12
Personal Care	1.08	1.03	-0.05	0.96	0.93	-0.03
Household Maintenance	3.05	2.90	-0.15	3.06	2.97	-0.09
Entertainment and Recreation	5.86	5.60	-0.26	5.57	5.41	-0.15
Education	-	-	-	0.79	0.77	-0.02
Health Care	-	-	-	3.99	3.88	-0.11
Business Services and Welfare Activities	2.39	2.28	-0.11	2.43	2.36	-0.06
New/ Used Vehicle Purchase	6.21	5.78	-0.43	8.06	7.69	-0.37
Vehicle Insurance	-	-	-	3.52	3.42	-0.10
Vehicle Operating and Maintenance	3.82	3.64	-0.17	3.75	3.63	-0.12
Air Travel	0.47	0.45	-0.02	0.51	0.50	-0.02
Public Transportation	0.20	0.19	-0.01	0.17	0.17	0.00
Savings	12.37	11.57	-0.79	13.99	13.47	-0.52

It is interesting to note that there is no appreciable shift in share of expenditure for public transportation, suggesting that individuals would first make adjustments elsewhere before they shift to public transportation in any significant way. This is a very critical finding with key implications for the transit industry. Although there are likely to be minor shifts to transit in response to higher fuel prices, it is likely that these shifts will be largely inconsequential even in the long run, unless transit services are dramatically improved. Households will cut back on everything from housing to discretionary recreation and travel, and switch to more fuel efficient vehicles, so that they can absorb the higher percent of income that they must allocate to fuel costs. This is consistent with the recent observation of the inelasticity of vehicular travel in response to fuel price increases. With an elasticity of -0.1, even a doubling (100 percent) of fuel price will bring about only a 10 percent decrease in vehicle miles of travel. Thus, it is clear that households are making a range of adjustments across various expenditure categories to accommodate the fuel price increase and maintain a largely steady level of vehicular travel (Pendyala, 2008). On the other hand, many of these adjustments (such as less entertainment and recreation, food consumption, and vehicle purchases) suggest that rising fuel prices can have substantial effects on regional economic activity as people decrease their discretionary activity engagement and goods consumption. In turn, these behavioral adjustments will have effects in the long term on the spatial distribution of population and employment, and on activity-travel patterns and demand. Such effects need to be reflected in integrated activity-based microsimulation models of land use and travel.

7. A SPREADSHEET TOOL FOR ESTIMATING VEHICLE FLEET COMPOSITION AND USAGE (VMT)

The research team has developed a simple spreadsheet that can be used to quickly compute changes in vehicle fleet composition and vehicle miles of travel that can result from a change in the fuel price – which may be best represented as a change in auto operating cost. The spreadsheet is not intended to replace a regional travel demand model in any way; ultimately detailed analyses of changes in travel patterns are best done using a comprehensive travel demand model system that is capable of representing the myriad changes in travel behavior characteristics that may result from a fuel price hike (or any pricing signal).

The spreadsheet is meant to be used as a quick-response tool that provides estimates of vehicle fleet composition and vehicle miles of travel for the Maricopa region when fuel price changes. The spreadsheet focuses on these two dimensions of behavior for two reasons:

a. Vehicle fleet composition constitutes a medium- to long-term adjustment in travel demand which is vital to computing fuel consumption, emissions, and fuel tax revenues. Thus, incorporating this dimension allows the analyst to capture longer term adjustments that may take place in the vehicle ownership characteristics and the implications from a tax revenue and energy/environmental perspective.

b. Vehicle miles of travel is ultimately the composite representation of all activity-travel decisions that households and their members make. Households, and the individuals that comprise them, make decisions about activities and trips to be undertaken, linking of activities and trips, modes of transportation to be used, destination choices, route choices, time of day choices, and accompaniment choices. All of these choices ultimately manifest themselves into the use of (or not) personal vehicles and a quick-response tool of the nature presented in the spreadsheet can best capture the many dimensions of travel behavior by considering vehicle miles of travel as the measure of travel demand. It is for this very reason that the disaggregate choice model presented in Section 5 also focused on analyzing VMT in conjunction with vehicle type choice.

Although some progress has been made in understanding how households adjust monetary expenditures in response to changes in fuel prices (see Section 6), there is much additional research that needs to be done to fully integrate travel demand with concepts of consumer monetary expenditures in the estimation of activity-travel patterns. Therefore, the spreadsheet does not explicitly consider household consumer expenditures in analyzing the impact of fuel price increases on vehicle fleet composition and utilization. However, the computations do implicitly take into account the notion that households may (at least in the short term) just absorb the higher fuel costs by adjusting household consumer expenditures, thus providing a very inelastic response to fuel price fluctuations. This pattern of behavior has been reported in the literature and is therefore reflected in the computations of the spreadsheet.

The spreadsheet workbook includes three separate worksheets. In the first spreadsheet, the user must provide some basic data regarding vehicle types, income quartiles, and elasticity values that should be used for the computations. In the first segment of the first worksheet, four vehicle types are incorporated at this time. However, a user can easily extend the spreadsheet to any number of vehicle types although some modifications of the spreadsheet would be required to accomplish that. This may indeed be warranted, given the interest in explicitly considering acquisition and ownership of hybrid and alternative fueled vehicles, and future versions of this spreadsheet can be made to automatically incorporate any number of vehicle types in a flexible framework. The user must specify the fuel efficiency of the vehicle fleet in the region under study for the vehicle types. The average fuel efficiency provided in the spreadsheet currently is based on the average reported in the National Household Travel Survey, 2009 Maricopa Region Add-on data set. The fuel efficiency figures are critical as these numbers are used to compute auto operating cost for each vehicle type based on the fuel price input by the user.

The second segment of the first worksheet provides elasticity values for vehicle fleet composition by income quartile. The definitions of the income quartiles are provided at the bottom of the first worksheet. The elasticity values used in the spreadsheet are based on results of extensive sensitivity analysis performed using the models described in Section 5 and previous work reported by Bhat and Sen (2006). The model systems offer a means of determining the shift in vehicle fleet composition in response to changes in fuel prices, while controlling for all other factors, including unobserved attributes. In general, these elasticity values should not be altered by the user unless the user has developed new models and has local knowledge of elasticity of vehicle fleet composition with respect to fuel price. One feature of the spreadsheet is that users are able to represent varying elasticity across income quartiles to reflect that lower income individuals are likely to be more elastic in their response than higher income individuals and households. A set of factors are provided on the side to vary the elasticity across income groups, but noting that the average elasticity value achieved must be consistent with that obtained through the application of models such as those reported in Section 5 and earlier by Bhat and Sen (2006).

The third segment of the first worksheet is also a table of elasticity values with the same feature of being able to vary the elasticity values across income groups. These elasticity values reflect the change in VMT by vehicle type in response to changes in auto operating cost (brought about by a change in fuel price) and are based on extensive sensitivity analysis performed using the model presented in Section 5 and reported earlier by Bhat and Sen (2006). These elasticity values represent the extent to which VMT will change per unit percent change in fuel price, while controlling for all other factors. Thus, once again, users are not advised to change these elasticity values unless they have explicit knowledge of such elasticity measures for their local area.

Following the specification of the fuel efficiency of vehicles and the elasticity values, the user can proceed to the second worksheet of the workbook. In the second worksheet, the user is expected to provide input values that drive the computations in the spreadsheet. First, the user needs to specify some basic characteristics for the region. This includes such items as the total number of households, the vehicle ownership rate (vehicles per household), and the gas prices for the base scenario and the alternate scenario of interest. The total number of household vehicles is computed within the spreadsheet as the product of number of households and the vehicle ownership rate. The number of vehicles of the types included in the spreadsheet analysis must also be provided by the user, perhaps based on an analysis of a travel survey vehicle file to identify the percent of all household vehicles that fall into the vehicle categories of interest considered in the analysis.

An analysis of a travel survey vehicle file will also aid the user in filling the second matrix of the input worksheet. This matrix provides the distribution of vehicles by type across income groups in the population. If one has local knowledge of the fleet composition of household vehicles, then this matrix can be altered to reflect local conditions. Essentially, this matrix should provide the distribution of vehicles by type across income groups for the base year (or base scenario). The spreadsheet will compute the new distribution of vehicles by type in the event of a fuel price change as specified by the user for the alternate scenario. It should be noted that there is no provision to alter the number of households or vehicles for the alternate scenario. This has been done on purpose to allow the user to see the impact *solely* of a fuel price change on vehicle fleet composition and utilization. If one were to change the number of households and vehicles per household values, then the change in VMT reported in the spreadsheet will be due to a combination of the fuel price change and the change in population totals. The analyst would have to undertake considerable post-processing to attempt to isolate the impacts of the fuel price change from the impacts of demographic changes. As such, the expectation is that the user will enter population numbers for households and vehicles and that these totals will be held constant across the scenarios.

The user needs to provide the base year VMT per vehicle for each type of vehicle in each income quartile. This can be determined based on an analysis of a vehicle file that includes information about annual mileage. This is a user input and can be altered to reflect local conditions. The base year count of vehicles in each cell (the third matrix in the worksheet), is computed by multiplying the percent of vehicles in each cell (as provided by the user in the previous matrix that depicted the distribution of vehicles by type across income groups) with the total number.

Finally, the third worksheet provides the results of the analysis. The worksheet starts by reproducing some basic values from the previous worksheets including the base and alternate scenario fuel prices, the percent change in fuel price implied by these values, and the total number of vehicles (the vehicle population) applied to both scenarios. First, the analysis sheet provides results of changes in the vehicle fleet composition that results from a fuel price change. The first matrix (corresponding to the base case) is the same one as that appearing in the previous worksheet. It simply shows the total number of vehicles in each vehicle category/class by income group. The matrix that is next to it presents the new vehicle fleet composition for the alternate scenario as a result of the change in fuel prices. Note that the fuel price affects *both* the total ownership of vehicles and the distribution of ownership of vehicles by type. In other words, the total number of vehicles (vehicle population) is allowed to change for the alternate scenario, but the user needs to understand that this change is purely due to changes in fuel price and not due to any other changes in the population totals. The distributions of vehicles by type for all income groups are presented for the alternate scenario. The final matrix in that row presents a measure of the difference with larger measures of difference highlighted in darker red color.

The annual VMT per vehicle for the base case is once again the same as that provided in the previous input worksheet. The annual VMT per vehicle is one of the critical computations performed in this worksheet. These computations are directly based on the elasticity values specified in the first worksheet of the workbook. Using the elasticity measures in the first worksheet, the tool computes the new annual vehicle miles of travel per vehicle for each vehicle type and income quartile. These values reflect the degree to which VMT is adjusted in response to the fuel price. The base case and alternate scenarios are compared to obtain the percent changes in the final step of that section of the worksheet.

The VMT per vehicle matrix is multiplied with the vehicle fleet composition matrix to compute total VMT for the region. The VMT is computed for each vehicle class by income group, both for the base case and the alternate scenario. Changes in VMT are recorded at the end of that section with larger changes in VMT reflected by cells colored in darker red. Fuel consumption is computed by considering VMT and fuel efficiency values (provided in the first worksheet of the workbook) to estimate annual fuel consumption.

The spreadsheet tool offers a concise and convenient way to quickly estimate the approximate shifts in vehicle fleet composition and VMT that may result in response to fuel price fluctuations. The spreadsheet is flexible in that the user can change input values, scenario parameters, and elasticity parameters based on local knowledge or the desire to analyze scenarios in different ways. For example, one could argue that the spreadsheet currently reflects changes in vehicle fleet composition and VMT, and must therefore be showing changes that would manifest over a medium term period of more than five years. However, one might want to estimate changes in VMT that could occur in the shorter-term, without considering medium-term shifts in fleet composition. In that case, a user could zero out the elasticity values for the vehicle fleet mix, thus removing any possibility that the vehicle fleet mix will change. In that case, the vehicle fleet mix would be held constant and VMT values would be adjusted in response to changes in the fuel price. One could consider such estimates to be shorter term responses that occur rapidly in response to a change in fuel price. However, one must note that short-term and long-term elasticities tend to be different, with longer term elasticities showing higher values than short-term elasticities. The values reflected in this spreadsheet may be considered as longer-term elasticity values; and hence, if one is aiming at getting shorter term impacts of a fuel price fluctuation, then it might be advisable to make the VMT elasticities smaller than those currently appearing in the spreadsheet tool. In the end, the spreadsheet is only a tool and the analyst should exercise appropriate judgement in using the tool for the intended purpose.

8. CONCLUSIONS

This report has attempted to present a synthesis of evidence on the potential impacts of fuel price fluctuations on travel demand, with a focus on travel behavior adjustments that might accompany a change in prices at the gas pump. Over the past few years, fuel prices have fluctuated considerably, leading to questions about the extent to which existing transportation planning models adequately address and reflect changes in travel demand that may be attributable to changes in fuel prices. This study, motivated by such questions, provides a synthesis of such evidence with a view to offer insights into how travel demand models need to be enhanced to truly reflect the effects of fuel price fluctuations on travel behavior.

An examination of the aggregate trends over the past few years suggests that there is some impact of fluctuating fuel prices on travel demand, but the effects of fuel price fluctuations cannot be isolated from impacts due to other economic changes such as the recession that has taken root ever since 2007. While travel demand appears to have changed modestly in response to fuel price increases, the bulk of travel demand changes over the past two years may be largely due to the downturn in the economy that has been particularly felt in the State of Arizona and Maricopa County. Much of the literature also notes that travel demand is very inelastic to fuel price fluctuations with elasticity values in the neighborhood of -0.1, although longer term elasticity estimates may be slightly higher. One of the aspects that has not been adequately explored, and could not be explored in this study (due to lack of data), is the notion of a threshold effect where travel demand is inelastic to fuel price fluctuations upto a certain price, and then shifts more noticeably beyond a certain threshold. It would be of value to conduct some well designed stated preference studies to gauge how individuals might respond when confronted with severe fluctuations in fuel prices that are unlikely to be realized in the real-world in the near term. An analysis of the National Household Travel Survey data also shows a reduction in travel in 2008 when compared with 2001, but once again, it is hard to distinguish the reduction due to the economic downturn from the reduction due to fuel price escalation in 2008.

The report presents two elaborate studies that have been undertaken as a part of this project to better understand changes travel behavior as a result of changes in fuel prices. The first study examines changes in vehicle fleet composition and utilization for households using a multiple discrete-continuous extreme value (MDCEV) model. The model system represents two choice processes that households undertake. The first choice dimension is discrete and considers the discrete choice of which vehicle type a household chooses to acquire during a vehicle transaction event. This discrete choice process is combined with a continuous component of determining the mileage or utilization of household vehicles. The discrete-continuous model system, estimated on a disaggregate behavioral survey data set, offers rich insights into how vehicle acquisitions (and therefore fleet composition) and utilization may change in response to changes fuel prices.

The second study addresses an area of interest that has not been examined much so far in the transportation literature. When fuel prices change, household expenditure budgets may be adjusted to absorb the higher transportation costs and there is substantial evidence in the past literature to suggest that households indeed do this. It should be recognized that a change in cost (such as fuel price) has an impact on monetary budgets and expenditures. The changes in travel demand that manifest from a change in fuel price are truly adjustments in monetary expenditures that households are making in response to the cost increase (or decrease). In other words, to truly capture the effects of a fuel price change on travel demand, one must first understand how households adjust monetary budgets/expenditures, and then see how those adjustments are manifest through changes in activity-travel demand. In future research, the profession would be well served by undertaking more integrated analysis of activity-travel patterns and household monetary expenditures, possibly by merging household activity-travel survey data with consumer expenditure data in statistically robust ways, or beginning to introduce questions about monetary expenditures in activity-travel surveys.

As transportation planning models continue to move forward in terms of behavioral and computational rigor, it is likely that their ability to truly capture the effects of fluctuating fuel prices on travel behavior will become increasingly better. For example, activity-based microsimulation models of travel demand offer a rigorous behavioral and computational framework for analyzing changes in travel due to changes in fuel prices. When fuel prices change, individuals may change their trip chaining patterns, consolidate errands and trips, alter destinations, or shift modes. All of these changes are highly inter-related to one another, and must be modeled at the level of the individual traveler while recognizing that these adjustments in behavior are constrained by time-space interactions, household schedules, and institutional obligations (e.g., work and school). In activity-based models, where tours are explicitly modeled, tour formation and stop generation is sensitive to logsum terms that carry up through the model chain from the mode choice step; these terms potentially capture the "cost" of traveling between origins and destinations and can be made to reflect the impacts of fuel price fluctuations. These models are also able to ensure that inter-dependencies among trips in a tour and across household members are adequately represented when analyzing changes in travel demand that may be brought about by a change in system conditions. Such models also provide the ideal framework for accounting for heterogeneity in the population, wherein individuals of certain socio-economic groups are likely to be more or less sensitive than others in response to changes in fuel prices.

In addition to developing activity-based microsimulation models of travel that can reflect the impacts of fluctuating fuel prices on individual travel behavior, it would be of value to examine current models for their ability to provide sensitivity to fuel price consistent with that reported in the literature and in this study report. This report is accompanied by a spreadsheet tool that can be used to assess changes in vehicle miles of travel and vehicle ownership as a result of a change in fuel price. The spreadsheet tool provides quick-response capabilities for estimating changes in travel demand consistent with elasticity values reported in the literature and computed based on disaggregate choice models presented in this project final report. Current transportation planning models can be subjected to a range of sensitivity tests (keeping all other variables unchanged) with regard to fuel price (or auto operating cost) and the changes in vehicle ownership and VMT can be obtained and compared against values that should have been obtained given the accumulated evidence on the (in)elasticity of travel demand with respect to fuel prices. If the model is not found to appropriately react to changes in fuel prices, then modifications to model parameters and specifications may be warranted to ensure that this aspect is represented in ways that would help inform policy and decision-making processes.

9. REFERENCES

American Automobile Association (AAA) (2009) 12 Month Average for Regular Gasoline: Average Weekly Gasoline Prices. Available at: http://www.fuelgaugereport.com/AZavg.asp. Accessed May 15, 2009.

Anas, A. (2007) A Unified Theory of Consumption, Travel, and Trip Chaining. *Journal of Urban Economics*, Vol. 62, No. 2, pp. 163-186.

APTA (2008) Public Transit Ridership Continues to Grow in First Quarter of 2008: Almost 88 More Million Trips Taken than 2007 First Quarter. News Release, June 2, 2008. American Public Transit Association, Washington, D.C. http://www.apta.com/media/releases/080602_ridership_report.cfm

Austin, D. (2008) Effects of Gasoline Prices on Driving Behavior and Vehicle Markets. Congressional Budget office, No. 2883. Washington, D.C.

Bhat, C.R. (2005) A Multiple Discrete-Continuous Extreme Value Model: Formulation and Application to Discretionary Time-Use Decisions. *Transportation Research Part B*, Vol. 39, No. 8, pp. 679-707.

Bhat, C.R. (2008) The Multiple Discrete-Continuous Extreme Value (MDCEV) Model: Role of Utility Function Parameters, Identification Considerations, and Model Extensions. *Transportation Research Part B*, Vol. 42, No. 3, pp. 274-303.

Bhat, C.R. and S. Sen (2006) Household Vehicle Type Holdings and Usage: An Application of the Multiple Discrete-Continuous Extreme Value (MDCEV) Model. *Transportation Research Part B*, Vol. 40, No. 1, pp. 35-53.

Bhat, C.R. and F.S. Koppelman (1999) Activity-Based Modeling of Travel Demand. In R.W. Hall (ed.) *The Handbook of Transportation Science*, Kluwer Academic Publishers, Norwell, Massachusetts, pp. 35-61.

Bhat, C.R. and N. Eluru (2009). A Copula-Based Approach to Accommodate Residential Self-Selection Effects in Travel Behavior Modeling. *Transportation Research Part B*, Vol. 43, No. 7, pp. 749-765.

Bhat, C.R., S. Sen, and N. Eluru (2009) The Impact of Demographics, Built Environment Attributes, Vehicle Characteristics, and Gasoline Prices on Household Vehicle Holdings and Use. *Transportation Research Part B*, Vol. 43, No. 1, pp. 1-18.

Brownstone, D. and T.F. Golob (2009) The Impact of Residential Density on Vehicle Usage and Energy Consumption. *Journal of Urban Economics*, Vol. 65, No. 1, pp. 91-98.

Bureau of Labor Statistics (BLS) (1998) Homeowner Expenditures Take More Out of Budgets in Northeast and West. *Monthly Labor Review*, U.S. Department of Labor Bureau of Labor Statistics, Washington, D.C. http://www.bls.gov/opub/ted/1998/Dec/wk3/art02.htm.

Bureau of Labor Statistics (BLS) (2001) BLS Interview Survey Form 2001. U.S. Department of Labor Bureau of Labor Statistics, Washington, D.C. http://www.bls.gov/cex/#forms.

Bureau of Labor Statistics (BLS) (2004) Consumer Expenditures in 2002. U.S. Department of Labor, Bureau of Labor Statistics, Report 974. Washington, D.C.

Bureau of Labor Statistics (BLS) (2003) 2002 Consumer Expenditure Interview Survey Public Use Microdata Documentation. U.S. Department of Labor, Bureau of Labor Statistics, Washington, D.C. http://www.bls.gov/cex/csxmicrodoc.htm#2002.

Bureau of Labor Statistics (BLS) (2009) Regional and State Employment and Unemployment. U.S. Department of Labor. Available at: http://www.bls.gov/schedule/archives/laus_nr.htm#2009. Accessed May 15, 2009.

Buss, D. (2008) Seismic Shift to Smaller Segments Rocks U.S. Market, Edmunds' Analysis Shows. Auto Observer Report. http://www.autoobserver.com/2008/05/seismic-shift-to-smaller-segments-rocks-us-market-edmunds-analysis-shows.html

Census Bureau (2009) American Community Survey 2004, 2005, 2006, 2007. Available at: http://factfinder.census.gov/servlet/DatasetMainPageServlet?_program=ACS. Accessed May 15, 2009.

Census Bureau (2009) Federal, State, and Local Governments Quarterly Summary of State and Local Government Tax Revenue. Available at: http://www.census.gov/govs/www/qtax.html. Accessed May 15, 2009.

Census Bureau (2009) Population Estimates. Available at: http://www.census.gov/popest/archives/. Accessed May 15, 2009.

Choo, S. and P. L. Mokhtarian (2004) What Type of Vehicles do People Drive? The Role of Attitude and Lifestyle in Influencing Vehicle Type Choice. *Transportation Research Part A*, Vol. 38, No. 3, pp. 201–222.

Choo, S., T. Lee, and P.L. Mokhtarian (2007) Do Transportation and Communications Tend to Be Substitutes, Complements, or Neither? U.S. Consumer Expenditures Perspective, 1984-2002. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2010, pp. 121-132.

CNN (2008) Toyota Set to Beat GM in Sales This Year. CNNMoney Website, July 23. http://money.cnn.com/2008/07/23/news/companies/toyota.ap/index.htm?postversion=2008072309

Congressional Budget Office (CBO) (2008) Effects of Gasoline Prices on Driving Behavior and Vehicle Markets. Congress of the United States. Available at: http://www.cbo.gov/ftpdocs/88xx/doc8893/01-14-GasolinePrices.pdf. Accessed May 15, 2009.

The Consumer Guide (2005) *Consumer Guide Automotive*. http://auto.consumerguide.com/.

Cooper, M. (2005) The Impact of Rising Prices on Household Gasoline Expenditures. Consumer Federation of America, www.consumerfed.org/.

Department of Energy (DOE) (1996) Policies and Measures for Reducing Energy Related Greenhouse Gas Emissions — Lessons from Recent Literature. US Department of Energy, Washington, D.C.

Dubin, J., and D. McFadden (1984) An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. *Econometrica*, Vol. 52, pp. 345-362.

Durbin, D-A. (2008) Minivan Sales Slow, Hit by Gas Prices and Image. *Los Angeles Times*, June 7. http://articles.latimes.com/2008/jun/07/business/fi-minivans7

Energy Information Administration (EIA) (2009) Weekly Retail Premium Gasoline Prices (Including Taxes). U.S. Department of Energy. Available at: http://www.eia.doe.gov/emeu/international/gas1.html. Accessed May15, 2009.

Environmental Protection Agency (EPA) (2005) *Fuel Economy Guide*, Environmental Protection Agency and U.S. Department of Energy. Website: http://www.fueleconomy.gov/feg/findacar.htm.

Environmental Protection Agency (EPA) (2006) *Greenhouse Gas Emissions from the U.S. Transportation Sector 1990–2003,* Office of Transportation and Air Quality (6401A) EPA 420 R 06 003 March. www.epa.gov/otaq/climate.htm.

Ewing, G. and E. Sarigollu (2000) Assessing Consumer Preferences for Clean-Fuel Vehicles: A Discrete Choice Experiment. *Journal of Public Policy & Marketing*, Vol. 19, No. 1, pp. 106-118.

Fang, H.A. (2008) A Discrete–Continuous model of Households' Vehicle Choice and Usage, With an Application to the Effects of Residential Density. *Transportation Research Part B*, Vol. 42, No. 9, pp. 736-758.

Federal Aviation Administration (FAA) (2009) Risks to the Forecast, FAA Aerospace Forecasts FY 2008-2025, U.S. Department of Transportation. Available at: http://www.faa.gov/data_research/aviation/aerospace_forecasts/2008-2025/media/Risks%20to%20the%20Forecast.pdf. Accessed May 15, 2009.

Feng, Y., D. Fullerton, and L. Gan (2005) Vehicle Choices, Miles Driven and Pollution Policies. NBER Working Paper Series, No. 11553, National Bureau of Economic Research, Washington, D.C.

Fetters, E. and H. Writer, H. (2008) Gas, Grocery Prices Drive Cost of Living Up. MSNBC News, http://www.msnbc.msn.com/id/25168646/.

Federal Highway Administration (FHWA) (2008) Traffic Volume Trends. Federal Highway Administration, US Department of Transportation, Office of Highway Policy Information, Washington, D.C. http://www.fhwa.dot.gov/ohim/tvtw/tvtpage.htm

Gicheva, D., J. Hastings, and S. Villas-Boas (2007) Revisiting the Income Effect: Gasoline Prices and Grocery Purchases. NBER Working Paper Series, No. 13614, National Bureau of Economic Research, Washington, D.C.

Goldberg, P. (1998) The Effects of the Corporate Average Fuel Efficiency Standards in the US. *Journal of Industrial Economics*, Vol. 46, No. 1, pp. 1–33.

Goodwin P., J. Dargay, and M. Hanly (2004) Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review. *Transport Reviews*, Vol. 24, No. 3, pp. 275–292.

Harris, E., and Sabelhaus, J. (2000) Consumer Expenditure Survey Family-Level Extracts, 1980:1 - 1998:2. National Bureau of Economic Research, Washington, D.C. http://www.nber.org/data/ces_cbo.html.

Hughes, J. E., C.R. Knittel, and D. Sperling (2006) Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand. *The Energy Journal*, Vol. 29, No. 1, pp. 93 – 114.

Inflation Data (2009) Historical Crude Oil Prices. Available at: http://www.inflationdata.com/inflation/Inflation_Rate/Historical_Oil_Prices_Table.asp. Accessed May 15, 2009.

Johansson, O. and L. Schipper (1997) Measuring the Long Run Fuel Demand of Cars: Separate Estimations of Vehicle Stock, Mean Fuel Intensity, and Mean Annual Driving Distance. *Journal of Transport Economics and Policy*, Vol. 31, pp. 277-292.

Jones, P. (1979) New Approaches to Understanding Travel Behaviour: the Human Activity Approach, In D. A. Hensher and P.R. Stopher (eds.) *Behavioral Travel Modeling*. Redwood Burn Ltd., London, UK, pp. 55-80.

Jones, P. M., F.S. Koppelman, and J.P. Orfeuil (1993) Activity Analysis: State-of-the-Art and Future Directions. In P. Jones (ed.) *Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, Gower, Aldershot, UK, pp. 34-55.

KFH Group (2008) How Transit Agencies are Addressing the Impact of Fuel Price and Ridership Increases. Prepared for American Public Transportation Association, Washington, D.C. Available at: http://www.apta.com/research/info/online/impact_of_fuel_price.cfm. Accessed May 15, 2009.

Kockelman, K.M. and Y. Zhao (2000) Behavioral Distinctions: The Use of Light-Duty Trucks and Passenger Cars. *Journal of Transportation and Statistics,* Vol. 3, No. 3, pp. 47-60.

Krisher, T. (2008) Toyota Takes World Sales Lead from General Motors. *USA Today*, April 23, 2008. http://www.usatoday.com/money/autos/2008-04-23-toyota-gm-sales_N.htm

Lee, L.-F. (1983) Generalized Econometric Models with Selectivity. *Econometrica*, Vol. 51, pp. 507-512.

Linn, A. (2008a) Long Distance Commuters' Road to Nowhere. High Gas Prices, Housing Market Downturn Leave Some Workers Stuck. MSNBC News, http://www.msnbc.msn.com/id/25722409/.

Linn, A. (2008b) Rising Gas Costs Crimping Budgets. MSNBC News, http://www.msnbc.msn.com/id/23637018/.

Litman, T. (2008) Transportation Elasticities: How Prices and Other Factors Affect Travel Behavior. Victoria Transport Policy Institute. Available at: http://www.vtpi.org/elasticities.pdf. Accessed May 15, 2009.

Luk, J. and S. Hepburn (1993) New Review of Australian Travel Demand Elasticities. Victoria: Australian Road Research Board.

Mannering, F. and C. Winston (1985). A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization. *Rand Journal of Economics*, Vol. 16, No. 2, pp. 215–236.

Mannering, F.L. and D.A. Hensher (1987) Discrete-Continuous Econometric Models and Their Application to Transport Analysis. *Transport Reviews*, Vol. 7, No. 3, pp. 227-244.

Mattson, J. (2008) Effects of Rising Gas Prices on Bus Ridership for Small Urban and Rural Transit Systems. Small Urban and Rural Transit Center, Upper Great Plains Transportation Institute, North Dakota State University. Available at: http://www.ugpti.org/pubs/pdf/DP201.pdf. Accessed May 15, 2009.

Mohammadian, A. and E. J. Miller (2003) Empirical Investigation of Household Vehicle Type Choice Decisions. *Transportation Research Record*, *Journal of the Transportation Research Board*, Vol. 1854, pp. 99-106.

Moriarty, P. (2002) Household Travel Time and Money Expenditures. *Road & Transport Research: A Journal of Australian and New Zealand Research and Practice*, Vol. 11, No. 4, pp. 14-23.

Motor Vehicle Division (MVD) (2009) Statewide Registered Vehicles, by Category. Arizona Department of Transportation. Available at: http://www.azdot.gov/mvd/statistics/registeredVehicles.asp. Accessed May 15, 2009.

Mouawad, J. and J. Werdigier (2007) Warning on Impact of China and India Oil Demand. *New York Times*, November 7. http://www.nytimes.com/2007/11/07/business/07cnd-energy.html

MSNBC News (2008a) Why Now is a Good Time to Buy a Car: Cost of a New Vehicle is Lower Than It Has Been in Years. MSNBC News, June 24, 2008, http://www.msnbc.msn.com/id/25287252/.

MSNBC News (2008b) Poll: Fuel Spike Curbs Vacations, Dining Out. MSNBC News, June 8, 2008, http://www.msnbc.msn.com/id/25237798/.

MSNBC News (2008c) Average Cost of Gas Nationwide Hits $4. Associated Press, MSNBC News, June 8, 2008, http://www.msnbc.msn.com/id/25045979/.

MSNBC News (2008d) Gas Prices Gouge Eating, Shopping Habits, Too - Americans Cutting Back on Other Expenses to Keep Tanks Full. MSNBC News, March 19, 2008, http://www.msnbc.msn.com/id/23636538/.

NBER (2003) The National Bureau of Economic Research (NBER) Archive of Consumer Expenditure Survey Microdata Extracts, Washington, D.C. Available at http://www.nber.org/data/ces_cbo.html.

Nicholson, A. J. and Y.H. Lim (1987) Household Expenditure on Transport in New Zealand. *Australian Road Research*, Vol. 17, No. 1, pp. 28-39.

Nicol, C. (2003) Elasticities of Demand for Gasoline in Canada and the United States. *Energy Economics*, Vol. 25, No. 2, pp. 201-214.

Oi, W.Y. and P. Shuldiner (1962) *An Analysis of Urban Travel Demands*. Northwestern University Press, Evanston, Illinois.

Pendyala, R.M. and K.G. Goulias (2002) Time Use and Activity Perspectives in Travel Behavior Research. *Transportation*, Vol. 29, No. 1, pp. 1-4.

Pendyala, R.M. (2008) Travel Trends and Conditions in an Era of High Gas Prices. Presentation at the Gas Price Summit, Arizona House of Representatives, Phoenix, AZ, June 24.

Peterson, J. (2006) The Economic Effects of Recent Increases in Energy Prices. Congressional Budget Office, No. 2835, Washington, D.C.

Pinjari, A.R. and C.R. Bhat (2010) A Multiple Discrete Continuous Nested Extreme Value Model: Formulation and Application to Non-Worker Activity Time-use and Timing Behavior on Weekdays. *Transportation Research Part B*, Vol. 44, No. 4, pp. 562-583.

Potoglou, D. (2008) Vehicle-type Choice and Neighbourhood Characteristics: An Empirical Study of Hamilton, Canada. *Transportation Research Part D,* Vol. 13, pp. 177–186.

Prais, S.J. and H.S. Houthakker (1955) *The Analysis of Family Budgets*. Second Ed 1961, Cambridge University Press, Cambridge.

Puentes, R. and A. Tomer (2008) The Road Less Traveled: An Analysis of Vehicle Miles Traveled Trends in the U.S. Metropolitan Policy Program at Brookings. The Brookings Institute, Washington, D.C. Available at: http://www.brookings.edu/reports/2008/1216_transportation_tomer_puentes.aspx. Accessed May 15, 2009.

Puller, S. L. and L.A. Greening (1999) Household Adjustment to Gasoline Price Change: An Analysis Using 9 Years of US Survey Data. *Energy Economics*, Vol. 21, No. 1, pp. 37-52.

Sanchez, T.W., C. Makarewicz, P.M. Hasa, and C.J. Dawkins (2006) Transportation Costs, Inequities, and Trade-Offs. Presented at the 85th Annual Meeting of the Transportation Research Board, Washington, D.C., January.

Smith, A. (2008) Ford Posts Largest Quarterly Loss Ever. CNNMoney website. July 24. http://money.cnn.com/2008/07/24/news/companies/ford/index.htm

Spissu, E., A.R. Pinjari, R.M. Pendyala, and C.R. Bhat (2009) A Copula-Based Joint Multinomial Discrete-Continuous Model of Vehicle Type Choice and Miles of Travel. *Transportation*, Vol. 36, No. 4, pp. 403-422.

Steinberg. A.B. (2007) Statement of Andrew B. Steinberg, Assistant Secretary for Aviation and International Affairs, U.S. Department of Transportation before the Committee on Commerce, Science, and Transportation. Available at: http://ostpxweb.dot.gov/aviation/Speeches/Steinberg_testimony.pdf. Accessed May 15, 2009.

Storchmann, K.H. (2001) The Impact of Fuel Taxes on Public Transport – An Empirical Assessment of Germany. *Transport Policy*, Vol. 8, pp. 19-28.

Thakuriah, P. and Y. Liao (2005) An Analysis of Variations in Vehicle-Ownership Expenditures. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1926, pp. 1-9.

Thakuriah, P. and Y. Liao (2006) Transportation Expenditures and Ability to Pay. Evidence from Consumer Expenditure Survey. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1985, pp. 257-265.

TRACE (1999) Elasticity Handbook: Elasticities for Prototypical Contexts. Prepared for the European Commission, Directorate-General for Transport, Contract No. RO-97-SC.2035.

Train, K. (1986) *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*. The MIT Press, Cambridge, Massachusetts.

Transportation Services Group (2009) Gasoline & Diesel (Use Fuel) Gallonage. Arizona Department of Transportation. Available at: http://www.azdot.gov/Inside_ADOT/fms/gallon2.asp. Accessed May 15, 2009.

Travel Model Improvement Program (TMIP) (2007) Fuel Price Increases and Impact on Driver Behavior. Federal Highway Administration, U.S. Department of Transportation. Available at: http://tmip.fhwa.dot.gov/resources/clearinghouse/docs/tmip/technical_syntheses/2007/june.pdf. Accessed May 15, 2009.

Turrentine, T., K. Kurani, and R. Heffner (2007) Fuel Economy: What Drives Consumer Choice? *Access*, University of California Transportation Center, Vol. 31, pp. 14-19. Available at: http://www.uctc.net/access/31/Access%2031%20-%2004%20-%20Consumer%20Choice.pdf. Accessed May 15, 2009.

Valley Metro (2009) Ridership Reports. Available at: http://www.valleymetro.org/valley_metro/publications/ridership_reports/. Accessed May 15, 2009.

Vlasic, B. and N. Bunkley (2008) At Ford, End of a Big Vehicle Era Takes a Toll. *New York Times*, July 25. http://www.nytimes.com/2008/07/25/business/25ford.html

Wadud, Z., D.J. Graham, and R.B. Noland (2009) Modelling Fuel Demand for Different Socioeconomic Groups. *Applied Energy*, Vol. 86, No. 12, pp. 2740-2749.

Wadud, Z., D.J. Graham, and R.B. Noland (2010) Gasoline Demand with Heterogeneity in Household Responses. *The Energy Journal*, Vol. 31, No. 1, pp. 47-74.

West, S. (2004) Distributional Effects of Alternative Vehicle Pollution Control Policies. *Journal of Public Economics*, Vol. 88, pp. 735–757.