

Spatial and Demographic Sub-Markets Informing Preferences for Electric Vehicles in Canada

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Summary

The present research seeks to identify both spatial and demographic sub-markets for EVs across Canada. Demographic sub-market identification consists of using latent class analysis to classify respondents into homogeneous groups based on their manifest responses. Working from this classification, spatial sub-market segmentation utilizes spatial classification methods to provide a second layer of analytical granularity. These preliminary models are then incorporated into discrete choice modelling frameworks. From this we provide greater clarity on the characteristics of these individuals, their regional and local locational contexts, the magnitude of the relationships, and feedback between them.

Keywords: Canada, latent class analysis, submarket segmentation, choice model, BEV, HEV, PHEV

1 Introduction

Consumers are increasingly presented with alternative options to the internal combustion engine (ICE) when buying a vehicle in Canada and around the world. Electric vehicles (EVs) in particular, which for the purposes of the present paper refers to Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), and Plug-in Hybrid Electric Vehicles (PHEVs), are viewed as a promising innovation for reducing fuel consumption and lowering greenhouse gas emissions in the transportation sector [1].

With EVs in the early stages of production and adoption, and considering the technological and operational differences compared to ICE vehicles, there is a clear need among private vehicle makers and utility companies as well as public-sector planners and policymakers to understand the market for such products and the interventions that can support and encourage their use. To that end, several studies have been undertaken that seek to identify the attributes of individuals interested in EVs and the characteristics of vehicles most appealing to them [2-7]. However, as with any product, there is likely significant heterogeneity in preferences for EVs. The present research seeks to identify both spatial and socioeconomic and demographic sub-markets for EVs across Canada.

2 Data and Methods

2.1 Data Sources

The data for this research comes from two separate sources. The first is data corresponding to census tracts in Canada with respect to their socioeconomic and demographic characteristics. Publicly-available data on characteristics such as age, household size, and median household income was obtained from the 2011 Canadian Census of Population and the 2011 National Household Survey. Additional information on vehicle ownership in each tract was obtained from IHS Automotive. After excluding census tracts without data from the National Household Survey or information on automobile ownership, the total sample consists of 5,230 tracts.

The second source is a sample of more than 20,000 Canadian households who were surveyed on a number of questions relating to their characteristics, their present automobile ownership, and stated preferences with respect to electric mobility [8]. Survey respondents were presented with four scenarios from which they could choose among ICE, BEV, HEV, and PHEV options, and each scenario altered the characteristics of the vehicles along several dimensions: performance, purchase and operating costs, charging features and availability, vehicle warranty, and cash and non-cash incentives. The attribute levels for each vehicle across the different scenarios are displayed in Table 1. The time spent considering each stated preference scenario was tracked, and cases that did not spend adequate time were removed. Cases that did not provide their household income were also removed from the survey sample. In total the survey sample for this research consists of 11,973 households.

Table 1. Relative Attribute Levels Used in Choice Scenarios

Attributes		ICE	HEV	PHEV	BEV
Purchase Price (\$)	Percentage to ICE	100 75	150 100	200 150 100	200 150 100
Annual Maintenance Cost (\$)	Percentage to ICE	100	100 75	100 75 50	75 50 25
Annual Fuel Charging Cost (\$)	Percentage to ICE	140 120 100	100 80	80 60 40	40 20
Acceleration (0 to 100km/h secs)	Percentage to ICE	100	150 100 50	150 100 50	150 100 50
Cash Incentive (\$)	Absolute	0	0	0 5000 10000	0 5000 10000
Gasoline Range (km)	Percentage to ICE	100	125 75	125 75	0
E-Range (km)	Absolute	0	0	30 60 90	150 250 350
Public Charging Time (hrs)	Percentage	--	--	1100 600 100	2*PHEV levels
Home/Work Charging Time (hrs)	Percentage	--	--	100 75 50	200 150 100

2.2 Research Methods

In this research we test the hypothesis that preferences for EVs are heterogeneous and shaped by both demographic and spatial factors. This hypothesis is tested across four steps:

1. *Capture information on the dominant socioeconomic and demographic characteristics of census tracts in Canada*
Using the 2011 Canadian Census of Population and 2011 National Household Survey and data on automobile ownership from IHS Automotive, we have obtained information on key socioeconomic and demographic characteristics of each census tract in Canada.
2. *Use this information to classify census tracts into more homogeneous groups or submarkets using latent class analysis*
Based on the information above, the latent class model classifies these census tracts into 9 distinct types that represent different submarkets of dominant characteristics in Canada. A latent class model is similar to traditional clustering algorithms such as Ward's, but is probabilistic in nature, can handle multiple variable types, and gives guidance to authors on the optimal number of classes.

3. *Employ latent class model results to classify survey respondents*

One benefit of latent class models is that once a classification solution is found for one sample, it can easily be extended to classify cases from an additional sample in the same manner. From this, the cluster solution from the latent class analysis in step 2 is used to classify survey respondents into the same class types. In essence, this step classifies respondents into the type of socioeconomic and demographic class or submarket that best matches their household profile.

4. *Examine differences in stated preferences with respect to alternative fuel vehicles using discrete choice modelling*

Finally, with the classes identified in the survey, we examine household preferences as they relate to the choice of alternative fuel vehicles for different socioeconomic, demographic, and spatial submarkets. This step uses discrete choice modelling techniques.

While this research is interested in identifying spatial submarkets of individuals with preferences towards alternative fuel vehicles, the absolute location of a survey household in space *does not explicitly matter*. Rather, we are matching the dominant characteristics of survey households with the dominant characteristics of census tracts in Canada. Based on these characteristics, we assume that the choicemaking behaviour of these households reflect what would be found among similar individuals in a census tract.

For example, if younger and highly-educated households in the survey show a preference for alternative fuel vehicles, then it may be that similar behaviour could be seen in larger areas where these types of individuals are more dominant. In contrast, while such household characteristics may prove important in informing preferences for EVs, if this household is in a neighbourhood that is predominately oriented to older families or retirees, then this area is not a key EV submarket relative to others in Canada.

Taken together, the structure of the methods for this paper are shown in Figure 1 below. Socioeconomic and demographic characteristics inform the delineation of submarkets in space. These latent classes in turn are used as an input in the choice model alongside information on different vehicle alternatives, such as their cost, performance, and charging characteristics and any other incentives. All of this information is then used to model the choicemaking behaviour of survey respondents and offer insight into the alternative fuel vehicle preferences of different socioeconomic, demographic, and spatial submarkets in Canada.

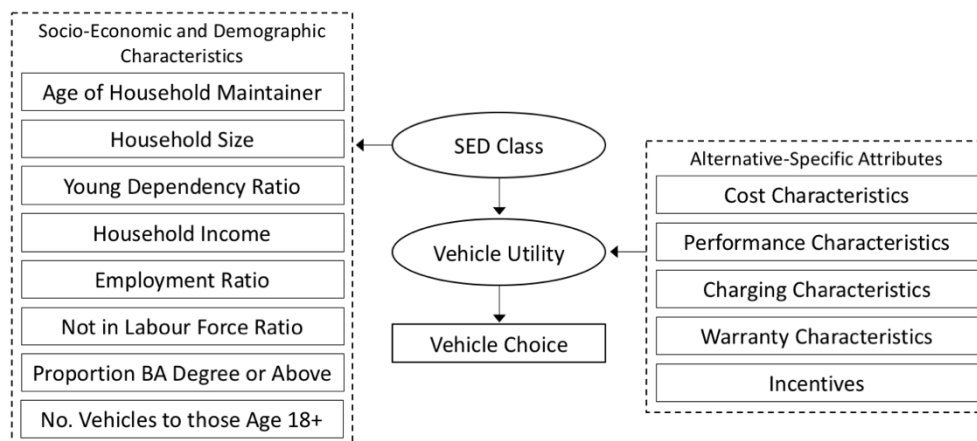


Figure 1. Choice Model Structure

3 Results

3.1 Latent Class Model

One benefit of latent class models over other clustering algorithms is that they offer the user the ability to select an optimal number of classes based on the Bayesian Information Criterion (BIC). In the present case, model runs performed in MPLUS 7.3 achieved a minimum stable BIC of approximately -60,000 at 9 classes,

after which models did not converge without error (Figure 2). The second statistic, entropy, offers information on the quality of the cluster solution in terms of the separation between classes. Ranging from 0-1, the 9-class model achieves good separation of classes with an entropy of approximately 0.88.

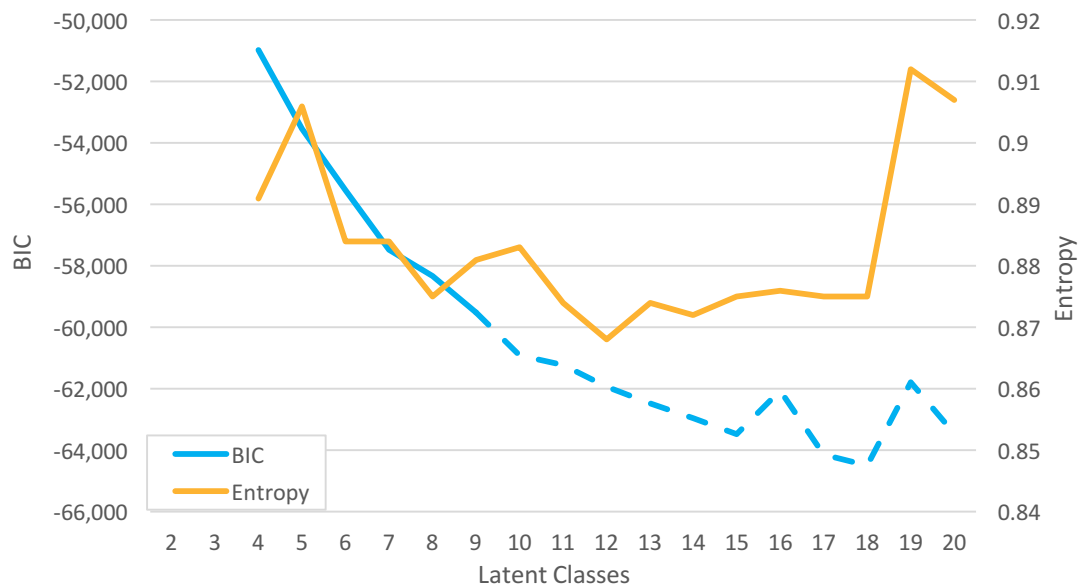


Figure 2. Latent Class Model Fit Statistics

Results from the latent class model are shown in Table 2 below. The numbers represent the mean value of the 8 indicators indicator for each of the 9 classes. The right-hand column displays the sample average of these values across all classes as well as the standard deviation of each indicator. By default, the latent class clustering routine in MPLUS assumes constant variance across classes to arrive at a clustering solution that is maximally homogeneous within-class, and heterogeneous across classes. Each variable has an associated measure of statistical significance, indicating whether the characteristics of the classes are statistically different from zero.

From Table 2 we can see that the characteristics of Class 1 for example fall largely near the mean values across all classes. On average, individuals within this type of census tract are 34.7 years of age and households contain 2.4 people. The young dependency ratio of 0.24 suggests there is on average 1 person under the age of 18 for every 4 people over the age of 18, the employment rate is 58% and 37% of individuals are not in the labour force. Average median household incomes are approximately 42,880, about 23% of people have a Bachelor's degree or higher, and there are about 3 vehicles for every 4 people over the age of 18. All together, there are 1,431 census tracts in Canada that match this profile.

Using this information in Table 2, we have profiled each of the 9 classes according to their general characteristics and present their names and general definitions in Table 3. These names have been retroactively applied to Table 2. Census tract classes range from more *Balanced* types that largely reflect mean values in the sample, to *Older Families* that have larger household sizes and greater young dependency ratios to *Young Professionals* that are younger and highly-educated.

Table 2. Latent Class Model Results – Census Tract Characteristics

	1.	2.	3.	4. Average	5. Older	6. Older	7. Young	8. Young	9. Older	
	Balanced	Balanced -	Balanced -	but Auto-	Families	Families	Non-	Profess-	Profess-	
<i>Variable</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	Average
										(Std. Dev.)
Age of HH Maintainer	34.7 ***	30.9 ***	37.8 ***	35.9 ***	39.5 ***	35.1 ***	25.8 ***	33.6 ***	35.0 ***	34.27 *** (2.6)
Household Size	2.4 ***	2.0 ***	2.6 ***	2.4 ***	2.8 ***	2.3 ***	1.8 ***	1.9 ***	1.8 ***	2.22 *** (0.2)
Young Dependency (%)	0.24 ***	0.18 ***	0.29 ***	0.25 ***	0.37 ***	0.32 ***	0.13 ***	0.16 ***	0.13 ***	0.23 *** (0.05)
Household Income (\$ thou.)	42.88 ***	40.10 ***	44.69 ***	42.63 ***	44.94 ***	39.71 ***	37.64 ***	40.10 ***	41.58 ***	42.77 *** (0.01)
Employed Ratio (%)	0.58 ***	0.52 ***	0.66 ***	0.66 ***	0.73 ***	0.48 ***	0.39 ***	0.63 ***	0.72 ***	0.60 *** (0.03)
Not in the Lbr. Force Ratio	0.37 ***	0.43 ***	0.29 ***	0.30 ***	0.23 ***	0.44 ***	0.56 ***	0.32 ***	0.23 ***	0.35 *** (0.03)
BA Degree or Above (%)	0.23 ***	0.22 ***	0.23 ***	0.25 ***	0.24 ***	0.15 ***	0.18 ***	0.32 ***	0.44 ***	0.25 *** (0.12)
No. Vehicles for those 18+	0.75 ***	0.68 ***	0.86 ***	5.14 ***	0.92 ***	0.54 ***	0.75 ***	0.59 ***	0.57 ***	1.20 *** (0.34)
N (Census)	1,431	623	1,464	27	652	222	108	438	265	5,230
<i>Notes:</i> * indicates statistical significance at the .10% level, ** at the .05% level, and *** at the .01% level or smaller										

Table 3. Class Names and Definitions

Class Name	Definition
1. Balanced	Characteristics of individuals are average across indicators. The age of household maintainers is approximately 34.7 years old, households feature 2.4 members with a young dependency ratio of 0.24, suggesting some children. Overall education levels are average with 23% of the population with a BA degree or above. Incomes are average as are rates of employment and labour force participation.
2. Balanced - Low	Characteristics of individuals are largely average, but generally lower than those in Class 1. The exception is rates of labour force participation, which are generally lower than other classes.
3. Balanced - High	Characteristics of individuals are largely average, but generally higher than those in Class 1.
4. Average but Auto-Oriented	Average age of household head, average household size and dependency ratio indicates some children, average education. Households are unique in owning many vehicles per person over the age of 18, but the absolute number of tracts that fit this profile is small suggesting this type is more of a statistical outlier attributable to the nature of the IHS dataset where some tracts are home to the registration of large commercial vehicle fleets.
5. Older Families	Households are older, larger, and have the most children among classes in the sample. Incomes are the highest among the classes, and households are auto-oriented, owning nearly 1 vehicle per person over the age of 18.
6. Older Families and Retirees	Age of household maintainers is average. Household size is average at 2.3 people and young dependency ratio is higher at 0.32, suggesting families with children. The proportion of those not in the labour force is also higher than other classes at 0.44, which can indicate the presence of more retirees or those engaged in household labour. Rates of education and automobile ownership are however lower than other classes.
7. Young Non-Professional	Individuals are younger and have lower levels of education, low levels of employment, and a high proportion of individuals not in the labour force. Household incomes are lower, but households are small and fairly automobile-oriented. Reasons for this mix of attributes could be areas of low socioeconomic status or high proportions of students in neighborhoods around Universities.
8. Young Professional	Highly educated and young with an average age of 33.6. Small household size indicates many single and two-person households and few kids. Incomes are average, but considering the number of smaller households overall, income per capita is relatively high. Few vehicles per household member over the age of 18.
9. Older Professional	Highly educated and majority employed. Average age of the household maintainer is older than for the young professional group at 35. Many single- and two-person households with few kids. Average household incomes are high at \$41,580 and individual incomes are also high. Few vehicles per household member over the age of 18.

3.2 Spatial Distribution of Classes

With the classification in place, we can now examine the spatial distribution of different socioeconomic and demographic submarkets in Canada. Figures Figure 3, Figure 4 and Figure 5 below show the distribution of these classes in the Greater Toronto and Hamilton, Montréal, and Vancouver areas respectively. To help identify each city's core areas we have overlaid each map with their rapid transit networks. In general, there is a pattern wherein more suburban areas of the city are either more *Balanced* or *Older Families* and *Retirees* characterized as older and more family-oriented with larger households and greater automobile ownership.

In contrast, neighbourhoods around each city's central area are predominately *Young* and *Older Professionals*: younger than their suburban counterparts with smaller household sizes, a higher proportion with a Bachelor's degree or above, and reduced automobile ownership per capita. While we have only shown three cities, a similar spatial distribution of neighbourhood class types can be found in almost every other larger city across Canada. We will return to this distribution after estimating the choicemaking behaviour of the different submarkets below.

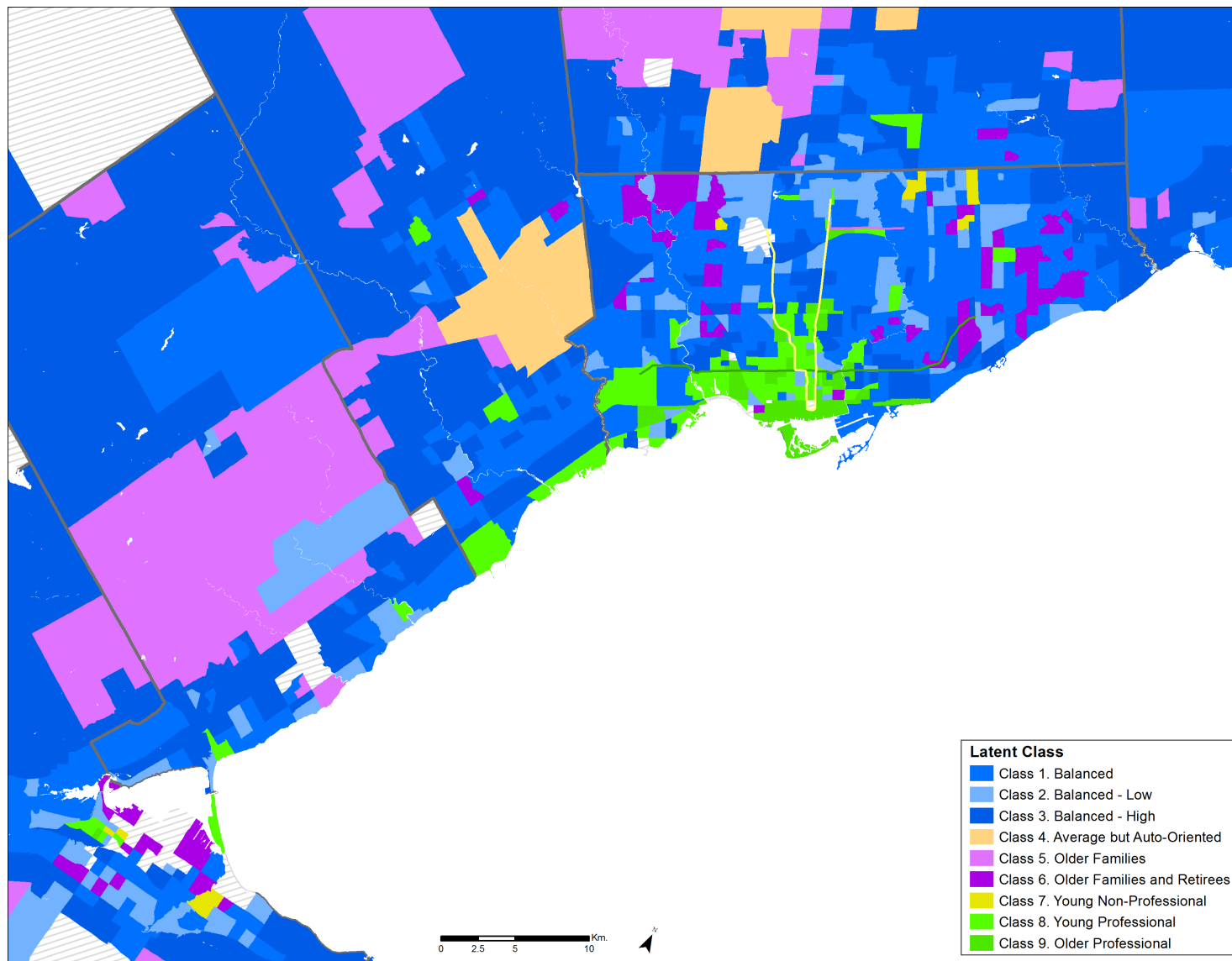


Figure 3. Spatial Distribution of Latent Classes: Greater Toronto and Hamilton Area

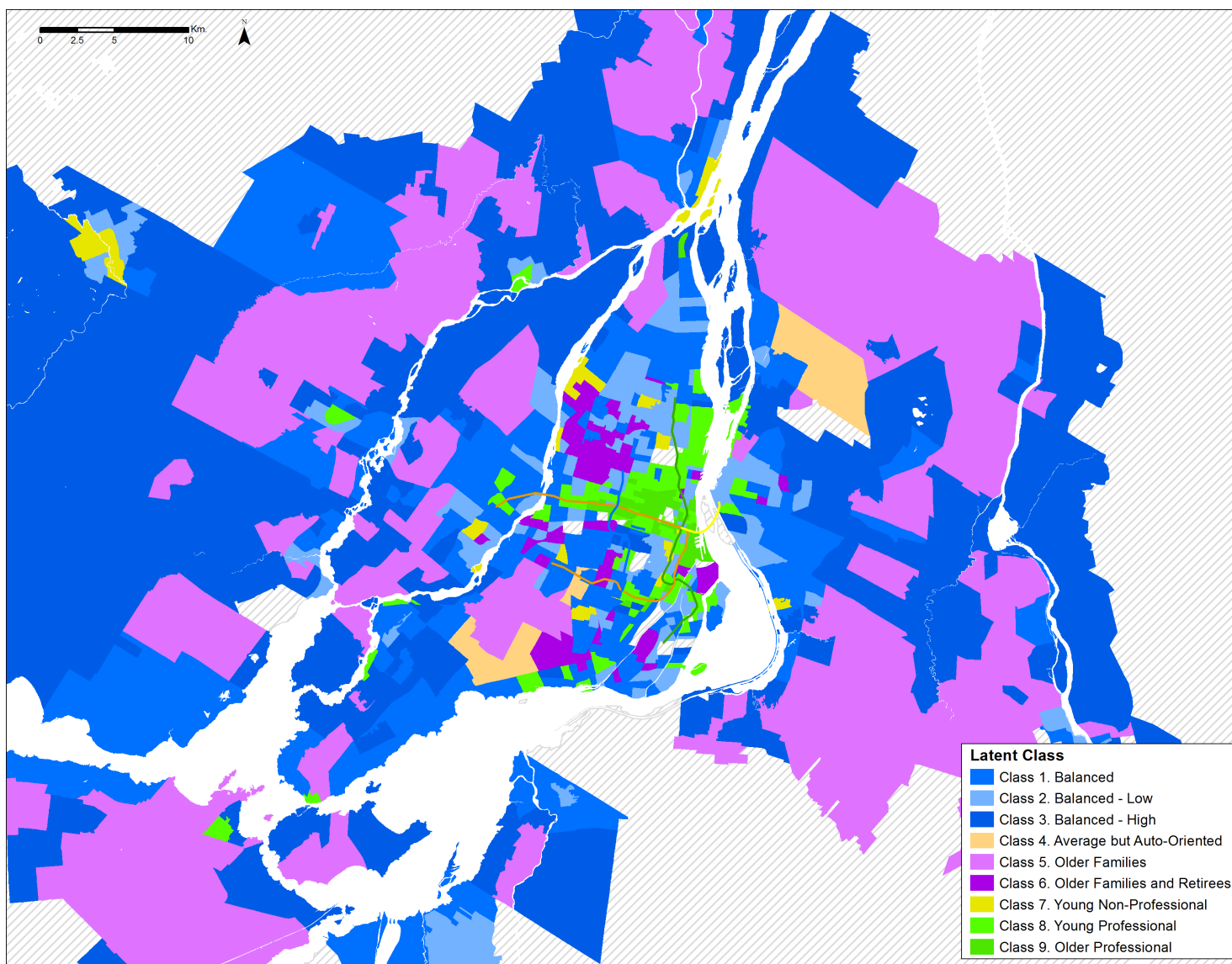


Figure 4. Spatial Distribution of Latent Classes: Greater Montreal Area

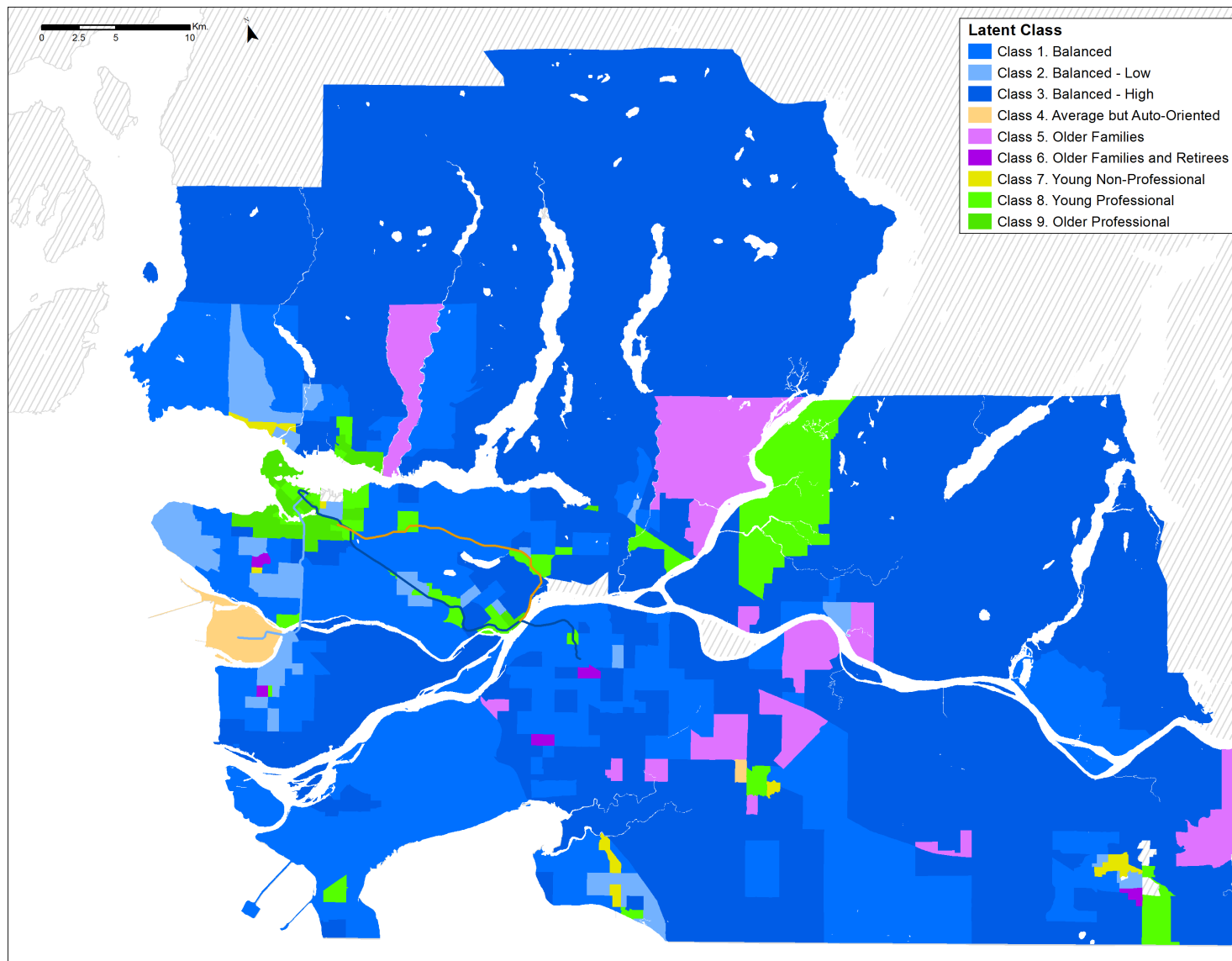


Figure 5. Spatial Distribution of Latent Classes: Greater Vancouver Area

3.3 Discrete Choice Model

Model results from the discrete choice analysis are presented in Table 4. Because there were zero cases in the survey that corresponded to Class 4 – *Average but Auto-oriented*, no model for this group was run. Across all groups we can see a general sensitivity to the price of a vehicle, and a generally negative appeal of alternative fuel vehicles compared to ICE vehicles among several groups. However, all groups appear to value cash incentives, reinforcing the importance of these programs for improving the appeal of alternative fuel vehicles across all submarkets in the sample. Still, aside from these more general outcomes, there is great variation in model outcomes across the classes.

A group of immediate interest is that of the individuals in Class 8 – *Young Professionals*. Here we can see from the positive constant value for Battery Electric that this group of individuals is predisposed to interest in BEVs compared to ICE vehicles. Similarly, HEVs are also valued compared to ICE vehicles, although this relationship is only significant at the 10% level. On top of this, Class 8 also values free parking as an incentive for purchasing an alternative fuel vehicle but does not appear to put much emphasis on a vehicle's warranty. Cash incentives can also help ease the negative effects of vehicle price.

The socioeconomic, demographic, and spatial characteristics of this submarket and their preferences towards BEVs likely reflects several themes. First, the factors of youth and high levels of education bolster the results of many other studies, reinforcing the notion that these types of individuals are key targets for EV adoption. However, while these types of households can be found in neighbourhoods across Canada, our research reveals areas in which these individuals are spatially concentrated. As we can see from Figures Figure 3, Figure 4 and Figure 5, the results for the *Young Professionals* model demonstrate that key target market areas for alternative fuel vehicles are within the central parts of Canadian cities. Together, smaller households and more central locations mean there are fewer demands placed on vehicles in terms of travel needs, aligning better with the characteristics offered by many alternative fuel vehicles. This also highlights the importance placed on free municipal parking as an incentive, as parking levels downtown areas are likely constrained or costly.

Interestingly, the *Older Professionals* in Class 9 do not share the same immediate interest in alternative fuel vehicles relative to ICE vehicles as those in Class 8, although BEVs are valued more than PHEVs. Here individuals are sensitive to price, maintenance costs, and vehicle performance relative to ICE vehicles. However, characteristics such as electric and gasoline range, vehicle warranty, and incentives that offer free municipal parking and HOV use are positively valued and when combined can begin to offset the negative constant on BEV and PHEV options. In this sense, those in Class 9 are an important target market for alternative fuel vehicles, so long as vehicle attributes and incentive programs can offset other negative feelings towards EVs.

In contrast to *Young* and *Older Professionals*, other groups show much greater predisposition to ICE vehicles over BEVs, HEVs, and PHEVs. This is likely associated with the demands put on vehicles at the household level in terms of the number of passengers, but also their spatial characteristics in Figures Figure 3, Figure 4 and Figure 5. Here we can see that these types of submarkets are predominately located in more suburban areas and it may be that their travel needs put alternative fuel vehicles outside the realm of consideration for many compared to ICE vehicles.

Table 4. Model Results – Survey Respondents

	1. Balanced	2. Balanced - Low	3. Balanced - High	5. Older Families	6. Older Families and Retirees	7. Young Non-Professional	8. Young Professional	9. Older Professional
<i>Variable</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>	<i>Coefficient</i>
<i>Constants</i>								
Battery Electric	-0.2413 ***	-0.2447 *	-0.1967 **	-0.1947 ***	-0.1504	-0.4273 ***	1.6993 ***	-0.1742 ***
Hybrid	0.0209	-0.4460	-0.2426	-0.1319 *	-0.1894	-0.5560 ***	1.3398 *	0.0361
Plug-in Hybrid	-0.3747	-1.3797 ***	-0.7851 ***	-0.5586 ***	-0.7800 **	-0.8567 ***	1.9459	-0.4760 ***
<i>Vehicle Cost Characteristics</i>								
Price (\$)	-0.0471 ***	-0.0369 ***	-0.0440 ***	-0.0411 ***	-0.0414 ***	-0.0417 ***	-0.0498 ***	-0.0452 ***
Maintenance Cost (\$)	-0.3183 ***	-0.0612	-0.2955 **	-0.1835 ***	-0.1770	-0.2144 ***	-0.7787	-0.2003 ***
Fuel Cost (\$)	0.1267 *	-0.0879	-0.0542	0.0972 ***	-0.0447	0.0792 **	0.3558	-0.0200
<i>Vehicle Performance Characteristics</i>								
Electric Range (km)	0.0005	0.0022 **	0.0007	0.0005 *	0.0015 **	0.0005	0.0001	0.0013 ***
Gasoline Range (km)	0.0005 ***	0.0005 *	0.0004 **	0.0004 ***	0.0005 ***	0.0004 ***	0.0012	0.0005 ***
Acceleration (sec.)	-0.0085	-0.0156	-0.0294 ***	-0.0124 ***	-0.0073	-0.0060	0.0259	-0.0109 ***
<i>Vehicle Charging Characteristics</i>								
Charging Station Availability	0.0026	-0.0107	0.0324	0.0262	-0.0063	0.0553 **	0.2050	0.0231
Charging Time – Public (hours)	-0.0504 ***	0.0360	-0.0293 *	-0.0213 ***	-0.0058	-0.0610 ***	-0.0113	-0.0430 ***
Charging Time – Home (hours)	-0.0123	0.0455	-0.0366	-0.0211 **	0.0149	-0.0452 ***	-0.1220	-0.0433 ***
<i>Vehicle Warranty</i>								
Warranty	0.1000 ***	0.0172	0.0470	0.0785 ***	0.0568 *	0.0834 ***	-0.2655 *	0.0595 ***
<i>Incentives</i>								
Free Parking	0.1222 *	0.0920	0.0863	0.0637 **	0.0592	0.0522	0.6544 **	0.0755 **
Free Toll Road Use	0.0088	-0.1169	-0.0277	-0.0139	-0.0159	0.0465	0.1326	-0.0159
HOV Use	-0.0389	0.0562	0.0819	0.0515 *	0.0496	0.0802 **	-0.0785	0.1061 ***
Cash Incentives	0.0298 ***	0.0393 ***	0.0373 ***	0.0405 ***	0.0267 ***	0.0372 ***	0.0650 *	0.0431 ***
N (Survey)	653	237	741	4,038	316	2,629	30	3,329
Pseudo-R ²	0.055	0.041	0.049	0.054	0.041	0.041	0.105	0.052

Notes: * indicates statistical significance at the .10% level, ** at the .05% level, and *** at the .01% level or smaller. No survey cases correspond to Class 4 and as such, this class is omitted.

4 Conclusions

While the benefits of EVs are promising, achieving large-scale reductions in fossil fuel consumption and greenhouse gas emissions requires their widespread adoption. Previous studies have sought to identify the characteristics of households and vehicles interested in EVs. However, little work has been done that uses this information to identify key socioeconomic, demographic, and most importantly, spatial submarkets of potential EV adopters.

Using a large primary survey dataset of household preferences for alternative fuel vehicles in Canada, we have identified 9 distinct types of neighbourhoods in Canada and associated their dominant characteristics with choicemaking behaviour with respect to EVs. One class in particular, that of *Young Professionals*, shows an immediate preference for BEVs, and together the choice and latent class models show that important submarkets of these individuals exist in the central areas of Canadian cities. *Older Professionals* are also a target market for EVs, and among this group cash and non-cash incentives appear to be strong contributors to positive preferences for EVs. This knowledge offers important information for targeted interventions to support EV adoption, such as increased marketing to these neighbourhoods on the part of automakers, the provision of charging infrastructure by municipalities, and the upgrading of electrical networks by utility companies.

Still, it is also important to note that many other neighbourhoods in Canada are not immediately interested in this type of vehicle. Model results reveal more suburban neighbourhoods feature older and larger households that show a strong preference for ICE vehicles. While we have identified key socioeconomic, demographic, and spatial submarkets for EVs, achieving the broader benefits of EVs will require a conversion of these neighbourhoods into EV adopters. In this sense, a combination of appealing vehicle characteristics and strong cash and non-cash incentives may be able to sway preferences among households in these areas in favour of EVs.

This research is not without its shortcomings. The method of classifying survey respondents based on their match to the socioeconomic and demographic characteristics of census tracts means we are only capturing the dominant characteristics of these neighbourhoods. It seems likely that other important pockets of preferences for EVs may exist but are not being captured. Future research should examine this issue from the perspectives of households in the 2011 Canadian Census and National Household Survey rather than studying the issue at the neighbourhood level. While the present study reveals areas where there is likely a dominant and immediate appeal for EVs, household-level research could offer more detail on the characteristics and location of other important spatial and demographic submarkets for alternative fuel vehicles in Canada.

5 Acknowledgments

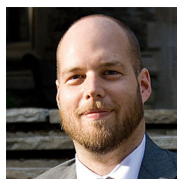
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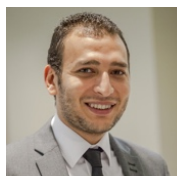
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Authors



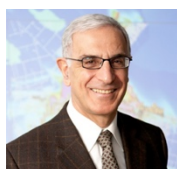
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