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A comprehensive analysis of household transportation expenditures relative to other goods and services: an application to United States consumer expenditure data

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Abstract This paper proposes a multiple discrete continuous nested extreme value (MDCNEV) model to analyze household expenditures for transportation-related items in relation to a host of other consumption categories. The model system presented in this paper is capable of providing a comprehensive assessment of how household consumption patterns (including savings) would be impacted by increases in fuel prices or any other household expense. The MDCNEV model presented in this paper is estimated on disaggregate consumption data from the 2002 Consumer Expenditure Survey data of the United States. Model estimation results show that a host of household and personal socio-economic, demographic, and location variables affect the proportion of monetary resources that households allocate to various consumption categories. Sensitivity analysis conducted using the model demonstrates the applicability of the model for quantifying consumption adjustment patterns in response to rising fuel prices. It is found that households adjust their food consumption, vehicular purchases, and savings rates in the short run. In the long term, adjustments are also made to housing choices (expenses), calling for the need to ensure that fuel price effects are adequately reflected in integrated microsimulation models of land use and travel.

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Introduction

In 2008, the real value of fuel prices rose to record levels in the United States (and many other countries around the world). Transit agencies reported significant increases in ridership (APTA 2008), and for the first time since the fuel crisis era of the late 1970s and early 1980s, total vehicle miles of travel (VMT) showed a decline between 2007 and 2008 in the United States (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 individuals and households started making adjustments to their travel behavior, resulting in a drop in VMT. Several media reports in 2008 anecdotally described these adjustments in consumption patterns and activity-travel behavior (MSNBC 2008a, b, c; Kaiser 2008).

While the fuel price increase has waned in the past couple of years or so, the higher fuel prices in 2008 have had a dramatic impact on the automotive industry. The big three automakers in the United States, who have relied heavily on the sales of large vehicles such as SUVs and trucks, reported record losses of staggering figures in 2008 (Austin 2008). This is because households are migrating to smaller and more fuel-efficient hybrid vehicles as they turnover their vehicle fleet in the household in response to the high price of fuel as well as related environmental issues. In the United States, the rise in fuel prices in 2008 was 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 created the perfect storm requiring households to adjust their consumption patterns, activity-travel behavior, and expenditures for various commodities and goods (Olvera et al. 2008).

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, and shopping), this directly leads to more activities and travel consistent with the behavioral paradigm that travel demand is a derived demand. Unfortunately, there has been 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, especially the types of trade-offs or adjustments that households would make in their consumption patterns. What are the short-term and long-term effects on consumption patterns in response to fuel price increases? In addition, there has been little research (other than research 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 paper 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). A multiple discrete continuous nested extreme value (MDCNEV) modeling methodology is employed in this paper 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 impacts on household consumption patterns in response to increases in fuel prices to show how the modeling methodology is suited to answering the types of questions raised in this introductory section of the paper. By considering a comprehensive set of expenditure categories, the model is able to provide a full picture of household adjustment patterns.

The paper starts with a brief discussion of this topic in the next section. Some key references that address transportation-related expenditures are identified and discussed to place this piece of work in the context of existing literature on the subject. The data set, modeling methodology, estimation results, and sensitivity analysis are then presented in the subsequent sections of the paper in that order. The final section offers concluding thoughts and directions for future research.

Understanding transportation-related consumer expenditures

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. 1990; Bhat and Koppelman 1999; Pendyala and Goulias 2002). While most travel demand models recognize this activity-based nature of travel demand, they 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 in the previous section, 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 a reason for the relatively little attention to the expenditure side of the enterprise is 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. Also, this has been true in several other developed countries. For example, Moriarty (2002) analyzed data for Australia and several OECD countries and found that the income share expended on transport expenses 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. The study also noted that, in developed countries, private motoring costs dominate total household transport expenses, accounting for about 80% of total household transportation expenditures.

There is also considerable academic research that has documented the relative inelasticity of demand to fuel price increases (Puller and Greening 1999; Nicol 2003; Bhat and Sen 2006; Li et al. 2010). In fact, several studies have found that the short-run price elasticity of fuel has decreased considerably over time. For example, Hughes et al. (2006) observed that the short-run price elasticity of gasoline demand ranged from −0.034 to −0.077 between 2001 and 2006, compared with −0.21 to −0.34 between 1975 and 1980. Other studies have also found similar results (Espey 1996; Small and Van Dender 2007). Using Consumer Expenditure Survey data, Cooper (2005) and Gicheva et al. (2007) have reiterated the notion of fuel price inelasticity by showing that household-level fuel expenditures increase in proportion to increases in fuel prices. Their finding is supported by the Bureau of Labor Statistics which reports that, between 2004 and 2005, household fuel expenditures for transportation increased by 26%, an amount that roughly coincides with the increase in fuel prices themselves. In a more disaggregate-level analysis focusing on fuel expenditure allocations to each of several vehicles in households with 1–4 vehicles, Oladosu (2003) found that only the newest vehicle in a household with multiple vehicles is expenditure inelastic. A number of other disaggregate-level studies have also looked at the impact of higher fuel price on household vehicle composition and usage. For example, Feng et al. (2005) found that an increase in fuel price reduces a two-vehicle owning household's probability to choose a combination of a car and a sports utility vehicle, with a corresponding increase in the household's probability of choosing two cars. Other studies (Ahn et al. 2008; Li et al. 2008; Bento et al. 2005) have found that higher fuel price (either due to an increase in fuel price itself or due to an increase in gasoline taxes) would affect households' vehicle composition in two ways: (a) by encouraging households to purchase more fuel efficient vehicles, and (b) by encouraging the scrappage of old "gas guzzling" vehicles. In addition, higher fuel cost would also reduce total vehicle miles of travel (VMT) (Feng et al. 2005; Bento et al. 2005, 2009), which can be translated into lower fuel consumption at the household level.

Overall, while the field is witnessing an increasing number of disaggregate-level studies focusing on household and individual travel responses to fuel price and related transportation expense increases, the general results of these studies and other aggregate-level studies suggest only small to moderate direct changes in vehicle ownership and use. As a result, any substantial changes in fuel prices (as witnessed in 2008) would lead to an increase in transportation expenditure, suggesting that the trend of a constant transport expenditure share may not hold any longer. Specifically, increases in fuel expenditures are likely to significantly decrease the disposable income available to households, which in turn may impact the overall consumption patterns for various goods and services as cost of living rises (Fetters 2008). In addition, increases in fuel-related expenditures may result in reductions of household savings, unless the household specifically adjusts all other consumption patterns to compensate for the rise in fuel expenditures. Any changes in consumption patterns are likely to have an impact on activity patterns as well.

Given that transportation accounts for nearly 20% of total household expenses and 12–15% of total household income, it is no surprise that the study of transportation expenditures has been of much interest. In fact, the study of household expenditure patterns can be traced as far back as the middle of the 19th century (e.g., Engel 1857). 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 explored the impact of several factors on household vehicle ownership expenditures, including socio-economic characteristics and geographic region of residence in the country. They noted that households with one or more vehicles spend, on average, 18 cents of every dollar on vehicles. In their second piece of work, they estimated Tobit models to understand the relationship between transportation expenditures (termed mobility investments) and ability to pay (measured by income). They found 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) examined whether transportation and telecommunications tend to be substitutes, complements, or neither. For this analysis, they examined consumer expenditures for transportation and telecommunications using the 1984–2002 Consumer Expenditure Survey data in the United States. They found 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), examined 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 found that such a trade-off relationship does indeed exist and that these expenditures cannot be treated in isolation of one another. Gicheva et al. (2007) studied 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 performed a statistical analysis to determine the extent to which rising fuel prices are affecting food purchasing and expenditures. They found 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 found that expenditure on food-away-from-home (eat-out) reduces by about 45–50% for a 100% 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 found 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. This paper aims to accomplish this goal by developing and estimating a multiple discrete continuous nested extreme value (MDCNEV) model of household expenditures. The model can then be used to understand the trade-offs that households make in response to rising fuel prices, and quantify the short- and long-term effects on other expenditure categories.

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 2-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 of this paper, the data was further processed in the following manner:

1. Different family files containing the annual expenditures were merged to form an annual expenditures file for the year 2002.[1]
2. The annual family file was integrated with the member file to form a single file including both individual and household level information.
3. Only households with complete information on all four quarters were extracted and selected for analysis. Other screening and consistency checks were applied as well.
4. 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 1 provides

[1] Note that the CEX data, while extensive in many ways, also collects expenditures in quarterly periods. In the current analysis, we used CEX estimates that translate these quarterly estimates into annual expenditures. Several assumptions are made in this conversion, and a description of these is beyond the scope of this paper. The reader is referred to BLS (2003) for the CEX survey documentation. By using annual expenditures, we are considering an annual time horizon for capturing expenditure pattern choices rather than smaller periods of time. However, by doing so, we are also ignoring seasonal variations in expenditure patterns (for example, more proportion of expenditure on clothing/apparel than in other categories during the holiday season). Also, the CEX survey does not collect location information on household residences or activity participation locations (i.e., locations where the actual spending take place). Hence, expenditures cannot be related to location characteristics, sales information, etc.

Table 1 Descriptive statistics of household expenditures and savings

Expenditure category	Number (%) of households (HHs) spending in	Average household expenditure ($/year)		Number of households who spent ONLY in this category
		For all HHs	For HHs spending in this category	
Housing (rent, property taxes, payments on mortgage principal, interest payments on property loan)	4,084 (100%)	8,691 (19.0%)[a]	8,691	0
Utilities (electricity, gas, water, sanitary services, fuel oil, coal, telephone and telegraph bills)	4,084 (100%)	2,866 (7.5%)	2,866	0
Food (food and non-alcoholic product purchases at grocery stores and at restaurants)	4,084 (100%)	5,297 (13.2%)	5,297	0
Alcohol and tobacco products (all alcohol and tobacco products purchased for home use as well as at restaurants)	2,966 (74.6%)	623 (1.6%)	858	0
Clothing and apparel (clothing, shoes, dry cleaning bills, watches, jewelry, etc.)	3,912 (95.8%)	1,252 (2.6%)	1,307	0
Personal care (services such as barber shops, beauty parlors, health clubs)	3,766 (92.2%)	257 (0.6%)	279	0
Household maintenance (household furniture/supplies/equipment, gardening and other household operation)	3,777 (92.5%)	1,482 (3.0%)	1,602	0
Entertainment and recreation (club/gym memberships, movies, etc., recreational trips, recreational/sports equipment)	4,016 (98.3%)	2,372 (4.9%)	2,412	0
Education (cost of books, nursery/elementary/secondary education, higher education and other education services)	2,595 (63.5%)	867 (1.4%)	1,364	0
Health care (hospital expenses, prescription drugs and medicines, health insurance and other health care expenses)	3,899 (95.5%)	3,026 (7.6%)	3,170	0
Business services and welfare activities (financial/legal/professional services, political/religious contributions)	3,669 (89.8%)	1,392 (3.0%)	1,549	0
New/used vehicle purchase (Net outlay of vehicle acquisition excluding trade in allowance, if any)	1,074 (26.3%)	3,499 (6.0%)	13,306	0
Gasoline and motor oil	3,833 (93.9%)	1,299 (2.9%)	1,384	0
Vehicle insurance	3,289 (80.5%)	955 (2.2%)	1,186	0

Table 1 continued

Expenditure category	Number (%) of households (HHs) spending in	Average household expenditure ($/year)		Number of households who spent ONLY in this category
		For all HHs	For HHs spending in this category	
Vehicle operating and maintenance (repair, greasing, tires, tubes, washing, parking, storage, tolls, interest, rental, etc.)	3,679 (90.1%)	1,433 (2.9%)	1,591	0
Air travel	1,289 (31.6%)	256 (0.5%)	812	0
Public transportation (fares on mass transit, taxicab, railway, bus, etc.)	1,443 (35.5%)	125 (0.3%)	354	0
Savings (income after taxes—total expenditure in above categories, or zero if the difference is negative)	2,566 (62.8%)	14,215 (20.9%)	22,625	0

[a] The percentage values represent the mean percentages of household income allocated to the different expenditure categories, where the mean is taken across all households. The percentage values do not represent the percentages of the average household expenditures in the various categories

the list of all aggregate expenditure categories, and the subcategories within these expenditure categories.

5. 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.
6. 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 (i.e., for households with positive savings), the budget is equal to the income; otherwise, the budget is equal to the sum of expenditures (as there is no savings).
7. All expenditures and savings were converted into proportions (or percentages) of the budget variable.

The final sample for analysis includes 4,084 households with the information identified above. A comparative analysis of the annual expenditures of these selected households with the larger unscreened CEX sample indicated no substantial differences in the 17 expenditure categories. Thus, to the extent that the CEX sampling procedures were focused on obtaining a representative sample of US households, the sample used in the current analysis may also be viewed as a reasonably representative sample of US households in terms of expenditures.[2] Descriptive statistics for expenditures on the 17 categories are furnished in Table 1 for this sample of households. It is found that all households incurred

[2] As in any choice modeling exercise, it is only necessary that the dependent variable (in our case, the expenditure amounts on various consumption categories) distribution in the sample be representative of the dependent variable distribution in the population for the usual maximum likelihood estimation approach (the so called exogenous sample maximum likelihood or ESML approach) to provide consistent estimates.

expenditures for housing, utilities, and food. Housing expenditures account for about 19% of income across all households, while food accounts for about 13% (see figures in parenthesis under the column “for all HHs” within the main “Average Household Expenditure ($/year)” column). For all other categories, at least some households did not allocate any expenditure at all. 90% or more households incur expenditures in each of the clothing, personal care, household maintenance, health care, business services, and entertainment and recreation categories. About three-quarters of the households incurred expenditures for alcohol and tobacco products while a lower 65% of households spent resources on education.

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% of sample incurs expenditures on fuel and motor oil and vehicle operating and maintenance expenses. About 80% 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% of household income, a figure that is quite consistent with reported national figures.

Only about 63% of the households reported 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, which may be the reason for an apparent negative savings. Also, households in the lower income brackets may not be able to save as they live paycheck-to-paycheck, leading to zero or small negative values of savings over the course of the year (a more detailed analysis of the data indeed showed that many households in the zero/negative savings category did fall into the lower income brackets). In the cases above, recoding negative savings values as zero has the advantage that it may be a good correction mechanism to obtain a more accurate indication of income for some households and also enables us to retain households in the low income category. However, some other 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 from other years may be used to pay the large payments. In this case, recoding negative savings values to zero would artificially inflate annual income. A more appropriate procedure would be to undertake an analysis over several years of annual expenditures (or even quarterly expenditures), so that such inter-temporal effects and dynamics in expenditure patterns can be accommodated. This is an important area for future research.

The last column of Table 1 indicates that no household consumes in just one single category. In fact, all households expend income on housing, food and utilities, and all households consume at least two additional categories beyond the three essential categories of housing, food, and utilities. The MDCNEV model used in the current paper 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-inflation data issues. Moreover, the MDCNEV model is based on the theory of random utility maximization, a theoretical framework embodying much of discrete choice modeling in the field of transportation and consumer demand.

Modeling methodology

The methodology adopted in this paper uses a resource allocation modeling framework, in which the household income is apportioned to the 18 categories (including savings) identified in the previous section. The MDCNEV modeling methodology, formulated by Pinjari and Bhat (2010), 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, and is based on the assumption 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 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 utility terms of different expenditure categories. This section presents the model formulation; the discussion on the MDCEV model is drawn from Bhat (2005, 2008) and that of the MDCNEV model is drawn from Pinjari and Bhat (2010).

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

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

In the above utility function, the total utility derived from the allocation process is assumed to be the sum of sub-utilities derived from the proportions allocated to each consumption category or alternative k (in the current empirical analysis, $k = 1, 2, 3, \ldots, 18$). 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[3]; 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 $\partial U(t)/\partial t_k|_{t_k=0}$, 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. The reader will note here 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: $\partial U(t)/\partial t_k|_{t_k > 0}$).

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:

$$\psi(z_k, \varepsilon_k) = \exp(\beta' z_k + \varepsilon_k) \tag{2}$$

[3] The terms “consumption” and “expenditure” are used interchangeably in this paper, as are the terms “category” and “alternative”.

In the above expression, the observed attributes are specified through the vector z_k of attributes characterizing alternative k and the decision-maker.[4] 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 $\alpha_k = 1$ 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 $\alpha_k \rightarrow 0$, the subutility function for alternative k collapses to $U_k = \gamma_k \psi_k \ln\left(\frac{t_k}{\gamma_k} + 1\right)$. α_k can also take negative values and, when $\alpha_k \rightarrow -\infty$, this implies immediate and full satiation (i.e., infinite decrease in the marginal utility).

The term γ_k ($\gamma_k > 0$) 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:

$$\sum_{k=1}^{K} t_k = T \text{ (where } T \text{ is the total budget) and } t_k \geq 0 \quad \forall k \quad (k = 1, 2, \ldots, K) \tag{3}$$

The analyst can solve for the optimal consumption pattern by forming the following Lagrangian and applying the Kuhn–Tucker (KT) conditions. As derived in Bhat (2008), these KT conditions collapse to:

$$\begin{aligned} V_k + \varepsilon_k &= V_1 + \varepsilon_1 \quad \text{if } t_k^* > 0 \; (k = 2, 3, \ldots, K) \\ V_k + \varepsilon_k &< V_1 + \varepsilon_1 \quad \text{if } t_k^* = 0 \; (k = 2, 3, \ldots, K) \end{aligned} \tag{4}$$

where $V_k = \beta' z_k + (\alpha_k - 1) \ln\left(\frac{t_k^*}{\gamma_k} + 1\right)$ $(k = 1, 2, 3, \ldots, K)$.

The stochastic KT conditions of Eq. 4 can be used to write the joint probability expression of expenditure allocation patterns (i.e., the consumption patterns) if the density function of the stochastic terms (i.e., the ε_k terms) is known. In the general case, let the joint probability density function of the ε_k terms be g (ε_1, ε_2,..., ε_k), let M alternatives be chosen out of the available K alternatives, and let the consumption amounts of the M alternatives be $(t_1^*,\ t_2^*,\ t_3^*, \ldots, t_M^*)$. As given in Bhat (2008), the joint probability expression for this consumption pattern is as follows:

[4] For notational simplicity, a subscript for decision-makers (or households) is not included. The coefficient vector β captures the impact of z_k on the baseline utility.

$$P\left(t_1^*, t_2^*, t_3^*, \ldots, t_M^*, 0, 0, \ldots, 0\right) = |J| \int_{\varepsilon_1=-\infty}^{+\infty} \int_{\varepsilon_{M+1}=-\infty}^{V_1-V_{M+1}+\varepsilon_1} \int_{\varepsilon_{M+2}=-\infty}^{V_1-V_{M+2}+\varepsilon_1} \cdots \int_{\varepsilon_{K-1}=-\infty}^{V_1-V_{K-1}+\varepsilon_1} \int_{\varepsilon_K=-\infty}^{V_1-V_K+\varepsilon_1}$$
$$g(\varepsilon_1, V_1 - V_2 + \varepsilon_1, V_1 - V_3 + \varepsilon_1, \ldots, V_1 - V_M + \varepsilon_1, \varepsilon_{M+1}, \varepsilon_{M+2}, \ldots, \varepsilon_{K-1}, \varepsilon_K)$$
$$d\varepsilon_K d\varepsilon_{K-1} \cdots d\varepsilon_{M+2} d\varepsilon_{M+1} d\varepsilon_1, \tag{5}$$

where J is the Jacobian whose elements are given by (see Bhat 2005) $J_{ih} = \frac{\partial[V_1 - V_{i+1} + \varepsilon_1]}{\partial t_{h+1}^*} = \frac{\partial[V_1 - V_{i+1}]}{\partial t_{h+1}^*}; \quad i, h = 1, 2, \ldots, M - 1.$

In the probability expression above, the specification of g (ε_1, ε_2,…, ε_K) (i.e., the error term structure) determines the form of the consumption probability expressions. To derive the MDCNEV probability expressions, Pinjari and Bhat (2010) used a nested extreme value distributed structure that has the following joint cumulative distribution:

$$F(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_K) = \exp\left[-\sum_{s=1}^{S_K}\left\{\sum_{i \in s\text{thnest}} \exp\left(-\frac{\varepsilon_i}{\theta_s}\right)\right\}^{\theta_s}\right] \tag{6}$$

In the above expression, s (=1, 2,…, S_K) is the index to represent a nest of alternatives, S_K is the total number of nests the K alternatives belong to, and $\theta_s (0 < \theta_s \leq 1;$ $s = 1, 2, \ldots, S_K)$ is the (dis)similarity parameter introduced to induce correlations among the stochastic components of the utilities of alternatives belonging to the sth nest.[5]

Without loss of generality, let 1, 2,…, S_M be the nests the M chosen alternatives belong to, let $q_1, q_2, \ldots, q_{S_M}$ be the number of chosen alternatives in each of the S_M nests (hence $q_1 + q_2 + \cdots + q_{S_M} = M$). Using the nested extreme value error distribution assumption specified in Eq. 6 (and the above-identified notation), Pinjari and Bhat (2010) derived that the expression in Eq. 5 simplifies to the following probability expressions for the MDC-NEV model:

$$P\left(t_1^*, t_2^*, \ldots, t_M^*, 0, \ldots, 0\right) = |J| \frac{\prod_{i \in \{\text{chosen alts}\}} e^{\frac{V_i}{\theta_i}}}{\prod_{s=1}^{S_M}\left(\sum_{i \in s\text{thnest}} e^{\frac{V_i}{\theta_s}}\right)^{q_s}} \sum_{r_1=1}^{q_1} \cdots \sum_{r_s=1}^{q_s} \cdots \sum_{r_{S_M}=1}^{q_{S_M}}$$
$$\left\{\prod_{s=1}^{S_M}\left[\frac{\left(\sum_{i \in s\text{thnest}} e^{\frac{V_i}{\theta_s}}\right)^{\theta_s}}{\sum_{s=1}^{S_k}\left\{\left(\sum_{i \in s\text{thnest}} e^{\frac{V_i}{\theta_s}}\right)^{\theta_s}\right\}}\right]^{q_s - r_s + 1} \left(\prod_{s=1}^{S_M} \text{sum}(X_{rs})\right)\left(\sum_{s=1}^{S_M}(q_s - r_s + 1) - 1\right)!\right\} \tag{7}$$

In the above expression, $\text{sum}(X_{rs})$is the sum of elements of a row matrix X_{rs} (see Appendix for a description of the form of the matrix X_{rs}).

As indicated in Pinjari and Bhat (2010), the general expression above represents the MDCNEV consumption probability for any consumption pattern with a two-level nested extreme value error structure. This expression can be used in the log-likelihood formation and subsequent maximum likelihood estimation of the parameters β, α_k, γ_k, and θ_s [subject to appropriate identification considerations; see Bhat (2008)] for any dataset with mutually exclusive groups (or nests) of interdependent alternatives (i.e., mutually exclusive groups

[5] This error structure assumes that the nests are mutually exclusive and exhaustive (i.e., each alternative can belong to only one nest and all alternatives are allocated to one of the S_K nests).

of alternatives with correlated utilities) and multiple discrete-continuous choice outcomes. Further, it may be verified that the MDCNEV probability expression in Eq. 10 simplifies to Bhat's (2008) MDCEV probability expression when each of the utility functions are independent of one another (i.e., when $\theta_S = 1$ and $q_S = 1\ \forall s$, and $S_M = M$).

Model estimation results

The MDCNEV model was estimated by normalizing the expenditures in each category by the total budget, so that the endogenous allocations to individual categories are in the form of percentages. 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 2. The baseline preference constants (elements of the β vector) in the first row are introduced with the housing category as the base category (i.e., the housing category is introduced with an effective coefficient of zero). These constants do not have any substantive interpretations, and simply capture generic tendencies to spend in each category as well as accommodate the range of the continuous variables in the model. However, all baseline preference constants, except the one for food, are negative, indicating the much higher percentage (100%) of individuals spending a non-zero amount of their budget on housing relative to other categories.

All satiation parameters (α_k) are fixed to zero in this model estimation effort to facilitate the estimation process. 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 [see Bhat (2008) for empirical identification constraints that generally need to be imposed when the satiation and translation parameters are both considered]. 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, as indicated in the "Modeling Methodology" section, these parameters account for diminishing marginal returns or satiation effects in the 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 [the reader is referred to Bhat (2008) for a detailed discussion on the role of the translation parameter]. All of the translation parameters are statistically significant at any reasonable level of significance (as evidenced by the large *t*-statistics provided beneath the coefficients), implying that there are zero consumption patterns and satiation effects for all categories. The value is highest for the vehicle purchase and savings categories, indicating that households are likely to allocate a large proportion of their budget to acquiring a vehicle and to savings, if they expend any money in these categories. The lowest value is for personal care, education, and public transportation, suggesting that the lowest proportion of money is allocated to these categories and satiation is reached very quickly for most households in these categories. These findings are all consistent with the descriptive statistics in Table 1.

Table 2 Estimation results of the MDCNEV model of household consumer expenditures

	Housing	Utilities	Food	Alcohol and tobacco products	Clothing and apparel	Personal care	HH maintenance	Entertainment and recreation	Education
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)
Satiation parameters	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)
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 (≤18 years)	0.206 (5.21)			−0.194 (−4.72)	0.395 (10.38)				0.724 (13.78)
Number of workers in the HH				0.147 (7.61)	0.124 (6.16)				0.235 (10.12)
Income 30–70k (base: income ≤30k)		−0.664 (−13.54)	−0.613 (−12.10)			−0.175 (−5.09)			
Income >70k	−0.158 (−4.33)	−1.273 (−15.62)	−0.999 (−13.63)			−0.196 (−3.85)			
HH w/2 cars (base: 1 car)									
HH ≥3 cars									
No. of vehicles									
NCar2									
NCar3									
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)		
Impact of the attributes of household head on baseline utility									
Non-Caucasian (base: Caucasian)				−0.150 (−3.15)				−0.140 (−2.93)	
Male (base: female)				0.191 (5.72)	−0.096 (−2.91)				−0.198 (−4.70)

Table 2 continued

	Housing	Utilities	Food	Alcohol and tobacco products	Clothing and apparel	Personal care	HH maintenance	Entertainment and recreation	Education
Age ≤50 years (base: age >50 years)	0.425 (13.97)			0.319 (7.62)				0.176 (4.45)	0.147 (2.77)
Education <bachelors (base: <high school)									0.612 (7.98)
Education ≥bachelors									1.217 (14.96)
Married (base: unmarried)				−0.146 (−3.74)					
Widowed/divorced/separated					−0.079 (−2.09)				
Impact of spatial and regional location variables on baseline utility									
Urban (base: rural)	0.578 (18.02)								
Northeast (base: South)	0.382 (10.02)				0.113 (2.55)			0.151 (2.89)	
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)

Table 2 continued

	Health care	Business services and welfare activities	New/used vehicle purchase	Gasoline and motor oil	Vehicle insurance	Vehicle operation maintenance	Air travel	Public transportation	Saving
Baseline constants	−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)
Translation parameters	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									
Children present (≤18 years)			0.149 (3.43)						−0.180 (−3.54)
Number of workers in the HH			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)	−0.353 (−7.93)		0.294 (5.82)	−0.303 (−7.16)	−0.184 (−5.20)		0.668 (7.52)		
Income >70k	−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)								−0.378 (−5.65)	−0.197 (−3.64)

Table 2 continued

	Health care	Business services and welfare activities	New/used vehicle purchase	Gasoline and motor oil	Vehicle insurance	Vehicle operation maintenance	Air travel	Public transportation	Saving
Impact of the attributes of household head on baseline utility									
Non-Caucasian (base: Caucasian)								0.313 (4.41)	
Male (base: female)									
Age $\leq$50 years (base: age $>$50 years)	−0.735 (−18.12)	−0.287 (−8.34)							
Education $<$bachelors (base: $<$high school)		0.272 (6.62)							
Education $\geq$bachelors		0.411 (8.27)							
Married (base: unmarried)	0.651 (11.28)	0.165 (4.90)							
Widowed/divorced/separated	0.463 (7.94)								

Table 2 continued

	Health care	Business services and welfare activities	New/used vehicle purchase	Gasoline and motor oil	Vehicle insurance	Vehicle operation maintenance	Air travel	Public transportation	Saving
Impact of spatial and regional location variables on baseline utility									
Urban (base: rural)								0.465 (3.95)	
Northeast (base: South)								0.624 (8.92)	
Midwest									
West							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 $\theta_1 = 1$ is 29.09

θ_2 for the nest containing food, alcohol and tobacco products, and entertainment and recreation is 0.707, *t*-statistic for $\theta_2 = 1$ is 22.19

θ_3 for the nest containing clothing and apparel and personal care is 0.651, *t*-statistic for $\theta_3 = 1$ 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 $\theta_4 = 1$ 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 four restrictions)

The coefficients associated with an array of explanatory variables are provided in the next several rows of the table. If there are no coefficients corresponding to a variable for certain expenditure categories, it implies that these categories constitute the base expenditure categories off which the coefficients on that variable for other categories need to be interpreted. Thus, a positive (negative) coefficient for a certain variable-category combination means that an increase in the explanatory variable increases (decreases) the likelihood of budget being allocated to that expenditure category relative to the base expenditure categories. For example, as household size increases, the proportion of total income share expended on food increases relative to other categories [see Gicheva et al. (2007) for a similar result]. This is also true for the income share spent on utilities, while the income share expended on housing tends to decrease with an increase in household size. 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, 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. These findings are consistent with expectations. For example, Bhat and Sen (2006) found that households with children are more likely to own spacious (and relatively expensive) SUVs and minivans relative to passenger cars, increasing expenditures on vehicle purchases.

Households with multiple workers tend to allocate a higher proportion of the budget to numerous categories including alcohol/tobacco, clothing, education, vehicle purchases, other transportation expenses, and savings. In an earlier study, Thakuriah and Liao (2005) also found a similar result in the context of vehicle purchases and transportation expenses. Higher income groups tend to spend a lower proportion of their resources on numerous expenditure categories including 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 [see Huggett and Ventura (2000) and Dynan et al. (2004) for related research on saving patterns of different income groups]. However, higher income groups do apportion a higher income share to air travel. 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,

$$\mathrm{NCar2} = \mathrm{Max}\{0,\ \text{number of vehicles in household} - 1\}.$$

For households with three or more vehicles,

$$\mathrm{NCar3} = \mathrm{Max}\{0,\ \text{number of vehicles in household} - 2\}.$$

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, on average, earn higher incomes than home renters (Paulin 1995; Di et al. 2007), 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. 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:

1. Housing, utilities, household maintenance, and business services and welfare activities.
2. Food, alcohol/tobacco products, and entertainment and recreation.
3. Clothing and apparel, and personal care.
4. 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 paper.

Sensitivity analysis

The model presented in this paper 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 paper. In the context of the current fuel price increase, 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 paper) 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% of its total budget (or income) in the base case, it was increased to 10% in the policy scenario. Subsequently, the model estimates were used to apportion the remaining 90% 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 3. The average increase in terms of percentage points (i.e., the increase in the percentage of total budget allocated to fuel expenditures after doubling each individual's fuel expenditure, averaged across all individuals) is 2.95. 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), while the difference of these two provides the average drop in percentage points for the various non-fuel expenditure categories (the sum of these drops across the different non-fuel expenditure categories is −2.95). As expected, the table shows that 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 2008; Kaiser 2008; MSNBC 2008c). The next category most affected is that of vehicle purchases, another finding that is consistent with recent reports of lagging sales of vehicles for

Table 3 Short-term and long term impacts of fuel price increase

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

virtually all automobile manufacturers (MSNBC 2008a). It is very possible that households 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 alcohol and tobacco products. 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 5,000 miles instead of 3,000 miles). Finally, household maintenance projects also seem to be potentially postponed as households grapple with the increase in fuel price.

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. 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 so that they can absorb the higher percent of income that they must allocate to fuel. This is consistent with the recent finding that the elasticity of vehicular travel to fuel prices appears to be about −0.1. Between 2007 and 2008, fuel price has increased by about 20% while the vehicle miles of travel has reduced about 2% (FHWA 2008). In other words, even a doubling (100%) of fuel price will bring about only a 10% 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 the economy as people decrease their discretionary activity engagement and goods consumption. In turn, these behavioral adjustments will have effects on the spatial distribution of population and employment, and on activity-travel patterns and demand, which need to be reflected in integrated activity-based microsimulation models of land use and travel.

Summary and conclusions

This paper presents a comprehensive analysis of household expenditures across an array of commodities and services consumed by households. While previous research focused exclusively on transportation expenditures or one or two categories besides transportation, this study examines the entire array of expenditure patterns across all categories. A multiple discrete continuous nested extreme value (MDCNEV) model is formulated and estimated on a comprehensive data set compiled from the 2002 Consumer Expenditure Survey data of the United States. The model system is capable of considering non-zero consumption/expenditure on multiple categories, zero consumption/expenditure on multiple categories, and correlations among utilities of similar categories of expenses. The modeling methodology is extremely flexible and accommodates differential satiation effects to reflect diminishing returns associated with household expenditures on various categories. Model results show that a range of household socio-economic and demographic characteristics affect the percent of income or budget allocated to various categories and savings. The nesting structure was found to offer superior statistical goodness-of-fit in relation to a model specification that does not incorporate a nesting structure (i.e., assumes independence across all category utilities).

The model was used to perform a sensitivity analysis to examine how households would adjust their consumption patterns, both in the short and long term, in response to increases in fuel price. It is found that, in the short term, households make adjustments in their savings rates, food consumption (such as eating out), and vehicle purchases. In the long term, households make similar adjustments to these categories, but also make major shifts in housing and utilities expenditures, suggesting that adjustments are made to residential location and/or housing unit type. Vehicle operating and maintenance expenses are also cut back, suggesting that individuals drive less, shift to more fuel-efficient vehicles in the long run, and cut back on the level of maintenance.

This study has several important implications for the field. From a methodological standpoint, the paper offers a robust approach for modeling household consumption patterns, including expenditures for transportation. As the profession moves towards integrated modeling of household and individual consumer choices, this approach makes it possible to incorporate considerations of monetary expenditures in activity-based models of travel demand. Such an integrated framework would allow activity-based travel demand models to lend themselves more directly to evaluating quality of life issues. From a policy standpoint, the analysis methodology and empirical results presented in this paper offer key insights into how consumers adjust their expenditures in response to rising fuel prices. It is found that individuals get affected in all categories as they try to maintain mobility levels and absorb the higher costs of fuel. It can be seen that individuals do not shift appreciably to transit, and yet cut back on such essential items as housing and food. These effects are likely to be more pronounced for lower income groups. The analysis conducted in this paper for the entire sample could be undertaken for various strata of society to examine the differential impacts of fuel price increases on consumption patterns and household welfare. Policymakers could use the information to formulate welfare strategies (e.g., having more income groups qualify for subsidized housing or food) and transportation policies (e.g., diverting funds to public transit enhancements) that would minimize the adverse impacts on the vulnerable segments of society. Ongoing research is focused on validating the results of this study with real-world data, conducting social equity comparisons across population subgroups, and exploring more disaggregate representations of expenditure categories.

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Appendix

For $r_s = 1, X_{rs} = \{1\}$.

For $r_s = 2, X_{rs} = \left\{ \frac{(q_s-1)(1-\theta_s)}{\theta_s} + \frac{(q_s-2)(1-\theta_s)}{\theta_s} + \cdots + \frac{2(1-\theta_s)}{\theta_s} + \frac{1(1-\theta_s)}{\theta_s} \right\}$.

For $r_s = 3, 4, \ldots, q_s, X_{rs}$ is a matrix of size $\begin{bmatrix} q_s - 2 \\ r_s - 2 \end{bmatrix}$ which is formed as described below.

Consider the following row matrices A_{qs} and A_{rs} (with the elements arranged in the descending order, and of size $q_s - 1$ and $r_s - 2$, respectively):

$$A_{qs} = \left\{ \frac{(q_s-1)(1-\theta_s)}{\theta_s}, \frac{(q_s-2)(1-\theta_s)}{\theta_s}, \frac{(q_s-3)(1-\theta_s)}{\theta_s}, \ldots, \frac{3(1-\theta_s)}{\theta_s}, \frac{2(1-\theta_s)}{\theta_s}, \frac{1(1-\theta_s)}{\theta_s} \right\}$$

$$A_{rs} = \{r_s - 2, r_s - 3, r_s - 4, \ldots, 3, 2, 1\}.$$

Choose any $r_s - 2$ elements (other than the last element, $\frac{1-\theta_s}{\theta_s}$) of the matrix A_{qs} and arrange them in the descending order into another matrix A_{iqs}. Note that we can form $\begin{bmatrix} q_s - 2 \\ r_s - 2 \end{bmatrix}$ number of such matrices. Subsequently, form another matrix $A_{irqs} = A_{iqs} + A_{rs}$. Of the remaining elements in the A_{qs} matrix, discard the elements that are larger than or equal to the smallest element of the A_{iqs} matrix, and store the remaining elements into another matrix labeled B_{irqs}. Now, an element of X_{rs} (i.e., x_{irqs}) is formed by performing the following operation: $x_{irqs} = \text{Product}(A_{irqs}) \times \text{Sum}(B_{irqs})$; that is, by multiplying the product of all elements of the matrix A_{irqs} with the sum of all elements of the matrix B_{irqs}. Note that the number of such elements of the matrix X_{rs} is equal to $\begin{bmatrix} q_s - 2 \\ r_s - 2 \end{bmatrix}$.

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