How Household Transportation Expenditures Have Evolved In Canada: A Long Term Perspective

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ABSTRACT

In recent years, increasing recognition of the challenges associated with global climate change and inequity in developed countries have revived researcher's interest towards analyzing transportation related expenditure of households. The current research contributes to travel behaviour literature by developing an econometric model of household budgetary allocations with a particular focus on transportation expenditure. Towards this end, we employ the public-use micro-data extracted from the Survey of Household Spending (SHS) for the years 1997 – 2009. The proposed econometric modeling approach is built on the multiple discrete continuous extreme value model (MDCEV) framework. Specifically, in our analysis, the scaled version of the MDCEV model outperformed its other counterparts. Broadly, the model results indicated that a host of household socio-economic and demographic attributes along with the residential location characteristics affect the apportioning of income to various expenditure categories and savings. We also observed a relatively stable transportation spending behaviour over time. Additionally, a policy analysis exercise is conducted where we observed that with increase in health expenses and reduction in savings results in adjustments in all expenditure categories.

Key words: Data pooling, transportation expenditure, scaled model, MDCEV.

INTRODUCTION

Household budgetary allocation in general and transport budgetary allocations in particular affect a whole range of travel behavior choice processes. Specifically, in the long term, residential location, housing inventory, and vehicle fleet ownership (type and number) are heavily reliant on household budgetary decisions while in the short term, daily vehicle type choice (from current household fleet) and usage decisions, activity participation, and location decisions are affected by expenditure allocation decisions. Clearly, these long term and short term decisions are likely to impact activity travel patterns significantly. Hence, it is beneficial to identify the determinants of budgetary allocations to understand how households respond to varying situations due to policy measures, environmental concerns, fuel price fluctuations, and economic challenges. In fact, given the strong influence on travel patterns, it would be useful to consider monetary allocation decisions as a precursor to modeling travel demand processes.

The examination of household budgeting is particularly relevant at this time because of the increasing recognition of the challenges associated with global climate change and inequity in developed countries. Transportation sector is one of the major contributors of greenhouse gas (GHG) emissions. Overall, it accounts for 14 percent of global greenhouse gas (GHG) emissions, and road transportation alone accounts for about 76 percent of the total transportation emissions (Wu et al., 1999). With the increasing recognition of global climate change issues, several countries are considering wide ranging measures to reduce the quantity of GHG emissions. A comprehensive understanding of household budgetary allocations through quantitative analysis will allow transportation professionals to simulate the positive and negative consequences of proposed policies targeting GHG reductions. For example, a framework to model households' response to policies such as gasoline tax or electric vehicle subsidy requires an understanding of how households adjust their monetary expenditures to maintain their mobility levels in response to these policies. Further, quantitative frameworks developed can also be employed to study the potential equity/distributional implications of private transportation usage *penalty* for vulnerable population segments. In fact, there is evidence indicating that a blanket increase in gas prices as a measure of reducing GHG emissions might adversely affect the lower income groups (Ferdous et al., 2010).

Modeling Budgetary Allocations

Factors affecting household budgetary allocations include household composition, employment status, household location, household evolution, and global socio-economic factors (such as economic, technological and cultural factors). Accommodating for the impact of current household characteristics in the budgetary allocation process is possible through cross-sectional databases. While such analysis is very useful, there is no consideration of household evolution and global socio-economic factors in the decision process. For example, how households respond to various temporal shocks – such as recession or a sudden spike in gas prices cannot be accommodated within the budgetary process unless we develop household budgetary allocation decision framework for a longer duration. To address this limitation, we could study household expenditure patterns over time employing longitudinal databases that track the expenditure patterns of the same households across multiple years. Unfortunately, longitudinal data collection is extremely expensive and provides challenges associated with respondent fatigue and retention (Hanly and Dargay, 2000; Yee and Niemeier, 1996). An alternative could be to pool multiple year cross-sectional databases (an approach gaining wide applicability in travel behavior literature recently; see, Anowar et al., 2016; Sanko, 2014; Dargay, 2002; Dargay and Vythoulkas, 1999) of household expenditure. The availability of cross sectional datasets for multiple years provides a useful compromise between a single year cross sectional dataset and a truly longitudinal dataset compiled across several years. Though the multiple waves are not compiled based on the same set of households, they still provide us an opportunity to examine the impact of changing economic, social, and cultural trends on household expenses and thus provide additional policy-relevant information. Moreover, the pooled database enables us to examine if the impact of exogenous variables has evolved over time.

The current research aims at investigating the factors affecting expenditure of households and its evolution in Canada using the public-use micro-data extracted from the Survey of Household Spending (SHS) for the years 1997 – 2009. The proposed econometric modeling approach is built on the multiple discrete continuous extreme value model (MDCEV) framework which recognizes that households choose to allocate budgets to multiple alternatives simultaneously. Further, to incorporate the effect of observed and unobserved temporal effects, we estimate two variants of the MDCEV model – scaled MDCEV (SMDCEV) and mixed MDCEV (MMDCEV) models and employ data fit comparison metrics to determine the appropriate model structure.

EARLIER LITERATURE

In this section, we provide a summary of the literature that examined, directly or indirectly, transportation expenditure patterns of households. Transportation expenditure typically examined in earlier literature includes the following dimensions: vehicle acquisition costs, gasoline costs, vehicle insurance costs, vehicle operation and maintenance costs, public transportation costs, non-motorized transportation costs, intercity travel costs, and recreational vehicle related costs. Earlier literature can be broadly classified into two categories: (1) studies that focus on transportation expenditure in conjunction with household expenditures for other commodities and services, and (2) studies that examine transportation expenditure exclusively[1].

Among the studies that have examined transport expenditure in the context of various other household budgetary decisions, Choo et al. (2007) investigated whether the relationship between transportation and telecommunication is substitutive, complementary, or neither. The authors argue that vehicle ownership imposes substantial costs on economically disadvantaged groups, thereby limiting other consumption/expenditure opportunities. In another study, using cluster analysis techniques, Sanchez et al. (2006) analysed the combined transportation and

[1] There has been recent research exploring transport and time budget allocation in a unified framework (see Konduri et al., 2011 and Anas, 2007 for such literature).

housing expenditure trade-offs that low-income working households make and reported that these expenditures cannot be considered in isolation. Very recently, Ferdous et al. (2010) reported that overall transportation expenditure allocation of households in USA is primarily affected by household socio-demographics. The authors found that households residing in urban areas allocate higher proportion of their income to housing as well as public transportation. They also conducted a sensitivity analysis to explore how households adjust their consumption patterns with rising fuel price. Policy analysis results indicated that in the short run, adjustments are made in savings rates, food consumption and vehicle purchase expenses while in the long term major shifts occur in housing and utility expenditures.

The second category of studies concentrate solely on examining the transportation related spending of households. Petrol or gasoline outlays constitute the biggest portion of the overall transportation expenses of households and thus, it can be modeled as a proxy to vehicle use. The expenditure functions developed can be used to analyse both the effectiveness and redistributive effects of price-based energy consumption reduction policies, such as petrol taxation (Asensio et al., 2003a; Oladosu, 2003). The authors concluded that household income, socio-demographics, residential location and vehicle fleet attributes are the most significant factors in the petrol expenditure allocation process of households. In another study, Asensio et al. (2003b) analysed the redistributive effect of urban public transport subsidies in Spain considering that the subsidies provided to the transit sector is directly related to the fare expenses incurred by households.

Rather than focusing on only one transport outlay category, Thakuriah and Liao (2005) explored the variation of a range of household vehicle ownership expenditures while controlling for socio-economic variables, demographics, lifecycle and geographic region of residence in the country. According to their findings, vehicle owning households would spend, on average, 18 cents on vehicles for every additional dollar in monetary expenditure. Similar research was conducted by Nolan (2003) using Irish Household Budget Survey micro-data considering three transport expenditure categories: gasoline cost and conveyance cost of bus and taxi. In a later study, Thakuriah and Liao (2006) investigated the relationship between transportation expenditures (termed as mobility investments) and ability to pay (measured by income). They found that increased income leads to increased overall transportation expenditures and *vice versa* – presumably because mobility investments fetch accessibility benefits which in turn contribute to higher income. In the most recent work, Thakuriah and Mallon-Keita (2014) analyzed how transportation expenses changed for US households from pre-recession (2005-2006) to recession periods (2007-2009) and noted a decline in the auto-related spending of households during the economic downturn.

Current Study Context

All of the studies discussed in the previous section highlight the recent progress in research on understanding household transportation budget allocation decision process. Although these attempts have provided important empirical evidence on the topic, extant studies suffer from one or more of the following shortcomings. First, the focus of traditional travel behaviour literature is on transportation related expenditure alone. There has been little research to analyse transport expenditure in conjunction with the array of commodities, goods, and services that households incur expenses on, thus limiting our ability to investigate the potential substitution or complementarity amongst the different expenditure categories (except Ferdous et al., 2010). Second, earlier studies have developed quantitative models almost exclusively with single year cross-sectional databases (except Thakuriah and Mallon-Keita, 2014). As a result, they are able to provide only a snapshot of the transportation expenditure pattern and not able to capture patterns that evolve with time due to technological advances or temporal factors. The current study builds on the work of Ferdous et al. (2010) and Thakuriah and Mallon-Keita (2014). Specifically, we adapt the comprehensive framework developed in Ferdous et al. (2010) for a pooled multi-year cross-sectional database to accommodate for the changes to the influence of exogenous variables with time. For instance, if there is a significant spike in households with multiple employed individuals (from say 1997 to 2007) the household expenditure pattern might alter substantially across these two databases. This is an example of how observed attributes affect expenditure allocation. The outcome based models can accommodate such transitions reasonably through appropriate model specification ("number of workers in a household" variable). However, say we are interested in measuring the impact of psychological stress due to uncertainty in the job sector between 2000 and 2010 on household monetary expenditures. This is the case of an unobserved variable specific to the study time period on the decision process. The accommodation of such unobserved effects becomes crucial in the analysis process (Train, 2009). Hence, in our study, we implement two modeling approaches - scaled MDCEV (SMDCEV) and the mixed MDCEV (MMDCEV) model - that simultaneously accommodate for the influence of observed and unobserved attributes on the budget allocation decisions of households across multiple time points.

In summary, the current study contributes to literature in two ways. First, *methodologically*, the study employs an approach to stitch together multiple cross-sectional datasets to generate a rich pooled dataset that will allow us to study the evolution of household budget allocation. Second, *empirically*, the study contributes to travel behavior and transport expenditure literature by estimating the MDCEV models using a rich set of exogenous variables including household socio-demographics, residential location characteristics and observed and unobserved effects of the year of data collection (and their interaction with other observed variables). Further, the research conducts an detailed policy scenario analyses to illustrate the applicability of the estimated model for understanding how spending patterns alter in response to changes in exogenous variables.

EMPIRICAL DATA

The primary data source used in this analysis is the Survey of Household Spending (SHS). This is an annual cross-sectional survey conducted by Statistics Canada since 1997 (Milligan, 2008). The survey primarily collects detailed information on household and family expenditures and spending habits in Canada (every year in the 10 provinces and usually every alternate year in the territories) on a wide variety of goods and services (see, Statistics Canada website http://www23.statcan.gc.ca/ for details on survey, sampling, and administration procedure). The SHS also collects information on individual and household socio-economic and demographic attributes, dwelling characteristics (such as type, age and tenure) and information on household equipment (such as appliances, electronics and communications equipment, and vehicles). For our analysis, we employed public-use micro-data extracted from the SHS for the years 1997-2009.

Dependent Variable Compilation

The reported expenditure categories were reorganized to create the following twenty alternatives:(1) food, (2) shelter, (3) secondary accommodation, (4) utilities, (5) alcohol and tobacco products, (6) clothing, (7) personal car, (8), household maintenance and operation (9) entertainment and recreation, (10) education, (11) health care, (12) business services, (13) automobile acquisition, (14) recreational vehicle, (15) gasoline costs, (16) vehicle insurance costs, (17) vehicle operation and maintenance, (18) public transportation, (19) non-motorized transport, and (20) intercity travel. We retained the transportation related expenditure categories as disaggregate as possible. In addition to these alternatives, a *savings (SAV)* alternative was created. Finally, from the survey database, for each survey year, 1,000 data records were randomly sampled and stitched together providing us with 13,000 observations in our pooled dataset. The definition of the expenditure categories is presented in Appendix B.

Descriptive Analysis

Table 1 provides a descriptive snapshot of the 21 expenditure categories modeled in the study. The first column represents the average spending of households across the entire sample and the values within the parenthesis represent the percentages of household income allocated to these expenditure categories. It can be observed that all of the households in the sample spend some non-zero amount of money in the *food* category which accounts for approximately 11 percent of their income. As expected, housing is the highest expenditure incurred (accounting for 11.9 percent of household income) while education and secondary residence being the smallest expenditures. Moreover, household maintenance and operation, utilities, entertainment and recreation also form a substantive portion of household expenses. We also observe that 90 percent or more households incur expenditures in each of the clothing, personal care, health care, and business and welfare activities categories.

In our study, we considered eight different transportation related expenditure categories including vehicle purchase/rent/lease, recreational vehicle purchase/rent and operation, gasoline and motor fuels, vehicle insurance, vehicle operation and maintenance, public transportation, non-motorized transport, and intercity travel. These categories combined account for 13.9 percent of household budget. More than one-third of the sample households allocate their resources to acquiring (purchase/rent/lease) personal automobiles while about one-quarter of the households spend money on recreational vehicle acquisition and maintenance. Of the households reporting non-zero monetary expenditures: about 85 percent spend money on fuel and motor oils while more than 70 percent incur insurance related costs. Interestingly, a sizeable number of households spend money on public transportation (more than 50 percent). On the other hand, a very small proportion of the households allocate resources on purchasing and maintaining non-motorized transports (approximately 17 percent). Expenses on intercity travel are incurred by about one-third of the households.

EMPIRICAL ANALYSIS

Several types of variables were considered in the model that we developed for examining expenditure allocation in each of the twenty-one outlay category as well as the household savings category. The choice of these independent variables was guided by prior research on expenditure patterns. The independent variables can be broadly classified into three categories: (1) household socio-demographics, (2) residential location characteristics, and (3) temporal variables. The *socio-demographic variables* that were employed in our analysis included presence of children of different age groups, presence of young members (18-24 years of age), number of full- and part-time working adults, household income (gross) and its type (paid income from employment), vehicle fleet size, tenure type, dwelling type, and family type. The *residential location* variables considered are: urban/rural location, population centre density, and region specific dummies to examine the degree of influence exerted by the region of residence on household expenditures. The regional dummies used are: Alberta (AB), British Columbia (BC), Ontario (ON), and Quebec (QC). In terms of *temporal variables,* we introduced a variable called "time elapsed from 1997" which is the time difference between the recent survey years (1998-2009) from the base survey year (1997). Both linear and polynomial effects of the time elapsed were tested. Moreover, interaction of exogenous variables with the time elapsed variable (linear and polynomial) were utilized to control for time varying variable effects. As a result, it would be possible to apply the developed model for future year scenarios in addition to capturing the time-based trends in household expenditure allocation patterns. The time elapsed effects were considered in the systematic utility as well as the unobserved component of the utility. To further explain the differences in unobserved component due to temporal changes we compiled and used data on annual economic indicators such as inflation rate, unemployment rate, gross domestic product, and wage rate for Canada from 1997-2009 (see, http://www.statcan.gc.ca/ and http://databank.worldbank.org/data/ for details). The final specification was based on a systematic process of removing statistically insignificant variables and combining variables when their effects were not significantly different.

Model Specification

The model estimation results are presented in Table 2 (the *t-stats* are presented in parentheses). 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. A blank entry corresponding to the effect of variable indicates no statistically significant effect at the 95 percent significance level for the variable on the choice process. For brevity, we have provided the mathematical formulations of the models in Appendix A.

Model Fit Measures

The model estimation process began with the estimation of the traditional MDCEV model. Next, scaled and mixed MDCEV models were estimated. Both of these two models are generalized versions of the standard MDCEV model. After extensive specification testing, the final log-likelihood values at convergence of the MDCEV, SMDCEV, and MMDCEV models were found as: -1660776, -1650649 and -1660672, respectively. The improvement in the data fit clearly demonstrates the superiority of the SMDCEV model over its other counterparts. We can also evaluate the models using a non-nested adjusted likelihood ratio test (Castro et al., 2012). For the test, first we calculated the adjusted likelihood ratio index $(\bar{\rho}^2)$[2] considering the log-likelihood value of the model with only the constants and translation parameters (-1677338) as the base case. With respect to this base model, $\bar{\rho}^2$ value for the scaled and mixed MDCEV models are 0.0156 and 0.0097, respectively. The $\bar{\rho}^2$ value reported in our study is in the same range as other MDCEV based $\bar{\rho}^2$ values reported. For example, Castro et al., 2012 reported a $\bar{\rho}^2$ value of 0.0402 for a 4 alternative model. Given that our model has 21 alternatives, it is not surprising to obtain a lower $\bar{\rho}^2$ value. Next, we tested if the calculated indices of the two non-nested models were significantly different. In particular, the probability that the difference in the indices (τ) could have occurred by chance is no larger than $\Phi\{-[-2\tau\, LL(C) + (M_2 - M_1]^{0.5}\}$ ($\Phi\{.\}$ is the cumulative standard normal distribution function). For our case, $\tau =$ 0.0059 and $\Phi\{.\}$ is literally zero, indicating that the difference in the indices between the two models is highly statistically significant and that the SMDCEV model is the superior model from data fit perspective. Hence, in the

[2] The adjusted likelihood ratio index $(\bar{\rho}^2)$ for the traditional MDCEV, scaled MDCEV, and mixed MDCEV models is computed as $\left(1 - \frac{LL(\beta)-K}{LL(C)}\right)$, where $LL(\beta)$ is the log-likelihood at convergence, K is the number of model parameters (excluding the baseline constants and translation parameters), and $LL(C)$ is the likelihood with only the constants and translation parameters.

subsequent sections, we discuss the results of the SMDCEV model only. The exogenous variables effects are discussed by variable group, followed by constant terms and scale component results.

Empirical Results

Household socio-demographics: Presence of children in the household is an important factor that affects the household budgetary allocations (Browning, 1992). Children from different age groups have different needs and requirements; thus, households need to allocate and adjust their budgets accordingly. In our study, we found that presence of toddlers (less than or equal to 4 years of age) contributed to higher apportioning of income to housing, personal care, household operations and maintenance, automobile acquisitions, and non-motorized transport expenses. On the other hand, lower proportions of income are allocated to secondary accommodations, education, health care, business service and welfare, gasoline, vehicle insurance, maintenance and operation, and public transportation categories. Increase in expenses in the automobile acquisition category might be explained by increased travel needs with the presence of toddlers. Similar resource allocation patterns were observed for the presence of young children (5-17 years of age) variable. However, households with young children spent more on education as opposed to households with toddlers while spending less on utilities, vehicle purchase and insurance, intercity travel, and savings. This result is intuitive, since expenditure on children generally tend to increase with age of children, particularly for child care (pre-school children) and education (older children) which might need to be drawn from other budget components such as transportation and savings (Soberon-Ferrer and Dardis, 1991). The negative effect of presence of children on public transport expenses is reflecting perhaps the returns to scale involved in driving children as and when required (Nolan, 2003; De Palma and Rochat, 2000; Bergantino, 1997). When young members (18-24) are present, households spend more on alcohol and tobacco, clothing, personal care, education, entertainment, public transportation, and intercity travel. Our results are in line with the results reported by Deaton et al. (1989).

We considered four variables representing different life-cycle stages of households. These are: single person, couples only, couples with a child, and other households (comprised of couple household with relatives or unrelated persons and lone parents). Compared to other households, single person households allocate higher proportion of their income to housing, secondary accommodations, alcohol and tobacco products, health care, business service and welfare activities, recreational vehicles, vehicle operation, intercity travels, and savings. The biggest proportional difference between couples only and other life cycle groups lay in their spending on transportation categories. For instance, couples only households spend more in acquiring recreational vehicles, but less in public transportation and non-motorized transport options. Lower spending in utilities may be attributable to the high percentage of tenants among them (utilities are frequently included in the rental cost). Moreover, being childless frees them of the responsibility and expenses of tending to children. As such, this might allow these couples to spend more in household equipment, accommodation besides their principal residence, such as owned and rented vacation homes and traveller accommodation in hotels, motels, campgrounds and tourist homes, participate more in recreational activities, and procure more recreational vehicles (Barr-Telford, 1994). Contrastingly, a household comprising of couples with a child tend to allocate lesser amount of resources to virtually all the expenditure categories considered except education.

Income share allocated to alcohol and tobacco purchases, clothing, personal care, vehicle purchase, motor fuel, and vehicle maintenance and operation tend to increase with increasing number of both full and part-time working adults. Interestingly, households with higher number of part-time workers incur more transportation expenses including public transportation and recreational vehicle purchases and maintenance. A similar result in the context of vehicle purchases and transportation expenses are reported by Thakuriah and Liao (2005). Households with multiple full-time workers allocate more resources to housing and savings. Household's current expenditure reflects both current income as well as potential future earnings (Bawa and

Ghosh, 1999). Employment status can be considered as an indirect proxy measure of future earnings. Overall, the results are indicative of the variation in household expenditure patterns that occurs due to varying employment status of its members.

As expected, household income was found to be one of the influential factors affecting household's decision regarding budget allocation. Compared to low income (income<30K) households, households with medium (income 30-70K) and high income (income>70K) spend higher proportion of their income on luxury and discretionary items including clothing, personal care, household operation and maintenance, entertainment and recreation, business service and welfare activities, and secondary accommodations. In the transportation expenditure categories, these households spend more on acquiring automobiles and recreational vehicles, as well as vehicle operation and maintenance. These findings are consistent with the results reported in the existing travel behaviour literature. For example, high household income has often been reported to increase the probability of owning multiple cars and their usage (Karlaftis and Golias, 2002; Matas and Raymond, 2008). Higher income not only increase their tendency to consume more (Bawa and Ghosh, 1999) but also allows them to have enough resources for saving as well (Dynan et al., 2000). In addition to the actual amount earned, income type was also found to significantly affect household budgets. Compared to households living on investment income or government transfer payments, households with paid employment (wages and salaries) as their major source of income allotted more to basic necessities as well as entertainment and recreation. The results are expected because increased paid income means higher spending capability.

To capture the budget allocation patterns of multicar households, we created three household types based on their vehicle ownership levels. These are: single vehicle households, households with two cars, and households with three or more cars. We found that vehicle owning households (irrespective of the vehicle fleet size) tended to spend lesser proportion of their resources to vehicle acquisitions. The finding is in contrast to the results reported by Ferdous et al. (2010). Presumably, these households are somewhat disinclined to increase their existing vehicle fleet size and hence, they are allocating less resources to vehicle purchases. As expected, these households allocate higher proportions of income to pay for gasoline, vehicle insurance, and vehicle maintenance costs. We also observed that two-vehicle owning households spend more on recreational vehicles.

Homeowners tended to shift their spending habit from housing and alcohol and tobacco products, and direct relatively more of their monetary income towards utilities, personal care, household operation and maintenance, health care, business and welfare activities, and secondary accommodations. All of the findings are consistent with expectations and corroborate the outcomes of previous research (for example, Hong et al., 2005; Paulin, 1995). These households also spend less proportion of their earnings on vehicle purchases, public transportation and non-motorized vehicles. On the other hand, they accrue more expenses on gasoline, vehicle insurance, vehicle operations and recreational vehicles. Similar to homeowners, single-detached households have reduced share of income apportioned towards housing and public transportation while spending more on utilities, household operation, and gasoline. Markedly different yet expected expenditure patterns were captured for households residing in apartments. Apartment residents are mostly renters (82 percent), therefore, in contrast to homeowners and single-detached housing dwellers, they do not have to pay for utilities and maintenance costs for the entire establishment by themselves, and thus perhaps they allocate reduced resources in these categories. Apartment dwellers used a larger proportion of their income on public transport and intercity travel.

<u>Residential location characteristics:</u> It is evidenced in consumer literature that households living in urban areas have different lifestyles and economic conditions (Bilgic and Yen, 2015). Their needs are also vastly different compared to the needs of those in rural areas and, therefore, they exhibit different spending patterns. In the current research context too, we captured the differences in the way that urban and rural consumers allocate their expenditures budgets. For instance, compared to their rural counterparts, households located in urban areas allocated larger

share of their income on housing, clothing, personal care, entertainment, education, vehicle operation, public transportation, and intercity travels. These findings might be attributed to higher availability of consumer goods (such as education, personal care services, internet, entertainment) and to higher rents and mortgage payments in urban areas (Fousekis and Lazaridis, 2001). Reduced gasoline expenses, recreational vehicle costs and savings were also observed for these households. Reduced gasoline expenditure by urban households may be reflecting the lower distances travelled to shop and to work due to the availability of alternative, cheaper forms of transport such as walking and taking transit (Nolan, 2003). According to Ferdous et al. (2010), these results are reflective of the typical "urban effect". In addition to location, population density of the area where the household is located also affected households' resource allocation decisions. As mentioned earlier, four regional dummies were used in our model estimation and several regional differences are noted from the analysis results. Intuitively, the differences are attributable to the regional variations in housing prices, income levels, and overall prices of goods and services across the provinces analysed (see, Ferdous et al., 2010 for similar interpretations).

Constant, interaction and scale terms: The constant variables do not have any substantive interpretations but simply capture the generic tendencies to spend in each category. Note that the baseline preference constants are introduced with the food category as the base category in the model specification. As can be observed from the results table, all baseline preference constants without exception are negative, indicating overall reduced spending of household budget on all other expenditure categories relative to food. This result is consistent with expectations because all of the households in the sample spend non-zero amount in the food category.

As discussed earlier in the methodology section, the translation parameters (γ_k) capture the extent of decrease in marginal utility across different expenditure categories. That is, for all expenditure categories except *food*, a higher value of γ implies higher spending and less satiation. There is no γ term for *food* category because it is always consumed by all households.

All of the translation parameters are statistically significant at any reasonable level of significance, thereby implying that there are clear satiation effects in household resource allocation. Specifically, it is found that the γ value is the highest for *savings* and *new/used automobile purchase* alternatives, indicating that households are likely to allocate a large proportion of their budget to savings and to acquiring a vehicle, if they spend any money in these categories. On the other hand, the lowest values are observed for *personal care, clothing,* and *household operations and maintenance* categories, suggesting that the lowest proportion of money is allocated to these categories and satiation is reached very quickly for most households in these categories.

Within the set of constant parameters, the impact of the time elapsed variable was examined. A declining time effect was captured for alcohol and tobacco products, clothing, entertainment, and business service and welfare categories while a positive time effect was observed for utilities, personal care, automobile acquisition, operation and maintenance, public transportation, recreational vehicle, and non-motorized transportation categories. As mentioned before, we tried interaction effects of the explanatory variables with the time elapsed variable in our model specification. The long list of highly significant interaction terms with the time elapsed since 1997 demonstrates how the impact of socio-demographic and residential location attributes on budget allocation decision of households is changing with time. Significant interaction terms include presence of children, presence of young members, single person, couple only, couple with one child, number of part-time workers, medium income, paid income type, ownership of cars, dwelling type (single detached, apartment), urban, medium density location, province of household resident (Alberta, British Columbia, Ontario, Quebec). For example, households with children aged 5-17 years are more likely to increase their gasoline expense with elapsing time, as are households owning one or two vehicles. Interestingly, households living in urban areas are more likely to reduce their public transport expenditure in the future years, presumably because transit become more affordable with progressing time. However, for the sake of brevity, a detailed explanation is not provided in the paper.

In the current empirical context, scale coefficient was estimated for the time elapsed variable. The parameter is highly significant indicating that there is indeed variation in the unobserved factors across the years. Fiebig et al. (2010) reported that scale heterogeneity is more important in more complex choice context. In our case, the results might be manifesting the difficulty in the allocation of resources.

Policy Simulation Results

In this section, we present the results of several policy simulations using the estimates of the SMDCEV model. The forecasting procedure was implemented by modifying the Gauss code that has been written and made available by Pinjari and Bhat (2011). Specifically, we assessed the impact of four different scenarios on household expenditure patterns. The scenarios considered are: (1) Zero gasoline expenditure, (2) A 15 percent increase in gasoline expenditure, (3) A 15 percent increase in health care expenses, and (4) A 10 percent reduction in savings. The policy simulations consider two possible time frames - long and short term. In the short term, households are unlikely to alter housing, utilities, education, health care, vehicle purchase, vehicle insurance and recreational vehicle purchase/maintenance. Hence, these alternatives were assumed to be unaffected by the changes in expenditure. On the other hand, in the long term, all alternatives are assumed to be affected by the changes in expenditure. The total budgets for each scenario were then calculated and distributed to the other alternatives (excluding the alternative being considered for policy scenario) to observe the change that occurs due to the proposed change in the chosen category for the policy analysis. The predicted changes in household expenditure occurring for different scenario compared to the base case are presented in Table 3.

Interesting patterns of expenditure adjustment could be observed from these results. When households incur no expenditure on gasoline (it might be considered as a proxy for capturing the effect of all households turning their vehicle fleet into electric), they tend to allocate the extra resources towards all the other expenditure categories, the highest being allocated to non-motorized transport category, in the short term and to recreational vehicle purchase in the long term. In the short term, however, expenses in the non-transportation category increases more than expenses in the transportation category. The opposite is observed in the long term. Interestingly, a tendency to spend more in recreational vehicle purchase than regular vehicle purchase was also observed in the long term.

When gasoline expenditure increases, households tend to rely more on non-motorized transportation for their travel and hence, we see higher spending in these categories, both in long and short term. However, no shift toward increased public transit usage was observed. Therefore, it can be argued that increasing gasoline price might not be as effective to drive people towards using public transit more. In the long term, as expected, there is reduction in budget allotments for the automobile purchase. As explained by Ferdous et al. (2010), Eltony (1993) and Pitts et al. (1981), households might either be postponing the purchase of more vehicles or buying cheaper automobiles in the wake of rising gasoline expenses.

We also observed that an increase in health expenditure, both in the long and short term, leads to a decrease in both transportation and non-transportation expenditure categories. The results indicate towards welfare impacts of increased health related expenses. Finally, we also see that due to a 10 percent decrease in savings, all alternatives (transportation and non-transportation) have increased spending outlays – particularly the discretionary alternatives. Overall, the policy simulation exercise illustrates the applicability of the proposed model for predicting changes in expenditure allocation in response to several policies such as gas price increase, locational benefits (such as subsidies to high rent residents in dense areas) when data on these policies is available.

CONCLUSION

The current research endeavours to bridge the gap in the literature by developing an econometric model of household budgetary allocations with a particular focus on transportation budget. Specifically, we aim to investigate the factors affecting expenditure of households and its evolution in Canada using the public-use micro-data extracted from the Survey of Household Spending

(SHS) for the years 1997 - 2009. In terms of methodology, we adopt multiple discrete continuous extreme value model (MDCEV) framework and utilize its two variants - scaled MDCEV (SMDCEV) and mixed MDCEV (MMDCEV) models - that simultaneously accommodate for the influence of observed and unobserved attributes on the budget allocation decisions of households across multiple time points.

The research supports the simultaneous exploration of different expenditure categories including transportation to get a more holistic picture of household budget allocation patterns. Moreover, the simultaneous examination also helps glean more information about potential trade-offs amongst different outlays of money. For instance, in our study, we found that households residing in single detached dwelling located in a medium-density urban area spend less on housing as well as public transportation, while spending more on gasoline. On the other hand, apartment dwellers in high density urban areas allocate higher proportion of their income on housing and public transportation while spending less on gasoline. The result might be suggesting that transportation related benefits of high density urban areas might be associated with increasing housing cost (Palm et al., 2014) and thus have intriguing implications for the "smart growth" policies intended towards reducing household vehicle ownership and usage. It can be argued that the policy of densification and diversification of metropolitan areas need to be complemented with strategies to reduce housing expenses. If gas price is lowered, it's the low density dwellers who are usually less inclined to use transit would be the beneficiaries in terms of reduced transportation cost – which would incentivize suburban living.

However, the research is not without limitations. There is a significant challenge in comparing expenditure allocations across multiple years. While there are inherent differences in prices and consumptions across the years, the model developed allocates the budget for one single year. Hence, across a household, there is consistency while on the other hand we might have differences across years. For example, 1000$ spending on health care in 1997 might not be the same as 1000$ on health care in 2009. A potential avenue for future research would be to consider normalizing all expenditures to a particular year to reduce variation across years.

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Table 1 Summary Profile of Expenditure Categories and Savings

Expenditure Category	Average Spending across Entire Sample (CAD $/yr) (%)	Across Non-zero Observations	
		Average Spending (CAD $/yr)	No. of Households (%)
Non-Transportation			
Food	6347.42 (10.9)	6347.42	13000 (100.0)
Shelter	6937.14 (11.9)	7050.49	12791 (98.4)
Secondary accommodation	680.73 (1.2)	1420.46	6230 (47.9)
Utilities	3253.97 (5.6)	3265.52	12954 (99.6)
Alcohol and tobacco products	1375.60 (2.4)	1646.67	10860 (83.5)
Clothing	2317.64 (4.0)	2340.87	12871 (99.0)
Personal care	866.73 (1.5)	870.08	12950 (99.6)
Household maintenance and operation	3581.60 (6.2)	3586.56	12982 (99.9)
Entertainment and recreation	3039.77 (5.2)	3081.97	12822 (98.6)
Education	765.67 (1.3)	1914.91	5198 (40.0)
Health care	1568.65 (2.7)	1607.47	12686 (97.6)
Business services and welfare activities	1859.63 (3.2)	1964.19	12308 (94.7)
Savings	19599.14 (33.7)	24784.79	10280 (79.1)
Transportation			
Automobile purchase/rent/lease	3313.32 (5.7)	9620.98	4477 (34.4)
Recreational vehicle	642.15 (1.1)	2785.44	2997 (23.1)
Gasoline and motor fuels	1740.98 (3.0)	2077.73	10893 (83.8)
Vehicle insurance	866.96 (1.5)	1210.98	9307 (71.6)
Vehicle operation and maintenance	570.24 (1.0)	758.38	9775 (75.2)
Public transportation	207.26 (0.4)	385.97	6981 (53.7)
Non-motorized transport	46.50 (0.1)	286.87	2107 (16.2)
Intercity travel	428.68 (0.7)	1381.11	4035 (31.0)

TABLE 2 Estimation Results

Variables	HOU	SECH	UTL	ATP	CL	PC	HHMO	ENT	ED	HL	BSWA	AUTO	RECV	GAS	VEHI	VOP	PT	NMT	INTT	SAV
Household Socio-demographics																				
Children present (≤ 4yr)	0.313	-0.111	---	---	---	0.339	0.347	---	-0.212	-0.208	-0.130	0.088	---	-0.090	-0.130	-0.150	-0.188	0.140	---	---
	(12.30)	(-3.43)	---	---	---	(13.63)	(7.30)	---	(-6.67)	(-8.07)	(-4.94)	(2.47)	---	(-3.69)	(-4.92)	(-2.73)	(-2.89)	(3.16)	---	---
Children present (5-17 yr)	0.054	---	-0.088	---	0.137	-0.058	0.073	0.147	0.757	-0.167	-0.235	-0.175	---	-0.280	-0.299	-0.196	-0.113	0.582	-0.189	-0.258
	(2.44)	---	(-3.83)	---	(6.23)	(-2.63)	(3.11)	(6.73)	(24.44)	(-6.91)	(-6.04)	(-5.98)	---	(-7.62)	(-14.32)	(-8.21)	(-3.83)	(13.99)	(-5.70)	(-10.19)
Youth present (18-24 yr)	---	---	---	0.040	0.073	0.061		0.091	0.402	-0.117	-0.112	---	---	---	---	---	0.096	-0.190	0.063	-0.124
	---	---	---	(1.72)	(3.33)	(2.76)	---	(4.46)	(14.36)	(-5.32)	(-5.10)	---	---	---	---	---	(3.42)	(-4.38)	(1.90)	(-4.96)
Family Life Cycle Stage (Base: Other Family Types)																				
Single person	0.367	0.482	0.208	0.258	-0.097	-0.085	0.116	0.153	-0.235	0.136	0.411	---	0.249	---	---	0.227	0.192	---	0.447	0.465
	(17.42)	(15.16)	(5.06)	(11.37)	(-4.48)	(-4.00)	(4.45)	(7.10)	(-4.86)	(5.13)	(14.64)	---	(4.73)	---	---	(9.16)	(5.50)	---	(13.33)	(15.85)
Couple only	---	0.252	-0.077	---	---	---	0.102	---	-0.533	0.133	0.117	---	0.238	---	---	---	-0.205	-0.364	---	0.147
	---	(10.28)	(-3.36)	---	---	---	(4.35)	---	(-12.52)	(5.50)	(4.58)	---	(7.18)	(3.74)	---	---	(-6.26)	(-6.36)	---	(3.65)
Couple with one child	-0.238	---	-0.191	-0.251	-0.129	-0.135	-0.122	-0.137	0.265	---	-0.156	-0.151	---	---	---	-0.115	-0.305	-0.151	-0.345	---
	(-6.88)	---	(-8.43)	(-11.79)	(-6.05)	(-6.01)	(-5.27)	(-6.32)	(6.40)	---	(-6.52)	(-4.83)	---	---	---	(-4.69)	(-10.59)	(-3.56)	(-10.54)	---
Working Status																				
No of full-time workers	0.089	---	---	0.046	0.135	0.095	0.044	0.033	---	---	-0.027	0.065	---	0.125	---	0.075	---	---	---	0.170
	(5.98)	---	---	(2.95)	(8.81)	(6.99)	(3.65)	(2.48)	---	---	(-2.06)	(2.94)	---	(11.01)	---	(4.46)	---	---	---	(12.10)
No of part--time workers	-0.056	---	---	0.049	0.104	0.039	---	---	0.106	---	---	0.039	0.053	0.087	---	0.067	0.049	---	-0.064	-0.057
	(-4.62)	---	---	(3.80)	(8.44)	(3.41)	---	---	(7.81)	---	---	(2.45)	(3.08)	(8.40)	---	(5.29)	(3.64)	---	(-2.23)	(-4.54)
Household Income (Base: Low Income <30K)																				
Medium income (30-60K)	---	0.366	-0.065	0.083	0.152	0.060	0.085	0.288	-0.050	---	0.220	0.270	0.223	0.086	---	0.102	-0.222	---	---	0.216
	---	(10.88)	(-3.17)	(2.35)	(7.07)	(2.85)	(4.03)	(8.11)	(-2.02)	---	(9.99)	(6.84)	(4.53)	(4.94)	---	(4.09)	(-8.50)	---	---	(9.02)
High income (>70K)	---	0.650	-0.138	---	0.369	0.177	0.299	0.522	---	---	0.499	0.254	0.270	---	---	0.156	-0.234	---	0.317	0.648
	---	(18.22)	(-6.41)	---	(14.90)	(7.19)	(12.40)	(20.91)	---	---	(19.29)	(5.82)	(5.19)	---	(-13.24)	(5.49)	(-8.43)	---	(11.58)	(23.37)
Employment Type (Base: Investment, Government Transfer and Other Types)																				
Paid income	0.086	-0.063	---	0.123	---	---	---	0.072	0.132	-0.116	---	0.099	0.105	---	---	-0.061	---	0.229	---	---
	(4.07)	(-2.48)	---	(5.39)	---	---	---	(3.64)	(4.55)	(-4.30)	(-8.28)	(2.83)	(2.81)	(3.71)	---	(-2.50)	---	(5.12)	---	---
Vehicle Fleet Portfolio (Base: HH w/0 Car)																				
HH w/1 car	---	---	---	---	---	---	---	---	---	---	---	-0.251	---	0.939	0.786	0.869	-0.333	---	---	0.055
	---	---	---	---	---	---	---	---	---	---	---	(-9.17)	---	(28.93)	(33.97)	(17.49)	(-15.70)	---	---	(3.47)
HH w/2 cars	---	---	---	---	---	---	---	---	---	0.116	0.099	-0.231	0.125	1.037	0.718	0.915	-0.347	0.047	---	---
	---	---	---	---	---	---	---	---	---	(3.86)	(6.18)	(-9.73)	---	(39.34)	(20.81)	(24.76)	(-25.38)	(2.11)	---	---

Variables	HOU	SECH	UTL	ATP	CL	PC	HHMO	ENT	ED	HL	BSWA	AUTO	RECV	GAS	VEHI	VOP	PT	NMT	INTT	SAV
Tenure Type																				
Home owner	-0.176	0.145	0.434	-0.176	---	0.052	0.184	---	---	0.247	0.200	-0.085	0.266	0.195	0.127	0.132	-0.308	-0.189	---	---
	(-8.55)	(5.22)	(21.17)	(-9.81)	---	(2.63)	(9.10)	---	---	(12.47)	(10.52)	(-3.09)	(6.18)	(8.98)	(5.59)	(6.59)	(-11.97)	(-4.44)	---	---
Dwelling Type (Base: Semi-detached, Terrace, Duplex and Other Types)																				
Single detached	-0.082	---	0.125	---	---	---	0.088	---	---	---	---	---	---	0.071	---	---	-0.146	---	-0.077	---
	(-3.61)	---	(5.52)	---	---	---	(3.90)	---	---	---	---	---	---	(2.95)	---	---	(-4.95)	---	(-2.09)	---
Apartment	0.340	0.100	-0.284	---	0.212	0.134	-0.193	---	---	0.078	---	---	-0.246	-0.086	-0.076	---	0.170	---	0.210	---
	(12.40)	(2.96)	(-10.72)	(-2.25)	(10.62)	(5.85)	(-7.25)	---	---	(3.40)	---	---	(-3.85)	(-2.85)	(-2.73)	---	(5.32)	---	(4.87)	---
Residential Location Characteristics																				
Urban	0.484	---	---	-0.073	0.077	0.095	---	0.202	0.227	---	---	---	-0.767	-0.247	---	0.058	0.812	---	0.299	---
	(23.43)	---	---	(-3.59)	(4.04)	(4.90)	---	(10.75)	(7.43)	---	---	---	(-21.86)	(-12.86)	---	(2.70)	(13.67)	---	(8.46)	---
Population Centre Density (Base: Low Density)																				
Medium density	-0.148	0.085	---	0.071	---	-0.072	---	---	-0.200	-0.084	---	---	0.489	---	---	-0.115	-0.342	0.147	---	---
	(-3.90)	(3.81)	---	(3.90)	---	(-4.14)	---	---	(-7.29)	(-4.91)	---	---	(14.21)	---	---	(-5.89)	(-14.92)	(3.93)	---	---
Province (Base: Other Provinces and Territories)																				
Alberta	0.133	---	---	---	---	---	---	0.083	0.138	0.404	---	-0.099	---	---	0.321	---	0.112	---	---	---
	(5.60)	---	---	---	---	---	---	(3.59)	(4.00)	(8.61)	---	(-2.68)	---	---	(6.36)	---	(3.73)	---	---	---
British Columbia	0.288	-0.155	-0.189	---	-0.132	-0.184	-0.152	---	---	0.052	-0.147	-0.194	-0.188	-0.080	-0.545	---	0.334	---	(0.060	-0.121
	(6.33)	(-5.01)	(-8.16)	---	(-5.73)	(-7.95)	(-6.52)	---	---	(2.20)	(-6.18)	(-5.20)	(-3.91)	(-3.29)	(-17.51)	---	(11.79)	---	(1.74)	(-4.83)
Ontario	0.296	-0.152	-0.053	---	---	---	---	---	-0.156	-0.218	---	-0.093	-0.293	---	0.294	0.075	0.062	---	-0.115	---
	(13.93)	(-5.30)	(-2.57)	---	---	---	---	---	(-4.63)	(-10.24)	---	(-2.82)	(-6.12)	---	(6.25)	(3.22)	(2.26)	---	(-3.42)	---
Quebec	---	-0.370	-0.185	0.068	-0.132	-0.136	-0.175	-0.273	---	---	-0.369	-0.089	-0.138	---	---	-0.060	-0.385	0.117	-0.684	---
	---	(-11.84)	(-4.33)	(3.11)	(-6.15)	(-6.34)	(-8.14)	(-6.27)	---	---	(-16.85)	(-2.66)	(-3.18)	---	---	(-2.52)	(-6.38)	(2.66)	(-15.78)	---
Temporal Variable																				
Time elapsed	---	---	0.015	-0.009	-0.022	0.024	---	-0.015	---	---	-0.019	0.021	0.017	---	---	0.010	0.013	0.030	---	---
	---	---	(5.24)	(-3.30)	(-8.32)	(11.38)	---	(-5.56)	---	---	(-6.70)	(6.23)	(4.21)	---	---	(1.89)	(1.72)	(4.92)	---	---
Interaction Terms (Variable* Time Elapsed)																				
Children present (≤ 4yr)	---	---	---	---	---	---	0.016	0.006	---	---	---	---	---	---	---	0.014	0.018	---	---	---
	---	---	---	---	---	---	(2.77)	(1.98)	---	---	---	---	---	---	---	(2.11)	(2.32)	---	---	---
Children present (5-17 yr)	---	---	---	-0.021	---	---	---	---	---	---	0.010	---	---	0.011	---	---	---	---	---	---
	---	---	---	(-8.09)	---	---	---	---	---	---	(2.38)	---	---	(2.52)	---	---	---	---	---	---
Youth present (18-24 yr)	-0.009	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
	(-3.36)	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

Variables	HOU	SECH	UTL	ATP	CL	PC	HHMO	ENT	ED	HL	BSWA	AUTO	RECV	GAS	VEHI	VOP	PT	NMT	INTT	SAV
Single person	---	---	-0.019	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
	---	---	(-4.27)	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Couple only	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	-0.011
	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	(-2.53)
Couple with one child	0.012	---	---	---	---	---	---	---	-0.042	---	---	---	---	---	---	---	---	---	---	-0.016
	(3.08)	---	---	---	---	---	---	---	(-9.34)	---	---	---	---	---	---	---	---	---	---	(-5.750
No of part--time workers	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	0.020	---
	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	(6.39)	---
Medium income (30-60K)	---	---	---	-0.014	---	---	---	-0.007	---	0.012	---	---	---	---	0.012	---	---	---	---	---
	---	---	---	(-3.16)	---	---	---	(-1.84)	---	(5.95)	---	---	---	---	(5.34)	---	---	---	---	---
Paid income	---	---	---	---	0.013	---	---	---	---	-0.015	-0.009	---	---	---	-0.006	---	---	---	---	---
	---	---	---	---	(5.16)	---	---	---	---	(-5.06)	(-3.93)	---	---	---	(-2.79)	---	---	---	---	---
HH w/1 car	---	---	0.010	---	---	---	---	---	0.007	0.006	---	---	---	0.014	---	-0.013	---	---	---	---
	---	---	(4.64)	---	---	---	---	---	(2.26)	(3.05)	---	---	---	(4.25)	---	(-2.24)	---	---	---	---
HH w/2 cars	---	0.009	0.006	0.005	---	---	---	0.008	0.008	0.009	---	---	---	0.016	---	-0.013	---	0.014	---	---
	---	(3.58)	(2.56)	(2.12)	---	---	---	(3.73)	(2.39)	(3.73)	---	---	---	(4.13)	---	(-2.00)	---	(3.09)	---	---
Single detached	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	-0.017	---	---
	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	(-3.23)	---	---
Apartment	---	---	---	---	---	---	---	---	0.014	---	0.009	---	---	---	---	---	---	---	---	---
	---	---	---	---	---	---	---	---	(3.63)	---	(3.46)	---	---	---	---	---	---	---	---	---
Urban	---	---	---	---	---	---	-0.012	---	---	---	---	---	---	---	-0.022	---	-0.018	---	---	-0.013
	---	---	---	---	---	---	(-6.76)	---	---	---	---	---	---	---	(-9.76)	---	(-2.28)	---	---	(-6.21)
Medium density	-0.012	---	---	---	-0.006	---	---	-0.009	---	---	---	---	---	---	---	---	---	---	---	---
	(-2.61)	---	---	---	(-3.09)	---	---	(-4.38)	---	---	---	---	---	---	---	---	---	---	---	---
Alberta	---	---	---	---	---	---	-0.012	---	---	-0.027	-0.008	---	-0.016	---	0.024	---	---	---	---	-0.012
	---	---	---	---	---	---	(-3.92)	---	---	(-4.44)	(-2.63)	---	(-2.63)	---	(3.70)	---	---	---	---	(-3.58)
British Columbia	-0.017	---	---	---	---	---	---	---	0.011	---	---	---	---	---	---	---	---	---	---	---
	(-3.06)	---	---	---	---	---	---	---	(2.69)	---	---	---	---	---	---	---	---	---	---	---
Ontario	---	---	---	---	---	---	---	---	---	---	---	---	---	---	0.032	---	---	---	---	---
	---	---	---	---	---	---	---	---	---	---	---	---	---	---	(5.62)	---	---	---	---	---
Quebec	---	---	-0.016	---	---	---	---	0.014	0.013	0.015	---	---	---	---	0.022	---	0.030	---	---	---
	---	---	(-2.95)	---	---	---	---	(2.54)	(3.28)	(5.45)	---	---	---	---	(7.48)	---	(4.16)	---	---	---
Constant Terms and Satiation Parameters																				

Variables	HOU	SECH	UTL	ATP	CL	PC	HHMO	ENT	ED	HL	BSWA	AUTO	RECV	GAS	VEHI	VOP	PT	NMT	INTT	SAV
Constants	-7.287	-9.357	-5.858	-7.864	-6.519	-6.279	-6.241	-6.853	-9.536	-7.222	-7.468	-9.306	-9.790	-8.596	-8.642	-8.916	-8.521	-10.197	-9.506	-8.502
	(-211.45)	(-230.49)	(-128.14)	(-232.35)	(-182.83)	(-148.40)	(-134.48)	(-209.82)	(-196.96)	(-222.60)	(-214.40)	(-203.52)	(-149.73)	(-367.90)	(-270.53)	(-170.69)	(-122.05)	(-168.56)	(-189.05)	(-265.42)
γ-parameters	6.765	6.442	4.998	6.238	4.941	3.718	4.982	5.450	6.179	5.540	5.381	8.779	6.811	5.940	6.251	5.324	5.058	5.136	6.810	9.477
	(281.58)	(327.42)	(139.60)	(368.57)	(174.91)	(103.04)	(119.31)	(217.02)	(250.19)	(279.33)	(267.27)	(332.08)	(219.59)	(279.87)	(375.34)	(301.25)	(262.55)	(158.02)	(285.24)	(439.55)
Scale parameter	-0.051 (-147.33)																			
Log-likelihood at convergence = -1650649																				

HOU = Shelter; SECH = Secondary Accommodation; UTL = Utilities; ATP = Alcohol and Tobacco Product; CL = Clothing; PC = Personal Care; HHMO = Household Maintenance and Operation; ENT = Entertainment and Recreation; ED = Education; HL = Health Care; BSWA = Business Services and Welfare Activities; AUTO = Automobile Acquisition; RECV = Recreational Vehicle; GAS = Gasoline Costs; VEHI = Vehicle Insurance Costs; VOP = Vehicle Operation and Maintenance; PT = Public Transportation; NMT = Non-motorized Transport; INTT = Intercity Travel; SAV = Savings.

TABLE 3 Policy Simulation Results

Expenditure Categories	Gas Expenditure = 0		Gas Expenditure Increased (15%)		Health Expenditure Increased (15%)		Savings Reduced (10%)	
	Short Term % Difference	Long Term % Difference	Short Term % Difference	Long Term % Difference	Short Term % Difference	Long Term % Difference	Short Term % Difference	Long Term % Difference
FD	3.41	2.56	-0.43	-0.15	-0.45	-0.51	9.83	7.67
HOU	---	2.48	---	-0.22	---	-0.58	---	8.57
SECH	7.62	5.75	-0.28	-0.09	-0.84	-1.03	29.56	22.82
UTL	---	2.79	---	-0.12	---	-0.55	---	8.02
ATP	5.13	3.79	-0.71	-0.28	-0.69	-0.79	17.31	12.75
CL	3.57	2.68	-0.43	-0.15	-0.44	-0.50	10.38	8.26
PC	3.55	2.65	-0.44	-0.16	-0.45	-0.53	10.44	8.10
HHMO	3.63	2.73	-0.40	-0.13	-0.44	-0.52	10.50	8.47
ENT	3.58	2.69	-0.39	-0.13	-0.45	-0.52	10.96	8.56
ED	---	4.50	---	-0.13	---	-0.65	---	8.95
HL	---	3.07	---	-0.14	---	---	---	9.47
BSWA	4.02	3.02	-0.47	-0.16	-0.54	-0.63	14.27	10.66
SAV	5.13	3.86	-0.52	-0.19	-0.63	-0.78	---	---
Non-Transportation	39.64	42.57	-4.07	-2.05	-4.93	-6.96	113.25	122.3
AUTO	---	7.53	---	-0.81	---	-1.22	---	38.52
RECV	---	12.56	---	0.73	---	-1.58	---	41.36
GAS	---	---	---	---	-0.53	-0.64	11.18	9.41
VEHI	---	4.52	---	0.14	---	-0.79	---	12.56
VOP	5.83	4.30	-0.12	0.13	-0.65	-0.78	16.04	12.38
PT	4.90	3.69	-1.01	-0.65	-0.89	-1.02	24.39	16.19
NMT	12.83	10.19	2.51	1.21	-1.01	-1.42	17.02	19.98
INTT	8.85	6.94	0.46	0.10	-0.97	-1.39	50.13	38.11
Transportation	32.34	49.73	1.84	0.85	-4.05	-8.84	118.76	188.51

HOU = Shelter; SECH = Secondary Accommodation; UTL = Utilities; ATP = Alcohol and Tobacco Product; CL = Clothing; PC = Personal Care; HHMO = Household Maintenance and Operation; ENT = Entertainment and Recreation; ED = Education; HL = Health Care; BSWA = Business Services and Welfare Activities; AUTO = Automobile Acquisition; RECV = Recreational Vehicle; GAS = Gasoline Costs; VEHI = Vehicle Insurance Costs; VOP = Vehicle Operation and Maintenance; PT = Public Transportation; NMT = Non-motorized Transport; INTT = Intercity Travel; SAV = Saving