ΕΘΝΙΚΟ ΜΕΤΣΟΒΙΟ ΠΟΛΥΤΕΧΝΕΙΟ
Σχολή Αγρονόμων & Τοπογράφων Μηχανικών

ΓΕΩΠΛΗΡΟΦΟΡΙΚΗ
ΜΕΤΑΠΤΥΧΙΑΚΟ ΠΡΟΓΡΑΜΜΑ

NATIONAL TECHNICAL UNIVERSITY OF ATHENS
School of Rural & Surveying Engineering

GEOINFORMATICS
POST-GRADUATE PROGRAMME

Electric Vehicles and Traffic Related Pollution Reduction: A simulation model for Hamilton, Ontario, Canada

By

Papargyri Evangelia

A Thesis

Submitted to National Technical University of Athens

In partial fulfillment of the requirements for the Degree

Master of Science, MSc

Athens, March 2014

Abstract

This paper analyzes the potential contribution of electric vehicles in greenhouse gas (GHG) emissions reduction over the next decade. The effect of electric vehicles (EVs) on traffic related pollution is assessed at the transportation link level in the Hamilton Census Metropolitan Area (CMA) following a simulation procedure from 2006 to 2021. The traffic emissions considered in this paper are: total hydrocarbons (HC), nitrogen oxides (NO_x), carbon monoxide (CO) and a basic estimate of carbon dioxide (CO_2). Emissions were estimated through a number of steps. Firstly, different EV market penetration scenarios were introduced (conservative, medium, optimistic) and compared to the base case scenario where no action or minimum policy controls are supposed to take place over the next couple of decades. Scenarios were determined through a comprehensive review of penetration estimates in the literature. Following these, the spatial distribution patterns of EVs were predicted using the vehicle registration data for the Hamilton CMA along with socioeconomic data obtained from 2006 census. Different distribution patterns of EVs adoption were assessed creating sub-scenarios, in order to reflect the possible changes in the future. Subsequently, the results from the regression model were used to properly modify the Origin-Destination (OD) matrices by type of vehicle. These matrices were used as input into our traffic simulation model (TRAFFIC) that assigns traffic on the network and estimates volumes for each of the links. MOBILE 6.2C[1] was customized to accept the new vehicle type and to compute the emission factors. The hourly emissions on each link were mapped through a geographic information system (GIS) framework after the integration of three parameters: street network, associated traffic flows and emissions (Link_emissions model). We conclude that different distribution patterns produce different spatial patterns of traffic related emissions in the links and even a modest adoption of EV technology may lead to significant reduction in traffic emissions

KEY WORDS: Electric mobility, electric cars, traffic emissions, transportation link level, regression model, simulation, Hamilton CMA.

[1] MOBILE 6.2C is a version of MOBILE 6 originally developed by U.S Environmental Protection Agency to reflect the vehicle fleet and it was then modified by Environment Canada to embrace Canadian conditions.

Acknowledgements

I would like to express my gratitude to my supervisors Dr. Yorgos Photis and Dr. Pavlos Kanaroglou for providing their guidance and wisdom to create this work.

First and foremost, I would like to express my greatest appreciation to Dr. Yorgos Photis who inspired me and motivated me to visit Mc Master and benefit from a high-quality institution. I am also grateful not only for his mentorship when I was in Canada , but also for continuously advising me until now.

I would like to acknowledge Dr Pavlos Kanaroglou as well, for giving me the opportunity to meet another world, incorporating me to CSpA and consulting me in general. He introduced me another way of thinking through insightful conversations at his office.

I am particularly thankful to Angeliki and Kostas Apostolou and Vina Kanaroglou for their kindness and hospitality and for making me feel like home.

I truly appreciate all people from CSpA for their assistance throught my time at Mac Master and my new friends for keeping me company when I missed my family and friends.

But, mostly, I want to thank my friend, roommate, colleague, my family -Natalie- for her support during all the difficult momemts that we went through. If it hadn't been Natalie to cook, I wouldn't have made it.

Lastly, I want to express my deep appreciation to my family, back in Greece for their support and encouragement all these months amd my friends for their communication.

Contents

List of Tables

List of Figures

Chapter 1

1. Introduction

Transportation in most of the urban regions of the world is dependent on the automobile. Suburbanization and urban sprawl has led people to use their car for every activity as houses and jobs are dispersed. As a result, auto-dependency has contributed to excessive congestion and air pollution that is detrimental to human health (Ministry of Transportation, 2011).

Transport sector accounts for 14% of global greenhouse gas (GHG) emissions, and road transportation is the biggest of those sources, responsible for about 76 % of total transport emissions according to Wu et al. (1999). In Canada, the transportation sector accounts for 75% of emitted carbon monoxide (CO), 67% of nitrogen oxides (NO_x), 49% of non- methane hydrocarbons (HC) and 25% of carbon dioxide (CO2) (OECD, 2007). It is reported that 84.4% of Canadian households owned or leased at least one vehicle in 2009 (Natural Resources Canada, 2009). The use of private vehicles by Canadians for daily trips is increasing while non-motorized travel for short distance utilitarian trips is declining. The urge for GHG emissions abatement and air quality improvement are forcing Canada's government to act on the road transportation sector.

In order to meet future mobility needs, fulfill all the goals set to attain urban sustainability and phase out dependence on oil, today's automobiles have to be superseded by more dynamic and envrinmentally friendly alternatives. Electric vehicles have been identified as being such a technology according to the German Advisory Council on Global Change (2011) which are the only technical alternative on the market available today to vehicles with internal combustion engine.

The electrification of road transport is considered as one of the most promising approaches as a step towards sustainability, helping to further reduce localized vehicle emissions and mitigate the associated health concerns. Many attempts to introduce electric vehicles (EVs) have failed over the years. Higher cost of EVs, challenges in battery technology, limited range of EVs, lack of infrastructure, consumer mindset, inadequate government support are some of the barriers to greater adoption of EVs. Consequently, policies to increase the number of EVs on the roads have become increasingly common in Canada in recent years and electric vehicles are expected to become even more attractive in the future, as technology and infrastructure improves due to zero tailpipe emissions, high efficiency and low operation costs.

With respect to the net result regarding GHG emissions from EV adoption the literature suggests some contradictory findings. According to Cherry et al. (2011) the actual amount of emissions created per kilometer driven depends on the electricity generation mix of the grid from which the battery is charged. The EVs emissions are released at the electricity-generating power plant, while the vehicle is used elsewhere. In China's case, pollution from electricity plants is spreading exposure to potentially harmful particulates in the air from urban populations to those in more remote rural regions. Notably, a significant portion of power generation uses coal, which, with today's technology, has a very high carbon footprint.The literature in evaluating the advantages and disadvantages of EVs underlines the importance of exposure of people to emissions from power generation. Huo et al. (2010) lamend that greater CO_2 reduction could be expected in future if coal combustion technologies improve and the share of nonfossil electricity increases significantly. Contrary to countries like China or Germany, Switzerland is largely free of CO_2-intensive energies and already today generates 60% of its electricity is from renewable sources-an ideal precondition for a truly sustainable electric car as reported by Beckmann (2010) giving a new insight in the need of adopting the new technology. For example, electricity from nuclear, hydro, solar, or wind-powered plants emits very low amounts of air pollutants. Ontario gets 64% of its electricity from nuclear power. The remainder comes from a mix of natural gas (9%), hydroelectricity (21%) and wind (4%) according to Canadian Nuclear Society (2013). Ontario has already eliminated coal's percentage.

While electric vehicle technology promises a decrease in emissions, a crucial strategy to promote the adoption of EVs is required. Due to urban sprawl, Hamiltonians are heavily dependent on private vehicles, rather than public transportation. Data from census demonstrated that 76% of employed persons in Hamilton commute using personal transportation (Statistics Canada, 2008). This is indicative of the extent of congestion and the resulting pollution emissions. Traditional government intervention policies into the market for new technologies include tax incentives and regulations that favour the adoption of beneficial technologies. In the case of electric vehicles, Ontario offers tax deduction, credits and HOV lane privileges to EVs owners. For example, they obtain special green license plates, which offer them high priority access to Ontario's high occupancy vehicle (HOV) lanes, even if there is only one person in the vehicle (Ministry of Transportation, 2011). It is also essential to highlight that although EVs are currently more expensive to purchase, they can save drivers from significant sums of money over time, in fuel and operation savings, depending on gasoline prices.

With regard to money saving some other concerns are arising. The introduction of more efficient technology (for example electric vehicles) is usually accompanied by rebound effects, which contradict the positive effect of increased efficiency. Increased fuel efficiency means lower fuel costs leading to lower costs for transportation services. In response to improvements in the fuel economy, people often increase vehicle miles traveled (VMT) and sometimes proceed to purchase bigger vehicles or more cars than actually needed in the family according to Haan et al. (2006). In general, when people save money from transportation they have the tendency to organize their lives by gradually increasing automobile's usage. For example, if an electric vehicle is purchased and used as a supplemental vehicle for short trips where the owner previously walked or biked, overall emissions would increase as the VMT would rise. To avoid the rebound effect people should be informed about sustainable transportation and be aware of environmental issues.

Several researchers have used survey data to draw conclusions about factors affecting EV demand. These studies generally outline the profile of potential EVs buyers and conclude that EVs owners tend to be in the highest income class and in the highest educational level according to Haan et al. (2006); Potoglou and Kanaroglou (2008); Curtin et al. (2009). The type of house and the capacity of owning free parking where the charging infrastructure could be located are also essential (Hess and Ong, 2002; Chu 2002). Therefore, it is reasonable to assume that raising car buyers' awareness over the benefits of EVs usage with regard to environmental issues and GHG emissions reduction, may increase EVs deployment in the market.

Since very few EVs were registered in the Hamilton CMA, it is not possible to assess consumer willingness to purchase electric vehicles on the basis of revealed purchasing behavior. Thus, this study was based on the type of persons already purchasing a hybrid electric vehicle to approximate who would be likely electric vehicle adopters. The counts of HEVs were used for the simulation of EVs and the assessment of the effect of EVs on emissions, following the assumption that similar penetration rate to that of HEVs could be found for EVs too (Cunnungham, 2009; Perujo and Ciuffo 2010). The owners of EVs have the same characteristics with those of hybrid cars as they share same components (batteries, electric motors).

This study offers insight on the potential contribution of electric vehicles in GHG emissions reduction over the next decade in the Hamilton CMA. Although much research has been conducted to evaluate potential demand and acceptance from users (O'Mahony, 2011; Potoglou, 2007; Franke et al. 2012; Krems et al. 2010), the willingness to pay for alternative fuel vehicles (Dagsvik 1996; Ito et al. 2011), the reliability of battery systems (Earley et al. 2011, the energy demand per vehicle (Bueno, 2012) less has been done to evaluate GHG emissions reduction at the link level after the introduction of EVs. This thesis attempts to add to the literature by combining various spatial distribution patterns of EVs influenced by socioeconomic differences with a set of integrated simulation models (MOBILE 6.2C, TRAFFIC, LINK EMISSIONS) to estimate the traffic related emissions in the area. The overall objective is to generate scenarios, using different adoption rates of the new technology and evaluate the results with regard to emissions produced in the Hamilton light-duty vehicle fleet. In particular the research focuses on the following questions:

- Projecting to 2021, what is the change on emissions when different rates of electric powertrains are introduced to the vehicle fleet?
- What contribution can electric vehicles make towards meeting GHG reduction targets?
- How different socioeconomic factors influence EVs distribution and emissions?

These results will be used to develop broad strategic goals which can facilitate the deployment of the sustainable transportation system. Study findings will help support informed decision-making regarding EVs development and deployment in support of energy and environmental policy. They will also dispel misunderstandings about EVs and emissions- such as the common misunderstanding that EVs would worsen air quality due to emissions from electricity generation for battery charging. Accordingly, there is a great need for generating future – year scenarios using simulation tools for assessing potential development policies. Additionally, the emissions are estimated at the link level, thus additional information on the spatial concentration of emissions will be provided compared to previous studies. Literature on pollution reduction due to the introduction of ‘cleaner’ vehicles lacks mapping. Maps are needed, for example, to identify pollution “hot-spots”, to show changes on spatial patterns of pollution resulting from policies and to provide estimates of exposure for epidemiological studies.

The integrated models were undertaken as part of a previous project completed for Environment Canada by the Centre for Spatial Analysis at McMaster University in Hamilton. The original projects aimed to estimate traffic related emissions of Canada’s major cities (Toronto, Vancouver) CSpA (2009).

The remainder of this thesis is organized in three chapters, as follows:

The **second chapter** provides details on the theoretical background, motivations and methodology for this thesis. We first review previous research that has attempted to predict EVs future market deployment and the estimated abatement in GHG emissions. Then, we focus on the factors that influence EVs ownership and uptake.

On the basis of this review, an appropriate modeling approach is selected to study the relationship between the contributing socioeconomic factors that influence EVs market deployment and the decrease in GHG link emissions (**Third chapter**). Furthermore, it provides the methodological framework that was followed in this study, the determination and description of the analysis techniques and the software that will be used for this study.

In the following chapter, **Chapter 4**, we analyze the case study after the implementation of the aforementioned methodological framework. A regression analysis is used to predict the spatial distribution patterns of electric vehicles with regard to socioeconomic characteristics.

The results are used to properly modify the Origin-Destination matrices which will be the input for TRAFFIC simulation model. The emission factors are calculated in MOBILE 6.2C and then future emissions are simulated and mapped through LINK EMISSIONS. Following these, the case study is presented where the aforementioned methodological framework is actually executed. A detailed description of regression analysis' results is provided, followed by the process of estimating emissions from the integrated models.

The **fifth chapter** provides integrated results of the analysis, the overall summary of the findings and the conclusions. A discussion of potential areas of research concludes the thesis.

Chapter 2

2. Literature Review

Transportation is inextricably interconnected with private car and development trends project substantial growth in road transport over the coming decades. According to a study conducted by the World Business Council for Sustainable Development (2004) automobile's owenership could increase from roughly 700 million to 2 billion over the period 2000-2050. Solomon et al. (2007) state that, globally, private cars account for almost 10% of total energy use and greenhouse gas emissions (GHG). These patterns forecast an excessive use of automobiles, resulting in a dramatic boost of gasoline and diesel demands, urban sprawl, and increasing levels of commuting trips and degradation of air quality. (Ministry of Transportation, 2011).

Transportation sector produced 24% of GHG emissions growth from 1990 to 2008 (Canada's Action, 2010), generates around 25% of EU greenhouse gas emissions (Climate Action, 2011) and accounts for 51% of pollution in India (Bhattacharjee, 2012). Reducing emissions from this sector will generate significant benefits towards sustainability. This could be accomplished by abating car ownership and use (travel demand), by using alternative fuelled vehicles or by improving roadways.

Towards this end, automobile manufacturers introduce electric vehicles that are associated with high efficiency, low operation costs and zero tailpipe emissions at an increasing pace. In the past, many attempts to implement electric vehicles have failed because of their limit range and the fear that a dead battery provokes, called "Range Anxiety" as reported by Accello (1997). Besides this barrier, researchers are concerned about the grid's capacity to withstand the growing demand of electricity when loading on the grid, especially during peak hours according to Nemry and Brons (2010). Over the last years auto industries introduce electric vehicles with gradually improving electric power capacity ratios. This strengthens electric vehicle's deployment as people get informed about technology and adopt it in phases.

First, hybrid electric vehicles (HEV) were introduced, which combined a gasoline-fuelled internal combustion engine and electric batteries to power electric motors. These cars could be used for short urban trips. Electricity is produced in the vehicle and it doesn't need to be recharged. The next generation was plug-in hybrid electric vehicles (PHEV), a hybrid with batteries that can be recharged by connecting a plug to an electric power source. For the first time the vehicles could connect to the grid to get electricity. Typically, they could be used at 100% electric in the city with a range limit of 50 km. Third, fully electric vehicles were introduced with a sufficient range of 200 km in the beginning (Transport Canada, 2011).

Technology is improving rapidly and within two years the range augmented up to 483Km through Tesla Motors' new model (Model S). It is expected that the range will continue to grow fast and the charging time will be shortened according to Ian Hobday, CEO of Liberty Electric Cars Ltd (Ian Hobday, 2013).

The Ontario government's vision is to have one out of every 20 vehicles driven in the province electrically powered by 2020. To support this vision, Ontario has announced a number of incentives to help individuals, businesses and organizations choose clean and efficient vehicles (Ministry of Transportation, 2010). Similar visions exist in many other countries such as Germany, UK, USA, Ireland and British Columbia (Dempsey, 2008; Pembina Institute, 2010). However, the actual amount of emissions created per kilometer driven depends on the electricity generation mix of the grid from which the battery is charged. For example, electricity from nuclear, hydro, solar, or wind-powered plants emits very low amounts of air pollutants.

Many researchers, taking the aforementioned visions into consideration, have attempted to analyze the impacts of new technology on society and especially the contribution to GHG emissions and to energy and oil consumption. Additionally, the market acceptance of new technology has been investigated along with projections over the rate that these new vehicle fleets enter the market (Perujo and Ciuffo, 2010; Cunningham, 2009).

The Boston Consulting Group (2009) analysis proposed three scenarios for the introduction of electric vehicles in the market. In the first -slowdown- scenario the EVs including hybrids, achieve a 12% uptake. The second-steady pace- scenario forecasts a 28% penetration rate of new technology, whereas the last scenario –acceleration-scenario, which proceeds with a 45% of the overall market share. The market penetration of BEVs and of PHEVs ranges between 0% and 5%. The authors developed three different scenarios to illustrate their expectations of the uptake of EVs in 2020 starting from 2008 in Western Europe, North America, Japan and China. In their view the most likely scenario to be realized is the steady pace scenario with reductions in CO2 emissions up to 40%.

Deloitte (2010) released a study analyzing electric car adoption taking into consideration market opportunity, target customers, barriers to adoption and market forecast. The study concluded with a rather conservative forecast of electric car sales accounting for 3.1% of the US market by 2020.

UMTRI (2009) conducted a report predicting PHEVs market uptake using six different models. The first 4 models assumed a fixed saturation level while the other two constituted a sensitivity analysis. According to the first set of models, PHEVs will range between 345 and 371000 units, reaching its peak between 2017 and 2020. The last model - which was the most preferable by the authors - sets 3 scenarios –Low, medium and high – as illustrated below with the latter one being very aggressive:

Table 1. Future scenarios- UMTRI

Scenarios	PHEVs Market penetration (Million units)		
	2015	2025	2035
Low	0.005	0.084	0.38
Medium	N/A	1.2	4.2
High	0.19	1.891	6.021

According to BERR & DfT (2008) the rate of EVs deployment is assumed to be non-linear. In order to forecast the future market share of EVs the authors constructed four scenarios:

- BAU Scenario: In this scenario it is assumed that the market continues along with the current situation and no new incentives are given in order to promote the diffusion of EVs.
- Mid-range Scenario: The environmental incentives are constant but the costs of EVs are comparable to ICVs by 2015.
- High-range Scenario: The costs of batteries have decreased and charging infrastructure is spread.
- Extreme-range Scenario: In the last scenario there is extensive demand for EVs at such extent that all new vehicles sales are EVs.

The forecasts of EVs penetration are illustrated in the following tables. Notably, the last scenario is very aggressive.

Table 2. Future Scenarios- BERR & DfT

Scenarios	Number of vehicles able to connect to grid					
	BEVs			PHEVs		
	2010	2020	2030	2010	2020	2030
BAU	3000	70000	500000	1000	200000	2500000
Mid-range	4000	600000	1600000	1000	200000	2500000
High-range	4000	1200000	3300000	1000	350000	7900000
Extreme- range	4000	2600000	5800000	1000	500000	14800000

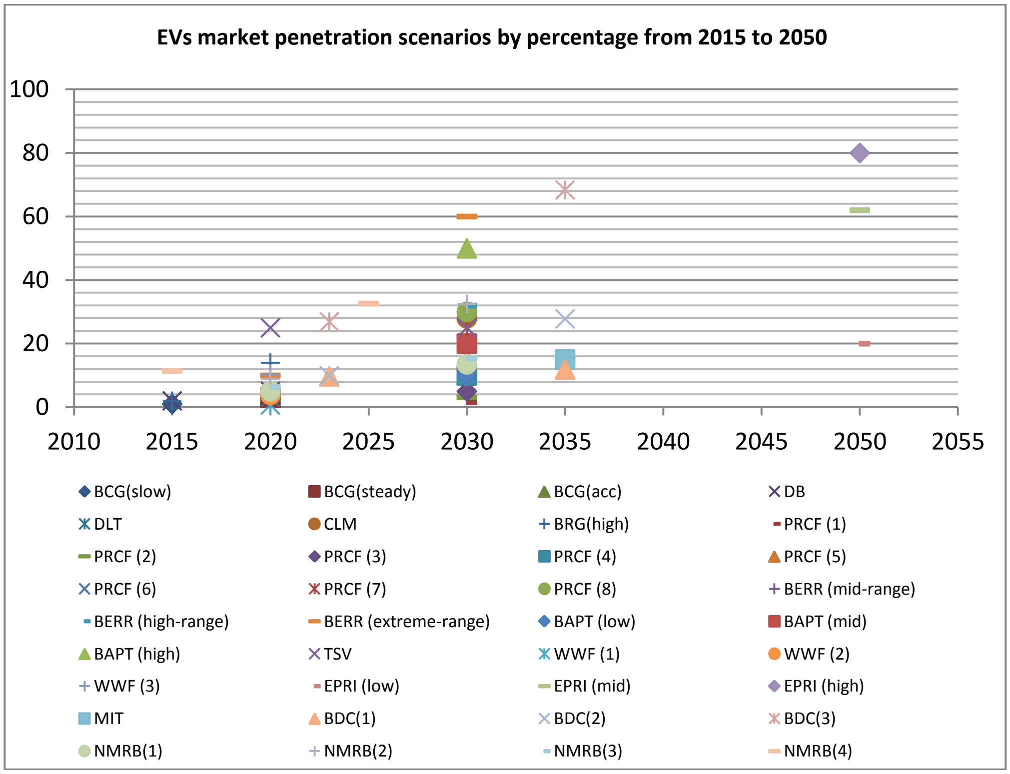
Scenarios	Percentage of vehicles able to connect to grid	
	2020	2030
Mid-range	2.50%	11.70%
High-range	4.90%	32%
Extreme- range	10%	60%

Hadley and Tsvetkova (2008) assume that the deployment of PHEVs will be constant at 25% of market share, in order to estimate the potential impacts of the new automotive technology on electricity demand, supply, prices and emissions in 2020 and 2030 in 13 regions.

Another report analyzing the potential contribution of PHEVs and BEVs to GHG emissions reduction over the next decade in Canada is that of WWF (2012). The authors build 3 different scenarios –unhurried, moderate and aggressive market penetration scenarios- to evaluate future carbon emissions savings by replacing gasoline consumption with electricity usage. Under the first two scenarios, a low exponential growth of 15% and 25% is expected capturing 0.7% and 3.9% of 2020 market share, whereas the more aggressive scenario presents a 35% exponential growth (10.4% of 2020 market share).

The forecasted market penetration outlook for EVs is not constant across studies resulting in different projections. After analyzing the literature review about 40% of the analysts expect EVs market uptake range to be between 2% and 5%, almost 30% suggest that EVs market penetration will fall between 5%-10% and the rest forecast a market share up to 25% in 2020. Estimates are based on different assumptions and simulation models.

In an attempt to investigate potential trends across scenarios, which will contribute to the configuration of the scenarios of this thesis, the following chart illustrates a summary consisting of the annual market penetration scenarios by percentage.



The studies used to the analysis were published between 2007 and 2012. The time that each study was released could have an impact on the market penetration scenarios because of different policies existing at that specific time, tax incentives, gas price and generally different economic conditions. It is observed that the years 2008, 2009 and 2010 share the same number of publications. When comparing scenarios from 2007 to 2012, it is remarkable that in 2007 both studies introduced aggressive scenarios with EVs reaching 80% of market share (EPRI and NRDC, 2007). In 2008, the possibility of low EVs deployment was implemented with 20% of the studied scenarios being conservative, in 2009, 50% and in 2010, 36% of the scenarios forecasted a market penetration under 5% of EVs uptake. Moreover, the methods used to forecast the EVs market adoption play a significant role in the projected rates (S-curve, exponential curve, different market and purchase models, general equilibrium model).

In scientific literature many studies have explored the advantages of EVs and report that a net abatement in greenhouse (GHG) emissions can be attained by replacing internal combustion engine vehicles (ICEV) with EVs [Kromer and Heywood (2007); Dijk and Yarime (2010); Parks et al. (2007); WWF (2012); Bradley and Frank (2009); Thiel et al. (2010)]. More specifically, EPRI and NRDC (2007) after applying a set of future penetration scenarios conclude that PHEVs can reduce GHG emissions up to 65% when compared to conventional cars and 40% when compared to HEVs. Same results are observed in “On the Road in 2035” report (2008). Baptista et al. (2009) conclude that the introduction of new technology leads to decrease in local pollution with 11%-26% reduction for CO, 30-35% for HC, 15-17% for NOx and 17-60% for PM. It is remarkable though that EVs' emissions are released at the electricity-generating power plant, while the vehicle is used elsewhere. O'Mahony et al. (2011) used COPERT 4 model to measure the potential reduction in tailpipe GHG emissions and concluded that there will be significant reduction in GHG emissions under the most likely scenario of 10% market penetration by 2020. Greater CO_2 reduction could be expected in future if the generated electricity derives from renewable sources [Huo et al. (2010); Cherry et al. (2011)]. With a decarbonized grid, PHEVs can reduce GHG emissions from 4% to 16% compared to HEVs according to The National Research Council (2010).

All the aforementioned studies focus on the benefits on the environment after the introduction of electric vehicles. With respect to the net result regarding GHG emissions from EVs adoption the literature suggests some contradictory findings. Zehner O. (2013) argues that battery electric vehicles (BEVs) are essentially trading one environmental problem for another rather than moving the ball forward on clean transportation. He states that electric cars lead to hidden environmental and health damages after considering their entire lifecycle. He makes a compelling case by arguing that the greenhouse gas (GHG) cost of electricity generation is too high, the production of BEVs is worse than gasoline vehicles, and that any personal automobile is ultimately worse for the environment than public transit. Most electric-car assessments analyze only the charging of the car. But a more rigorous analysis would consider the environmental impacts over the vehicle's full life cycle, from its construction through its operation and on to its eventual retirement at the junkyard. Cherry et al. (2011), in addition, conclude that the actual amount of emissions created per kilometer driven depends on the electricity generation mix of the grid from which the battery is charged. In China's case, for a conventional car, emissions are worse in urban areas, whereas emissions associated with electric vehicles are concentrated in the populated regions surrounding China's mostly coal-fired power stations. Even when this difference of exposure was taken into account, the total negative health consequences of electric vehicles in China exceeded those of conventional cars. Notably, a significant portion of power generation uses coal, which, with today's technology, has a very high carbon footprint.

The literature in evaluating the advantages and disadvantages of EVs underlines the importance of exposure of people to emissions according to the kind of power generation. Huo et al. (2010) stated that greater CO_2 reduction could be expected in future if coal combustion technologies swap with renewable sources and the share of nonfossil electricity increases significantly. On the other hand, even if renewable sources could be applied as primary source of electricity generation on a large scale, manufacturing the vast number of photovoltaic cells required would have venomous side effects according to Intergovernmental Panel on Climate Change (2011). Butcher (2012) contradicts the previous statements, arguing that even with fairly "dirty" electricity, EVs are cleaner than ICEs. When burning gasoline it is produced 21-58% more carbon dioxide than getting the same amount of energy from the electric grid for a car of similar shape and size.

Switzerland is largely free of CO_2 as 60% of its electricity stems from renewable sources. This could be an ideal precondition for a truly sustainable electric car as reported by Beckmann (2010) giving a new insight in the need of adopting the new technology. For example, electricity from nuclear, hydro, solar, or wind-powered plants emits very low amounts of air pollutants. Ontario follows a greener path having already eliminated coal's percentage. The region gets 64% of its electricity from nuclear power. The remainder comes from a mix of natural gas (9%), hydroelectricity (21%) and wind (4%) according to Canadian Nuclear Society (2013).

While electric vehicle technology promises a decrease in emissions, a crucial strategy to promote the adoption of EVs is required. Traditional government intervention policies into the market for new technologies include tax incentives and regulations that favor the adoption of beneficial technologies according to a report commissioned by Tesla (2014). In the case of electric vehicles, UK offers 5000 pounds grant for every model S purchased, no road tax, exemption from London congestion charge. In Denmark, electric cars are exempted from environment tax and they deserve free parking in large cities. Similar patterns are followed in other countries as well. The US government offers a $7500 federal tax credit with the purchase of a new Tesla acquired for personal use. Other incentives given by US government are: a discount in electricity bill, free downtown parking, reduced rates for electric vehicles charging during off-peak hours or even fast-track permitting and customer support to make homes EVs ready in less than a week. Ontario offers an incentive of up to $8500 for purchased or leased EVs, tax deduction, credits and HOV lane privileges to EVs owners. For example, owners of electric vehicles can obtain special green license plates which offer them high priority access to Ontario's high occupancy vehicle (HOV) lanes, even if there is only one person in the vehicle (Ministry of Transportation, 2011). It is also essential that although EVs are currently more expensive to purchase, they can save drivers from significant sums of money over time, in fuel and operation savings, depending on gasoline prices.

With regard to money saving some other concerns are arising when a new energy-efficient version of private car hits the market. People know that EVs consume less and they feel justified in using them more frequently, which in turn augments energy consumption and thus negates the efficiency benefits. This phenomenon is called the rebound effect and contradicts the positive effect of increased efficiency. Santarius (2012) described a Japanese study, which found that hybrid car buyers drove 1.6 times more distance after the purchase of their new cars in comparison to their old vehicles. Three financial rebound effects dive deeper into the seas of the economy. First, there is the income effect, which says saving energy saves money and that money is either spent on an increased use of the same product or on an alternative product that also consumes energy and resources. Second, the reinvestment effect states that when companies save energy through better process management or more efficient machinery, this money is of course reinvested. Increased fuel efficiency means lower fuel costs leading to lower costs for transportation services. In response to improvements in fuel economy, people often increase vehicle miles traveled (VMT) and sometimes proceed to purchase bigger vehicles or more cars than actually needed in the family according to Haan et al. (2006). The third financial rebound effect that Santarius identified is called market price effect. It basically points out that when energy prices fall due to reduced demand in one sector, other sectors increase their demand (and their consumption) simply because it got cheaper. For example, if an electric vehicle is purchased and used as a supplemental vehicle for short trips where the owner previously walked or biked, overall emissions would increase as the VMT would rise. To avoid the rebound effect people should be informed about sustainable transportation and eco-taxes and be aware of environmental issues such as emissions trading so that rebound effects will be partially contained.

In order to determine the factors that influence the EVs market share from buyer's point of view an appraisal of market penetration was conducted. Much research has focused on capturing the characteristics of potential EVs buyers which will be more or less similar to the characteristics of HEVs buyers. Because the decision to buy an EV is part of the total vehicle purchase process, studies dealing with car ownership were also assessed.

According to Hybrid Auto Market Analysis (2007) the hybrid automobile market is divided into different demographic groups including age, gender, generation and social class, education, work, marital status and location of residence as high proportion of the target market live in urban areas. Curtin et al. (2009) conducted a survey to assess the conditions under which U.S consumers would buy a PHEV and concluded that age of householder, income, home ownership, gender, education and geographic location have a major impact on preferences for PHEVs. The most important result was that age along with education influenced PHEVs purchase more than income because it is associated with environmental and technological views. A survey was also designed by Haan et al. (2006) in order to compare buyers of hybrid and conventional vehicles and resulted to define gender, income, education and age as the most important variables that influence HEV ownership. Potoglou and Kanaroglou (2008) tried to model car ownership and specified that household structure, working adults, income, household type, education and mixed density index highly affect the possession of a vehicle. Another variable that impacts alternative fuel vehicles' ownership is the exposure to alternative technologies according to Stuben and Sterman (2008) because when people stay updated on new technologies the probability of purchasing a "greener" vehicle increases. Another study held by Choo and Mokhtarian (2002) focused on assessing the variables that affect vehicle type choices and deduced that along with other characteristics age plays a major role, as older people tend to purchase larger or more luxury cars.

- Definitions of explanatory variables

Household income is a variable that influences significantly car ownership in general and EVs ownership in particular, as it provides a household with the financial means to afford a vehicle and especially an EV that is more expensive (Bhat and Pulugurta, 1998; Chu, 2002; Lane, 2005) . A single-parent family is more unlikely to own many cars because of the high costs of maintenance, making household type an important variable (Hess and Ong, 2002; Potoglou and Kanaroglou, 2008; Chu, 2002). The type of dwelling is important as well. Detached and semi-detached houses usually come with available parking and extra space suitable to locate the charging infrastructure that EVs need. The level of education of members in a household consistently appears to influence EVs adoption because of increased environmental sensitivity for GHG, increased concern for CO2 reductions and willingness to adopt new technologies in order to mitigate costs associated with conventional vehicle (Chu, 2002; Haan et al. 2006; Stuben and Sterman, 2008). The number of children in a house might increase the number of vehicles owned because of additional needs for non-working trips. Children in Hamilton area are strongly dependent on their parents for their mobility as activities like schools or sports are inaccessible by bike or walk. Older people are as well auto-dependent and in conjunction with the level of education, they are more likely to own an EV (Curtin et al. 2009; Choo and Mokhtarian, 2002). Another characteristic that is involved in the process is the number of working adults. As this number increases the probability of owning a car augments as well, because the household can afford a more expensive vehicle (Potoglou and Kanaroglou, 2008). The variable - number of licensed drivers - is contradicting because it is likely to be co-determined with car ownerships levels according to Bhat and Pulugurta (1998). Residential location variable is also found to influence car ownership decisions. A study held by Bento et al. (2005) demonstrated that households have fewer cars when their locations are close to the centre of the city and these people are more likely to own EVs because of their limited range.

All the aforementioned variables were selected to participate in the analysis process, as according to the literature they are considered to highly affect EV’s ownership.

Chapter 3

3. Data and Methodology

This chapter provides an overview of the data and the methodology adopted in this study and used to interpret the results and draw conclusions about the impact of electric vehicles in traffic related pollution reduction.

3.1 Study Area

The effect of EVs on traffic related pollution is assessed at the transportation link level in the Hamilton Census Metropolitan Area (CMA). The Hamilton CMA is a key component of the Greater Toronto and Hamilton Area (GTHA), the largest urban region in Canada and the ninth largest CMA in Canada with a population growing almost 4% between the 2006 and 2011 censuses (Statistics Canada, 2012b). It is located between the US border at Niagara Falls and Toronto, on the western shore of Lake Ontario. The Hamilton CMA is divided into eight municipalities as shown in the map (Burlington, Stoney Creek, Glanbrook, Ancaster, Hamilton, Dundas, Flamborough, Grimbsy) as shown in Figure 1. Grimbsy area though, was not included in the traffic simulation model.

Figure 1. Subregions of Hamilton

The traditional economic activity of Hamilton has been the heavy steel industry, located along the harbour of the city. This fact justifies the poor air quality of Hamilton and the need to improve it. The last years, service sector has also started developing in terms of employment and tends to surpass manufacturer sector. The study area is divided into 223 Traffic Analysis Zones (TAZ) which are connected through 831 network links. These links include 223 pseudo links which connect the centroid of each TAZ to the main network of the Hamilton CMA. Figure 2 depicts the study area and its subregion along with the arterial and the main highways.

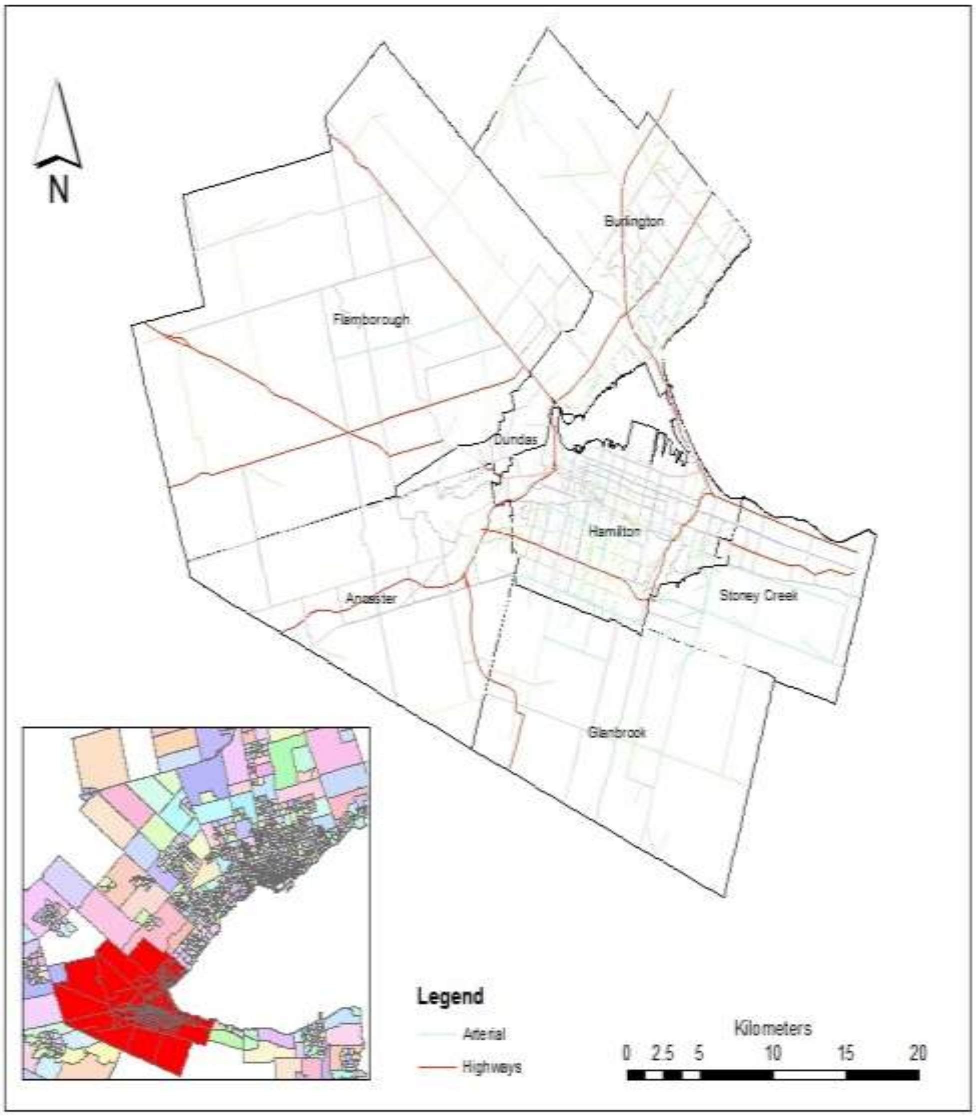


Figure 2. Arterial roads and highways in Hamilton

The major provincial highways are Queen Elizabeth Way (QEW), Hwy 401, Hwy 403, Hwy 407, and some local highways are Lincoln M. Alexander Parkway and Red Hill Valley Parkway.

3.2 Data

The data used for this study were derived from three sources. The first set of data includes demographic and socioeconomic characteristics of people at the census tract level, taken from 2006 Canadian Census and converted, when needed, into proportional data. The last set of data was the vehicle registration data obtained from POLK (www.polk.com). OD matrices were derived from household travel surveys (TTS, 2006).

3.2.1 Canadian Census Data

Demographic, social and economic data were derived from this source. This information was available in different levels of aggregation, but census tract was selected in order to match with the vehicle registration data. The data were converted when needed into proportional data or into binary categorical data. Variables like population, average income, number of vehicles, number of licenses per census tract were used as is. The number of children, adults or seniors, males and females, full time workers and part time workers, owned dwellings or rented and in general variables that were split into subclasses were converted into proportional data. Lastly, income was introduced as a set of dummy variables defined by the categories:

- low -less than CAD 30000 (1 if income belongs to this category, 0 otherwise),
- medium -CAD 30001-80000 (1 if income belongs in the second case, 0 otherwise)
- high -CAD 80001 and more (reference variable).

The variables that were selected to constitute our database are shown in Table 3 in Appendix.

3.2.2 Vehicle Registration Data

Polk data provided information on the vehicle type, fuels, model years and Gross Vehicle Weight Rating (GVWR) for every passenger car registered in the study area. The distribution of vehicles in Hamilton by model year is illustrated in Figure 3 and the distribution of HEVs in Fig.4. After 2000 we observe a great explosion in car ownership. Currently, 88,85% of cars in Hamilton CMA use gasoline, 2.66% flex fuel, 2,48% diesel, 0,003% petrol , 0,001% electricity, 5,58% use unknown fuel type and 0,42% are hybrids according to POLK data. As the car dependency augmented, actions promoting sustainability of the transportation system had to be taken. With regard to these actions, beyond 2000, automobile manufacturers commenced to introduce a new generation of cars that produce fewer emissions and use little gasoline, hybrids.

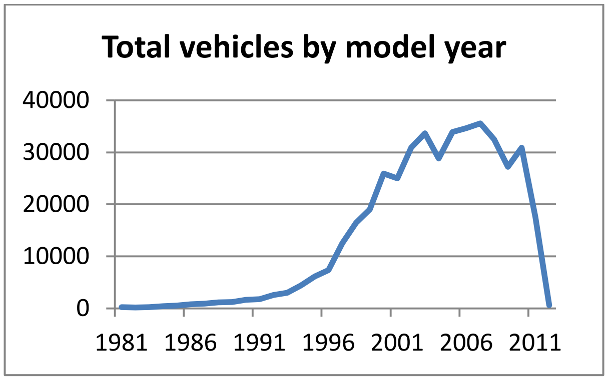


Figure 3. Vehicle's distribution by model year

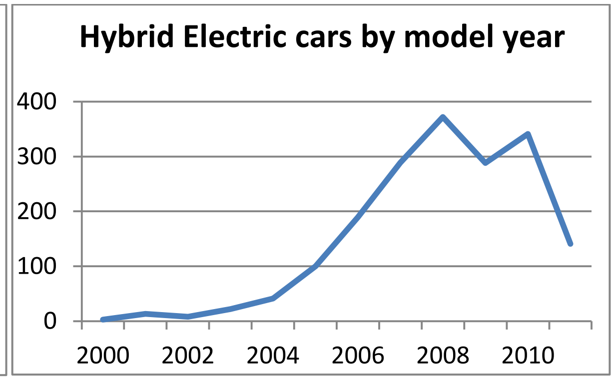


Figure 4. HEVs distribution by model year

The total number of electric vehicles in 2012 was only 3. Since very few EVs were registered in the Hamilton CMA the study was based on the counts of HEVs for the simulation of EVs and the assessment of the effect of EVs on emissions, following the assumption that similar penetration rate to that of HEVs could be found for EVs too [Cunnungham (2009);Perujo and Ciuffo (2010)]. The owners of EVs have the same characteristics with those of hybrid cars as they share same components (batteries, electric motors).

In 2008 the number of hybrid cars was 848, number that almost doubled during the next 4 years. The distribution of HEVs can be observed in the following figure. There were two census tracts with high counts of HEVs (ctuid 5370061in Hamilton and 5370206 in Burlington). The two municipalities owned a number of "green" vehicles and these were registered in the two aforementioned CTs. In order to avoid a misappraisal these extreme values had to be adjusted to include only the vehicles owned by people. This was achieved by attributing to both CTs, the average of the counts of the neihbouring CTs.

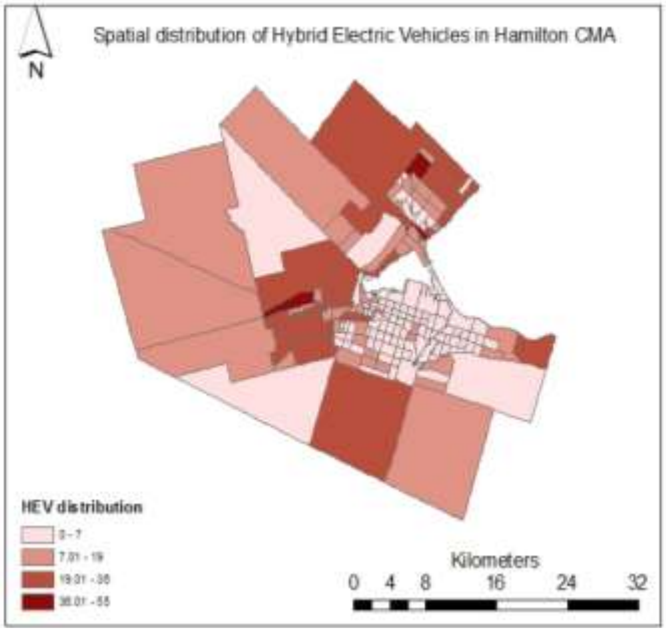


Figure 5. Spatial distribution of HEVs

We observe that people in downtown Hamilton don't own many HEVs, fact that can be explained firstly by the kind of people living in the centre of Hamilton. Ontario's government provides welfare to people in need like unemployed, drug addicts and generally persons with disabilities. Secondly the small distances of everything in the centre of a town make car use unnecessary. High counts of HEVs can be seen in Dundas, a subregion in Hamilton with highly-educated people and also in Burlington with a significant concentration of people with high incomes. The distribution of income and education is depicted in the following figures.

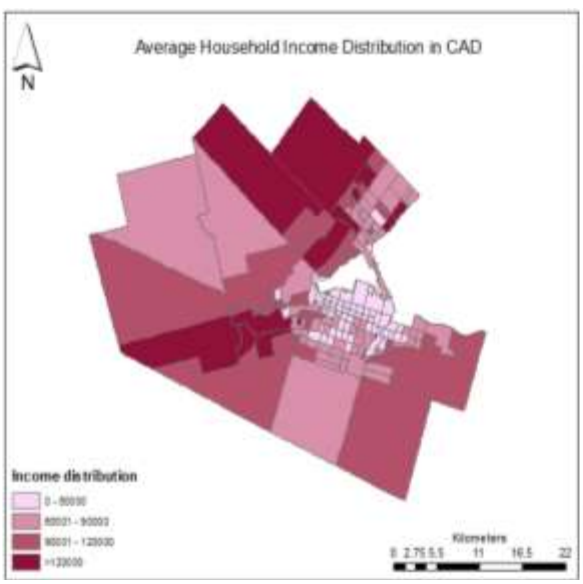


Figure 6. Average income

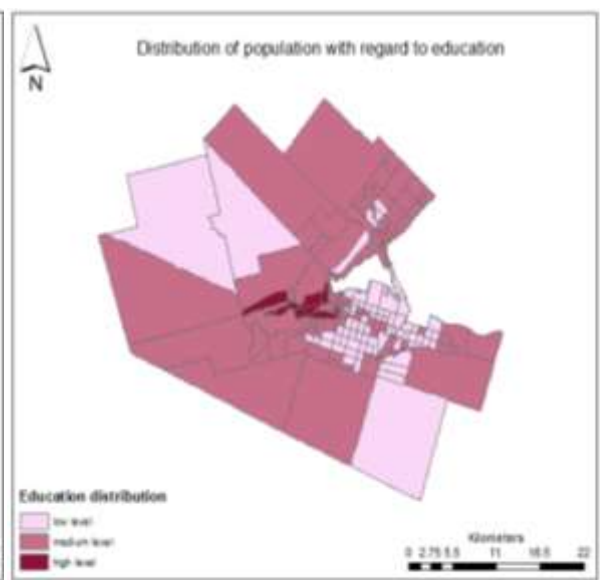


Figure 7. Population distribution

The distribution of HEVs per census tract for years 2008 and 2012 and the descriptive statistics are shown in Figures 8 and 9. A similar trend is presented in both graphs, with a narrow peak and a skew to the right, matching Poisson’s distribution.

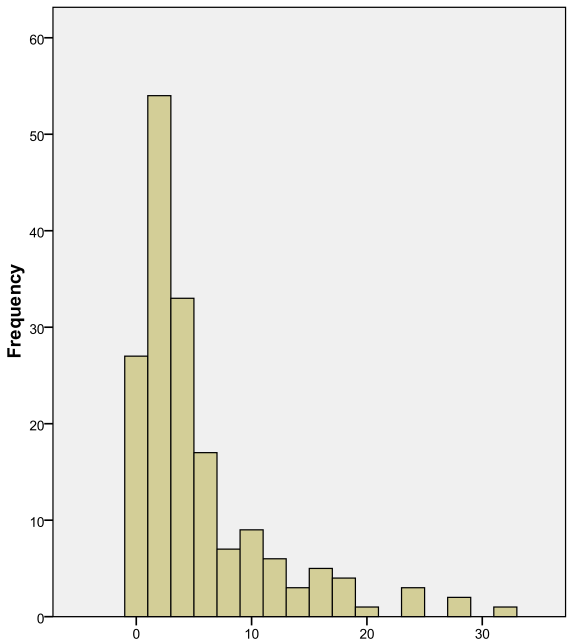


Figure 8. HEVs distribution in 2008

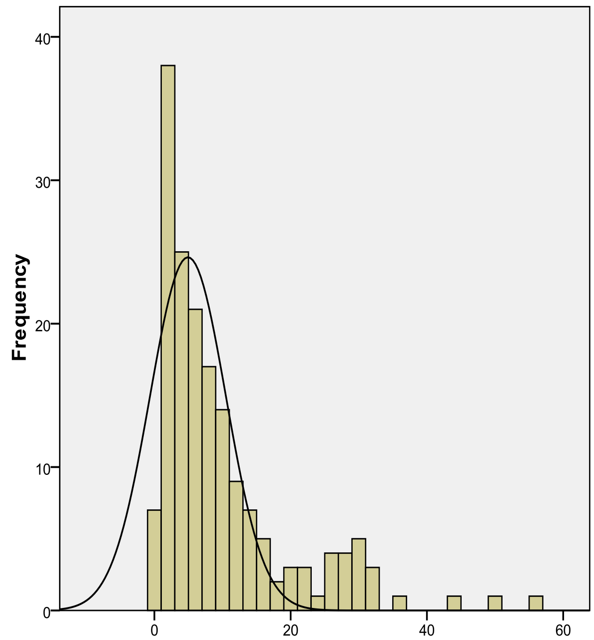


Figure 9. HEVs distribution in 2012

Table 3. Descriptive statistics for number of electric cars in 2008 and 2012

		NHEV08	NHEV12
N	Valid	172	172
	Missing	0	0
Mean		4.92	9.44
Std. Deviation		6.049	9.989
Variance		36.595	99.784
Skewness		2.057	1.873
Std. Error of Skewness		.187	.187
Kurtosis		4.484	3.895
Std. Error of Kurtosis		.371	.371

Table 3 presents descriptive statistics of hybrids for 2008 and 2012. The mean has doubled concluding that there was a significant increase in the number of hybrid cars during these 4 years.

In the following section we describe the methods utilized to approach the problem; that is, the different regression models used, in order to select the appropriate weights in our case, the tests implemented to check for the significance of the models and the integrated models that participated in the process.

3.3 Methods -Determination of analysis techniques

In order to define different distribution patterns of electric vehicles and accurately reflect socioeconomic variations inside Hamilton CMA a regression analysis is required. Regression analysis is used for this research because a regression model can estimate the statistical significance of multiple factors (variables) in one model. The impact of each variable on the dependent variable can be tested as an additional effect. The variables which show significance, can be interpreted that affect the dependent in addition to the rest of the independent variables.

The number of electric vehicles per census tract is a count variable that takes on positive integer values (0, 1, 2 …) reflecting the number of occurrences of an event which cannot happen a negative number of times. The number of EVs will be the dependent variable in the analysis. The appliance of a linear or log-linear regression model with ordinary least squares (OLS) when the dependent variable is discrete should be avoided because the results from such models could be negative and not integer, inconsistent with the initial assumption. The generalized linear models (GLiM) can provide accurate results for data sets having binary, categorical and count dependent variables (Dobson A. J., 2002). A GLM in general, can be constructed by choosing an appropriate link function and response probability distribution according to Agresti (2002). From a methodological standpoint, the most common approach to analyze count data is to apply Poisson or negative binomial regression models because of the distributional property (i.e random, discrete and non-negative) of counts. Because the number of EVs is discrete and non-negative integer value, the Poisson regression technique is a natural first choice for modeling. Although the Poisson regression model has desirable statistical properties for describing this type of data, it has an important constraint which is that the mean must equal the variance. This can account for the observed pattern in count data that variability increases with level.

When the variance is greater than the mean, the data are overdispersed. Overdispersion is the result of Bernoulli trials with unequal probability of independent events (also known as Poisson trials). To adjust for this overdispersion, Poisson regression model is not suggested, alternatively the negative binomial regression will be implemented [Lord and Mannering

(2010); (Hauer E., 2001); (Hilbe J.M., 2007); .Count regression models are generally fit as loglinear models; that is, it is the logarithm of the mean that is modeled as linear function of predictors, or equivalently, the mean is modeled as an exponential function of the predictors. This implies, for example, a proportional relationship with a variable, rather than an additive one.

Deriving the negative binomial regression model can start with a Poisson model, which is defined by the following equation:

$$\boldsymbol{P(n_i) = \frac{\lambda_i * \exp(-\lambda_i)}{ni!}} \qquad (1)$$

Where $P(n_i)$ is the probability of n HEVs existing in a census tract i over the specific time period and λ_i is the expected HEVs frequency for census tract i. The expected HEVs frequency is assumed to be a function of explanatory variables such that:

$$\boldsymbol{\lambda_i = \exp(\beta X_i)} \qquad (2)$$

Where X_i is a vector of explanatory variables that could include the area of the census tract i and the socioeconomic characteristics of its residents that determine the possession of HEVs; and β is a vector of estimate coefficients. With this form of λi, the coefficient vector β can be estimated by the maximum likelihood method.

To overcome the overdispersion problem, negative binomial regression can be applied by relaxing the assumption that the mean of the number of HEVs equals the variance. To do this, an error term is added to the expected HEVs frequency (λi) such that the equation becomes

$$\boldsymbol{\lambda_i = \exp(\beta X_i + \varepsilon)} \qquad (3)$$

Where exp(ε) is a gamma-distributed error term with mean one and variance α. This gives a conditional probability

$$\boldsymbol{P(n_i|\varepsilon) = \frac{\exp[-\lambda_i * \exp(\varepsilon)][\lambda_i * \exp(\varepsilon_i)]^{n_i}}{n_i!}} \qquad (4)$$

The form of the model equation for negative binomial regression is the same as that for Poisson regression. The log of the outcome is predicted with a linear combination of the predictors:

$$\boldsymbol{\log(\text{Number of EVs}) = \text{Intercept} + b_1X_1 + b_2X_2 + \cdots + b_nX_n} \qquad (5)$$

This implies:

$$\boldsymbol{\text{Number of EVs} = e^{(\text{Intercept}+b_1X_1+b_2X_2+\cdots+b_nX_n)} = e^{(\text{Intercept})} * e^{(b_1X_1)} * e^{(b_2X_2)} * e^{(b_nX_n)}} \qquad (6)$$

To avoid multicollinearity the variance inflation factor (VIF) should be identified. VIF is the measure of how highly correlated each independent variable is with other predictors in the model. Values larger than 10 for a predictor imply large inflation of standard errors of regression coefficients due to this variable being in model. Inflated standard errors lead to small t-statistics for partial regression coefficients and wider confidence intervals.

--Tests of significance of model fit

In GLiMs, the test statistic is a chi-square test which is the difference between two deviances; the first deviance is that from the base model and the second deviance is that from a more complex model. The chi-square test examines the reduction in deviance from the addition of one or more predictors to a base model which is the null model containing only the intercept. The degrees of freedom for the chi-square test equal the number of predictors added to the base model to form the more complete model. (Fox J., 2008)

Omnibus test

$$\boldsymbol{X^2 = -2 * [LL(\beta_R) - LL(\beta_u)]} \qquad (7)$$

Where

- $LL(\beta_u)$ is the log likelihood of the unrestricted model
- $LL(\beta_R)$ is the log likelihood of the restricted model (without independent variables)

Omnibus test could be used to estimate the Pseudo R ρ^2 (Rho square)

$$\boldsymbol{\rho^2 = 1 - LL(\beta_u)/LL(\beta_R)} \qquad (8)$$

Having the pseudo R it is possible to estimate R^2 through empirical relation set by Domencich and Mcfadden (1975)

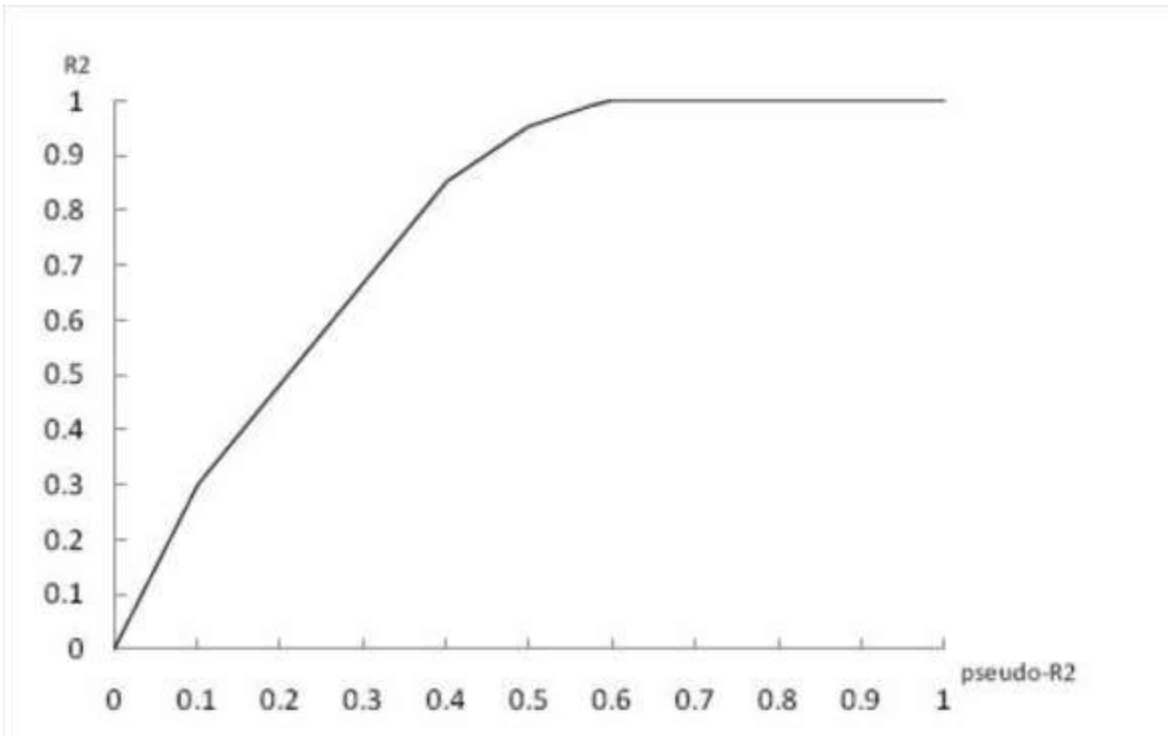


Figure 10. Estimation of R^2 by Domencich and Mcfadden

3.3.1.Model adequacy

The appropriate graphical method for assessing model adequacy is to plot the residuals against the predicted outcome values. For nonlinear models though, such as Poisson or negative binomial regression, raw residuals will always be heteroscedastic and asymmetric, so alternative types of residuals must be used. (Cameron A.C. and Trivedi P.K., 1998), (Hardin J.W. & Hilbe J.M, 2007) (Hoffman J.P., 2004). The scatterplot helps to detect non-linearity, unequal error variances and outliers. The plot of residuals versus each predictor should be a random cloud and no pattern should appear. Observations with values larger than 3 in absolute value are considered outliers.

3.3.2.Tests of overdispersion

The likelihood ratio test or the Score test (also known as the Lagrange multiplier test) is used to test data for overdispersion. These tests are asymptotically equivalent, meaning that they will produce the same result with very large sample sizes. The likelihood ratio test is a nested model test that compares the deviance of a model with fixed overdispersion parameter (a) to the deviance of a model with estimated parameter. Comparing the difference in deviances to a chi-square distribution will determine whether overdispersion is present or not as Hilbe (2007) has suggested.

3.3.3.Integrated models

Three models were used to carry out the objective of the report: MOBILE 6.2C, TRAFFIC and LINK EMISSIONS. These integrated models were developed for a series of previous projects at CSpA in order to estimate traffic emissions in Hamilton, Toronto and Vancouver.

3.3.3.1.MOBILE 6.2C

MOBILE 6.2C is the Canadian version of MOBILE 6 Vehicle Emission Modeling Software, developed by the US Environmental Protection Agency (EPA) and is used to support air quality planning and emission inventory development. The model is designed to predict emission factors in grams per kilometer or grams per hour under various conditions for any calendar year between 1952 and 2050 for 19 different pollutants including: hydrocarbons (HC), carbon monoxide (CO), oxides of nitrogen (NOx), carbon dioxide (CO2), particular matters with 2.5 cm diameter (PM2.5), particular matters with 10cm diameter (PM10) and air toxics in response to a set of vehicle fleet, operational and climate characteristics.

Factors considered in emissions model development include vehicle fuel and technology, facility type, meteorology, vehicle speed, vehicle class and age, vehicle fleet distribution and emission control standard. Emission factors are characterized by vehicle fuel and technology, facility type, speed and calendar year (EPA, 2003).

The output from Mobile 6.2C is a set of emission factors which depend on the meteorology of the study area (hourly temperature, humidity and daily barometric pressure), the type of vehicle (passenger vehicles, light duty commercial, medium duty commercial, heavy duty commercial and public transit buses), the type of emissions, the type of the road (freeway or arterial) and the day of the computation (weekday or weekend). All these are parameters that influence the estimation of emission factors.

Mobile 6.2C classifies vehicles are based on the Gross Vehicle Weight Rating (GVWR) as illustrated in Table 4: US Federal (Highway Administration Quick Response Freight Manual)

Table 4. Vehicles classification. Source: EPA

Vehicle Type	Mobile 6.2 C Fleet Number	Mobile 6.2C Description
Light duty passenger vehicles(LDPVs)	1	LDGV Light-Duty Gasoline Vehicles (Passenger Cars)
	14	LDDV Light-Duty Diesel Vehicles (Passenger Cars)
Light duty commercial	2	LDGT1 Light-Duty Gasoline Trucks 1 (0-6,000 lbs. GVWR, 0-3,750 lbs.

vehicle(LDCVs)	3	LDGT2 Light-Duty Gasoline Trucks 2 (0-6,000 lbs. GVWR, 3,751-5,750 lbs. LVW)
	4	LDGT3 Light-Duty Gasoline Trucks 3 (6,001-8,500 lbs. GVWR, 0-5,750 lbs. ALVW)
	5	LDGT4 Light-Duty Gasoline Trucks 4 (6,001-8,500 lbs. GVWR, greater than 5,751 lbs. ALVW)
	15	LDDT12 Light-Duty Diesel Trucks 1and 2 (0-6,000 lbs. GVWR)
	28	LDDT34 Light-Duty Diesel Trucks 3 and 4 (6,001-8,500 lbs. GVWR)
Medium duty commercial vehicles(MDCVs)	6	HDGV2b Class 2b Heavy-Duty Gasoline Vehicles (8,501-10,000 lbs.GVWR)
	7	HDGV3 Class 3 Heavy-Duty Gasoline Vehicles (10,001-14,000 lbs.GVWR)
	8	HDGV4 Class 4 Heavy-Duty Gasoline Vehicles (14,001-16,000 lbs.GVWR)
	9	HDGV5 Class 5 Heavy-Duty Gasoline Vehicles (16,001-19,500 lbs.GVWR)
	10	HDGV6 Class 6 Heavy-Duty Gasoline Vehicles (19,501-26,000 lbs.GVWR)
	11	HDGV7 Class 7 Heavy-Duty Gasoline Vehicles (26,001-33,000 lbs.GVWR)
	16	HDDV2b Class 2b Heavy-Duty Diesel Vehicles (8,501-10,000 lbs.GVWR)
	17	HDDV3 Class 3 Heavy-Duty Diesel Vehicles (10,001-14,000 lbs. GVWR)
	18	HDDV4 Class 4 Heavy-Duty Diesel Vehicles (14,001-16,000 lbs. GVWR)
	19	HDDV5 Class 5 Heavy-Duty Diesel Vehicles (16,001-19,500 lbs. GVWR)
	20	HDDV6 Class 6 Heavy-Duty Diesel Vehicles (19,501-26,000 lbs. GVWR)
	21	HDDV7 Class 7 Heavy-Duty Diesel Vehicles (26,001-33,000 lbs. GVWR)
	22	HDDV8a Class 8a Heavy-Duty Diesel Vehicles (33,001-60,000 lbs.
Heavy duty commercial vehicle vehicle(HDCVs)	13	HDGV8b Class 8b Heavy-Duty Gasoline Vehicles (>60,000 lbs. GVWR)
	23	HDDV8b Class 8b Heavy-Duty Diesel Vehicles (>60,000 lbs. GVWR
Transit buses	26	HDDBT Diesel Transit and Urban Buses

Emissions differ depending on the vehicle age, type, and fuel. Emissions are also correlated with break wear, tire wear, hot soak, refueling, engine's start and exhausts when the vehicle is running. The type of the road is also important according to CSpA (2009) as on highways for example higher speed is developed and congestion and commercial truck traffic are noticed. On weekends congestion is reduced, leading to considerably decreased traffic emissions. The user selects pollutants, vehicle fleet, date and hour to be modeled and adjusts road type, fuel characteristics and other parameters. The emission factors generated, produce emissions for different vehicle type, age, speed indicated for the scenario.

3.3.3.2.TRAFFIC

TRAFFIC is a simulation model developed by CSpA to estimate traffic flows, congested travel speeds on the road network of a city and integrate with the emission factors from MOBILE 6.2C to proceed into aggregated estimates for individual pollutants on each link. The input in TRAFFIC is a road network consisting of links and nodes with attributes informed about speed, length, design capacity, link direction, road type and truck usage and an origin –destination matrix for passenger and commercial flows. The O-D matrices are derived from household travel surveys for passenger trips that occur every five years in Canada or estimated from models for commercial trips (TTS, 2006). The Stochastic User Equilibrium (SUE) is the traffic assignment used to estimate the flows on each link, connecting origin and destination under the principle that travel time on all used paths in the city is less than or equal to travel time on any un-used path and simulating the way travelers choose their paths. The software is customized to allow the user to run traffic assignments for weekdays or weekends for any given hour of the day. Since there is information about design capacity, the OD matrices are expressed in passenger car equivalency units (PCE) as shown in table according to Kanaroglou and Buliung (2008).

Vehicle Classes	PCE values
LDPV	1
LDCV	1
MDCV	2
HDCV	2.5

The traffic assignment algorithm proceeds to estimate link flows by defining free flow travel times for all links and starting iteration until convergence is reached.

The result is a table summarizing the total flows of the road network. The software also takes the output from MOBILE6.2C (emission factors) to translate traffic flow for a particular vehicle type into pollution by road link for each of 19 pollutants.

Emission estimates for the different types of vehicles are required for future years as well in order to simulate the future conditions the best possible. The future trips are affected by population and employment growth. The new O-D matrices are created by forecasting the number of new dwellings and population as a consequence and by predicting employment numbers through regression models. Thus, having the road network and future O-D matrices leads to estimate future emissions by road link as reported by CSpA (2009).

3.3.3.3.LINK EMISSIONS

This program allows users to extract and display hourly congested emissions in the Hamilton CMA for 2006, 2011, 2016 and 2021. It is a geographic information system (GIS) framework which is used to display the results from MOBILE 6.2C and TRAFFIC. It generates results either in tabular format or in the form of GIS shapefiles on the link for selected date and time after the integration of three parameters: street network, associated traffic flows and emissions. The outputs are expressed in grams or grams per km and constitute the final results for the study.

The three models are the components used to apply the selected methodological framework, which is described in the following section.

3.4 Methodology

As a means to effectively approach a research topic, the development of the appropriate methodological framework that will lead to the problem's solution is the most essential. The suggested framework should constitute a system with clearly defined boundaries, components and interfaces. The methodological framework is the root of the documentation and forecasting before the intervention of scientists in space according to Koutsopoulos (2006). The following graph depicts the general methodology when willing to approach this kind of problems and then the same scheme is adjusted to meet the needs of this study.

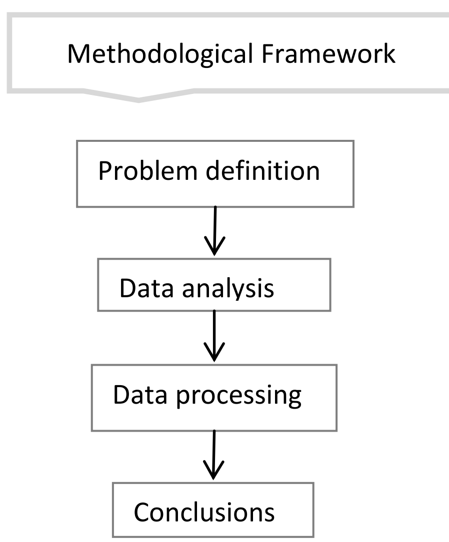


Figure11. General methodological framework

In the order that were implemented the steps followed in the analysis are now described. First, data from Polk were complemented with the Census data and they were used in a regression analysis framework to conclude to the socioeconomic factors that influence EV ownership.

The potential distribution pattern of EVs should be calculated at CT level. One method was to assume that the number of EVs will be equally dispersed to each census tract. This method was soon rejected as different people can afford and are willing to buy an EV. For example, in downtown Hamilton or Burlington where there exist mostly appartements and there is no space to locate the charging equipment it is more difficult for EV ownership. Another method was to estimate the distribution of EVs by mathematical modeling based on current EV distributions and socioeconomic and demographic characteristics in order to understand the contributing factors when buying an EV. Given the vehicle registration data and data from Census, a statistical analysis was conducted to determine the effects of these characteristics on the number of EVs in order to be able to identify the weights that will affect the future EVs distribution. The variables that mostly influence the EV ownership according to the bibliography were included in the models and they are discussed later.

The outputs from the regression analysis were different distributions of EVs (three different models). In order to determine how different socioeconomic factors influence traffic related emissions after the adoption of electric vehicles, the predicted values from the regression analysis were used as weights to modify the O-D matrices which determine the spatial distribution of EVs. By applying the weights, the O-D matrices for 2021 were modified with regard to the trips made by each vehicle type.

Subsequently, the user-equilibrium traffic assignment algorithm incorporated into TRAFFIC module assigned the trips to the road links of the network and computed the weekday and weekend link flows and the congested speeds. Figure 10 represents all the steps taken from the determination of EV distribution to the creation of O-D matrices and the estimation of on-road link emissions.

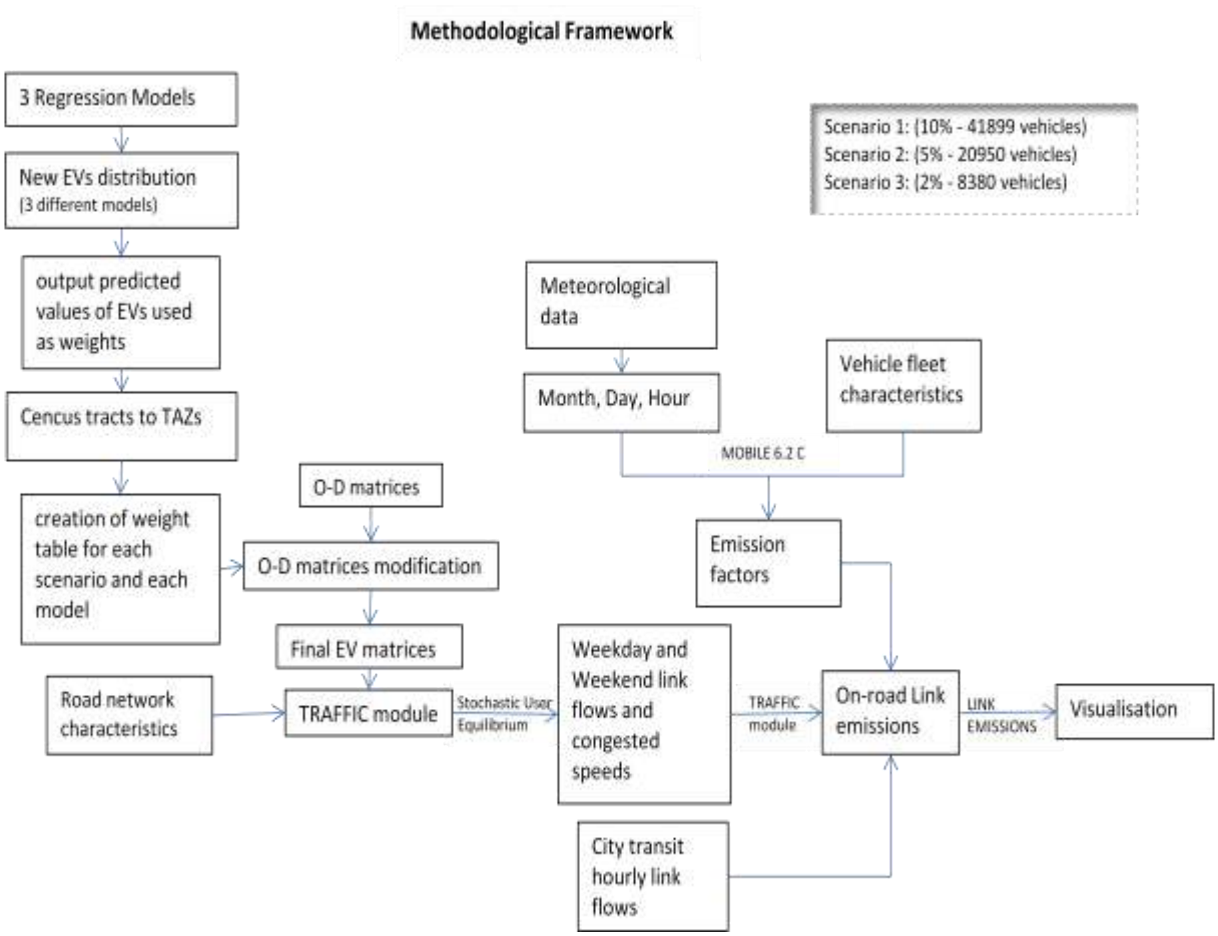


Figure 12. Methodological framework selected for the process

As mentioned earlier, MOBILE6.2C and TRAFFIC aren't flexible to the introduction of a new vehicle category and it would acquire lengthy software modifications to incorporate one. To avoid this process, it was assumed that LDPV and LDCV were equivalent in traffic flow assignment due to their PCE value being equal. These two classes were combined into one to create the LDV class and EVs were introduced in place of LDPV. The LDV O-D matrices were created by adding the trips of passenger and commercial vehicles for all 24 hours of the days cell by cell. The EVs O-D matrices were based on the assumption that a percentage of trips made by LDV from a zone *i* to another zone *j* was made by EVs. For the base case scenario the fraction used was the percentage of EVs per census tract and it was multiplied against LDV O-D matrices. The output matrices are the requested EV matrices whilst the matrices arising after subtracting EV tables from LDV are the final LDV O-D matrices. For example, if there were 10 trips made by LDV at 4 am and the percentage illustrates that 20% were made by EVs then 8 trips were made by LDVs and 2 by EVs. The modification was applied to the trips originating from zone *i* from 4am to 4pm and from 7 pm to 4 am. For the rush hours (4pm to 7pm) when people return from their work the changes were applied to trips ending in zone *j*.

The weights were computed per census tract. The study area though, was divided to Traffic Analysis Zones (TAZs) and the TRAFFIC module was designed to accept this division. To make the modification CTs and TAZs were joined spatially in ArcGIS. Some values had to be fixed though due to the transition from 173 census tracts to 223 TAZs. There were TAZs that included more than one census tract in its boundary, thus the average of the proportion from all tracts in the boundary was taken as TAZs' value. Also, there were census tracts concentrating more than one TAZ. In this case, the same proportion value was given to all TAZ belonging to the same census tract. After this modification the tables with the weights were used to modify the base case matrices along with the future O-D matrices.

The emission factors for the Hamilton CMA were computed at MOBILE 6.2C after initiating vehicle fleet characteristics and the specific hour, day and month of the year. For the estimation of the emission factors a similar process occurred. The emission factors for LDPV and LDCV were added together into one class LDV after they were calculated. While EVs produce zero tailpipe emissions, they still produce particulate matter created by the tires and the breaking systems as conventional vehicles USEPA (2003). Thus, to calculate emission factors for EVs all the emission outputs from the simulation were converted to a value of zero except brake and tire from $PM_{2.5}$ and PM_{10} which were added together to constitute the particulate matters. Therefore HC, CO, NO_x, CO_2 values were turned to zero and from PM BRAKE and TIRE remained stable while the rest (SO_4, OCARBON, ECARBON, GASPM, SO_2, NH_3) were nullified.

The future EV's counts can either be computed by a mathematical procedure or by using the outputs from the regression analysis as weights to distribute the predetermined number of EVs to the census tracts with regard to each scenario. The mathematical process would be the estimation of the values of all independent variables used in the regression analysis in 2021 and the calculation of EVs count from the equation. This approach is very complicated and it is likely to cause bias in the calculation of EVs number due to errors in variables' estimation. The predicted EV counts in each census tract divided by the total number of EVs were used as the weights to distribute the 10%, 5% and 2% of cars respectively in 2021. Once the distribution was completed for each scenario and regression's model the EVs were converted into proportion by dividing the counts by the total registered vehicles in each census tract which were then used as weights to modify the future O-D matrices. The matrices for 2021 were then created based on CSpA's report (2009) with respect to estimations over population and employment growth and were modified with regard to the weights arising from the regression analysis.

Lastly, the emission factors were combined with the traffic volume outputs to estimate the traffic related emissions. Finally, the contribution of EVs to the emissions reduction was evaluated and the results were visualized through LINK EMISSIONS program.

Chapter 4

4. Analysis

The aim of the study is to evaluate the changes in overall traffic emission in the Hamilton CMA after the introduction of EVs. To accomplish this goal, the travel pattern of all vehicle types should be determined. Since no previous data on travel patterns existed for EVs, O-D matrices should be created. This was achieved by modifying O-D matrices for other vehicle classes. Following this, different EV market penetration scenarios were introduced and compared to the base case scenario where no action took place. Therefore, the first hypothesis –Scenario 1- constitutes the most optimistic scenario, describing the distribution pattern after the introduction of 10% of EVs. Under the optimistic scenario we assume that an ambitious 10% (41899 vehicles) of vehicles will be replaced by EVs in 2021, as 30% of the reviewed scenarios estimate a market penetration ranging from 10% to 20% in 2030. This is based on the Hybrid- Technology scenario of Balducci (2008). Scenario 2 refers to moderate market growth of EVs which will result in attaining 5% (20950 vehicles) of market share by the end of 2021. Under the conservative scenario – Scenario 3- EVs will capture 2% of total vehicle fleet (8380 vehicles) by 2021 according to literature.

The regression models were created based on current HEVs distribution. Since very few EVs were registered we made the assumption that they would follow the HEVs distribution as they share common characteristics. In these models, the EV count was used as the dependent variable as it is influenced by the changes in social, economic and demographic characteristics. A generalized linear model (GLM) analysis was carried out to investigate the demographic and socioeconomic factors affecting EV ownership. Since the dependent variable is a count data as mentioned earlier, it may not be reasonable to assume that the data were normally distributed. As a result the traditional linear model is not applicable. As mentioned in the previous chapter, the most common approach to analyze count data is to apply Poisson or negative binomial regression models because of the distributional property of counts. This part of the study models the number of EVs that should be distributed in Hamilton CMA. Although the Poisson regression model has desirable statistical properties for describing count data, it has an important constraint which is that the mean must equal the variance. This can account for the observed pattern in count data that variability increases with level.

The descriptive statistics from Table 1 illustrate that the mean of the variable tested is 9.44 while the variance is 99.784. The variance is greater than the mean, so the data are overdispersed, which suggests that the results of the modeling would be biased if this research used the Poisson regression model.

Another way to decide if negative binomial regression was more suitable was to fit the data to distribution. To determine this we made use of @RISK software, which concluded that NBR (negative binomial regression) fits better to the data than PR (Poisson regression), as it is shown below. Figure 11 depicts that NBR describes adequately the data and table 5 presents the differences between the distribution statistics of the two methods. Blue color describes our data whilst red color represents the negative binomial distribution.

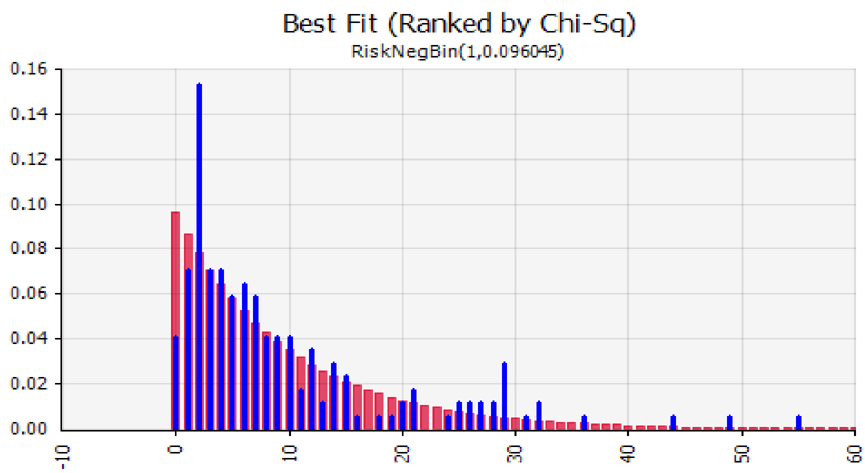


Figure 13. Negative Binomial Regression Distribution

Table 5. NBR's statistics

		Input	NegBin	Poisson
Fit				
	Function		RiskNegbin(1,0.096045)	RiskPoisson(9.4118)
	Method		MLE	MLE
Rankings By Fit Statistic [2 Valid Fits]				
	Akaike (AIC)		#1	#2
	Bayesian (BIC)		#1	#2
	Chi-Sq Statistic		#1	#2

Distribution Statistics				
	Minimum	0	0	0
	Maximum	55	+Infinity	+Infinity
	Mean	9.4118	9.4118	9.4118
	Mode	2	0	9
	Median	6	6	9
	Std. Deviation	9.9683	9.8991	3.0679

	Skewness	1.882	2.0025	0.326
	Kurtosis	6.9357	9.0102	3.1063

In order to predict EVs distribution, a statistical analysis is required and considerate choice of the variables that will constitute the model and reflect who is willing to buy an EV is also needed.

Much research has focused on capturing the characteristics of potential EVs buyers, as these groups tend to dictate the consumption behavior of HEVs buyers. To accomplish this, many studies on market penetration have been reviewed including surveys which gather people's characteristics. Because the decision to buy an EV is part of the total vehicle purchase process, studies dealing with car ownership were also reviewed in the previous chapter.

4.1 Models

When developing a model, one of the most important rules is to adequately describe the data, using the minimum number of variables. In order to assess a statistical model and evaluate its results all the indicators and the statistical tests should be taken into consideration along with the logical consistency. After a few trial-and-errors we concluded to three different models. Each model included the minimum number of variables ensuring that no important variable was omitted from the equations and cause bias in the estimates of remaining coefficients.

Three hypotheses were proposed to examine the factors that contribute to EV ownership. For the development of the models, the best combined independent variables that attribute proper results without bias were selected based on aforementioned relative research. The aspects that influence PHEV ownership according to Curtin et al. (2009) and vehicles in general, as reported by Potoglou and Kanaroglou (2008) are illustrated in the following table in Models 1 and 2 respectively. In Model 3 another variable that was mentioned in other studies -the average number of persons per household- was added as it influences the number of cars that a family could own.

Table 6. Initial variables generating the models

Model 1	**Model 2**	**Model 3**
income	household structure	household structure
age of householder	working adults	household type
education	income	education
home ownership	education	average number of persons per HHLD
gender	household type	age
geographic location	mixed density index	gender

In order to validate the models a graph should be created to check if any of the residuals is excessive or significantly large. Residuals are found to be inside the desired range between [-3.3 – 3.3].

4.1.1 Model 1

The first hypothesis is based on the study of Curtin et al. (2009) who concluded that the age of householder, income, house ownership, gender, education and geographic location have a major impact on preferences for PHEVs. Older people with high income and highly educated are more likely to own an EV as they are aware of the new technologies and are able to afford a more expensive car. In addition, they use the car for shorter distances for shopping or entertainment, as most of them are retired. The combination of these aspects along with the limited range of EVs make these types of vehicles approachable. The location plays a significant role as well, as people who work in the same census tract of their residence can own an EV more easily, due to their limited range.

After applying the Poisson regression model, the goodness of Fit test results that the ratio of deviance to degrees of freedom is 4.564. This is yet another indicator that the Poisson model is not a good fit. From the other side when the negative binomial regression was applied to the same dataset the ratio of deviance to degrees of freedom was 0.584 which is closer to 1. The model with the smallest AIC value is selected. Because models with a larger number of parameters fit better, this second part penalizes more complex models that use more parameters to achieve the same fit, as indicated by the log likelihood. In addition, the BIC values are smaller in the negative binomial model than Poisson which leads to the conclusion that negative binomial regression fits better to the dataset.

Table 7. Statistics for Model 1

Goodness of Fit[b]						
	Negative binomial regression			Poisson		
	Value	df	Value/df	Value	df	Value/df
Deviance	94.569	162	.584	739.427	162	4.564
Scaled Deviance	94.569	162		132.008	162	
Pearson Chi-Square	111.371	162	.687	907.420	162	5.601
Scaled Pearson Chi-Square	111.371	162		162.000	162	
Log Likelihood[a]	-146.742			-370.990		
Akaike's Information Criterion (AIC)	1065.365			1357.979		
Finite Sample Corrected AIC (AICC)	1066.260			1358.874		

Bayesian Information Criterion (BIC)	1090.452			1383.066		
Consistent AIC (CAIC)	1098.452			1391.066		

The results after applying the negative binomial model are illustrated in the following table.

Table 8. Regression's results for Model 1

Parameters	B	St.Error	p-value
Model 1			
Intercept	3.188	0.726	0.000
LEDU	-2.043	0.0159	0.006
[INC=1]	-1.784	0.3496	0.000
[INC=2]	-0.927	0.1951	0.000
[INC=3]	0[a]	.	.
SEN	1.055	0.014	0.000
PWSCT	2.301	0.0002	0.001
MAL	-0.003	0.0585	0.961
ODWE	-0.002	0.0058	0.752

The independent variables were checked for their significance and for their logical consistency. Those that had a p-value less than 0.05 and the sign of the coefficient being same of a priori expectation were added in the model. Home ownership and gender were excluded from the model due to their insignificance and the opposite sign of the coefficient. The variable LEDU has a coefficient of -2.043, which is statistically significant. This means that for each one unit increase on LEDU, the expected log count of the number of HEVs owned decreases by 2.043 cars. The dummy variable INC is also statistically significant. If a person moves from the third category (high income) to the second or first, the expected log count of EVs will decrease by 1.784 and 0.927 respectively. Association was also observed between the number of EVs registered in a census tract and the age of residents. Specifically, those census tracts with great number of seniors were more likely to own more EVs.

In the next iteration the two variables that were insignificant were omitted. The variables were tested for collinearity, but it was found that they were not correlated. The results of the final model are depicted in the following tables. The Goodness of Fit test was slightly different but all the variables were now significant.

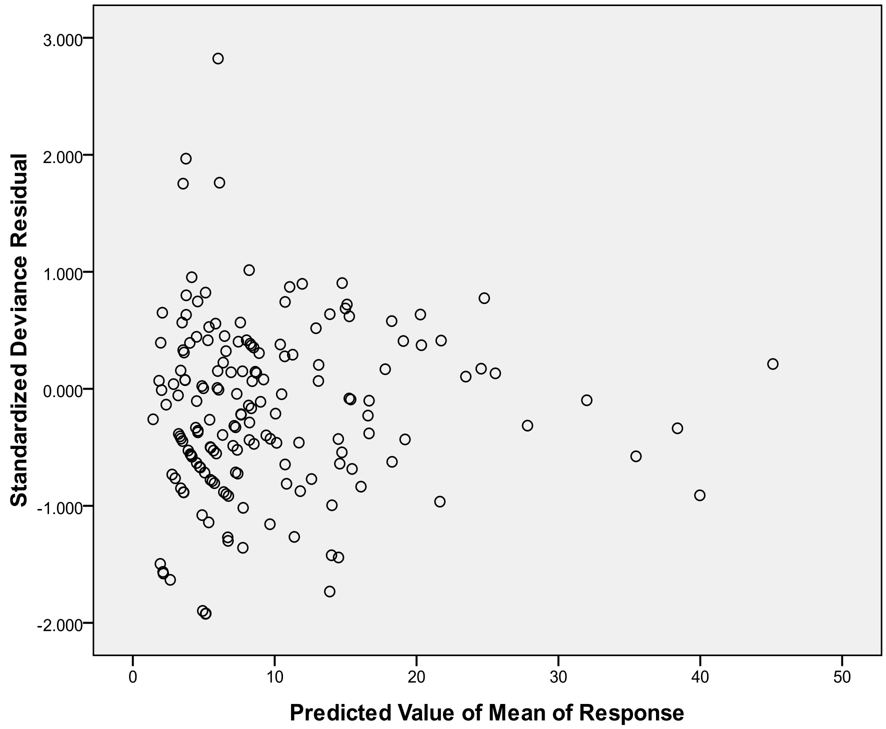
Goodness of Fit[b]

	Value	df	Value/df
Deviance	100.532	164	.613
Scaled Deviance	100.532	164	
Pearson Chi-Square	115.456	164	.704
Scaled Pearson Chi-Square	115.456	164	
Log Likelihood	-126.742		

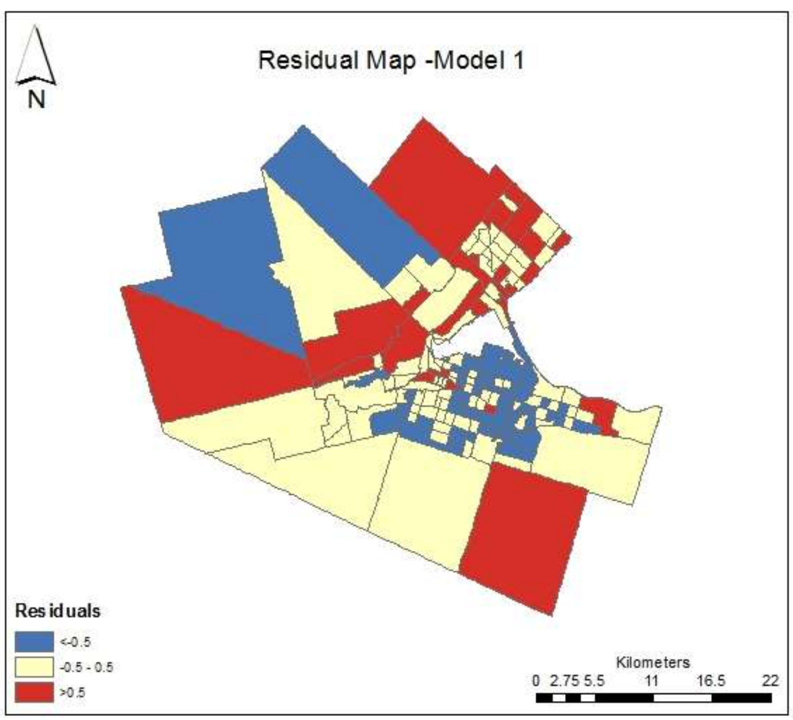
Omnibus Test[a]	Likelihood Ratio Chi-Square	df	Sig.
	192.238	5	.000
Lagrange Multiplier Test	**Likelihood Ratio Chi-Square**	**df**	**Sig.**
Ancillary Parameter	78.506	1	0.000

The Goodness of Fit test after subtracting the insignificant variables is improved. The Omnibus Test provides tests of the model as a whole. The likelihood ratio chi-square is the result after comparing the model to a model without any predictors (null model) and it proved significant. The Lagrange Multiplier test checked the fixed ancillary parameter for overdispersion, as Hilbe (2007) has suggested and concluded that the model is highly significant.

In order to check if any of the residuals is excessive or significantly large, the following graph was created. As a result, the model is exactly predicting the responses. For census tracts with fewer counts of EVs a wider range of residuals is observed. The residual is the difference between the predicted values and the observed and is mapped below. The tracts with the major differences can be observed with the blue and red color. Burlington and Hamilton present heterogeneity along with some other tracts in the study area.



Standardized Deviance Residual
3.000
2.000
1.000
0.000
-1.000
-2.000
0
10
20
30
40
50
Predicted Value of Mean of Response



N
Residual Map -Model 1
Residuals
<-0.5
-0.5 - 0.5
>0.5
Kilometers
0 2.75 5.5 11 16.5 22

4.1.2 Model 2

The second model takes into consideration the independent variables that impact the vehicle ownership as analyzed by Potoglou and Kanaroglou (2008). In their study they concluded that household structure and type, income, the level of education, the working adults and the mixed density index influence vehicle ownership. The –mixed density index- variable was excluded from the beginning due to lack of data. The variable selected to represent household type was the single-parent households (SINPAR), as this type is deterrent to own an EV due to their high costs of maintenance. The other variables that belong to the same group (household type) were not added to avoid collinearity. The variable chosen to represent household structure was the couples with children at home (CWCHILD). This variable was expected to influence positively the model, as the number of children in a house might increase the number of vehicles owned because of additional needs for non-working trips.

Both Poisson and negative binomial regression were applied to this model as well. Overdispersion was obvious in this model too, as the ratio of deviance to degrees of freedom is 4.685 for the Poisson distribution. The AIC value is smaller in the negative binomial model, the same for BIC value as well leading to the conclusion that negative binomial regression fits better to this dataset than Poisson.

Table 9. Statistics for Model 2

Goodness of Fit[b]						
	Negative Binomial Regression			Poisson		
	Value	df	Value/df	Value	df	Value/df
Deviance	101.875	163	.625	763.609	163	4.685
Scaled Deviance	101.875	163		126.350	163	
Pearson Chi-Square	142.136	163	.872	985.104	163	6.044
Scaled Pearson Chi-Square	142.136	163		163.000	163	
Log Likelihood[a]	-135.105			-283.081		
Akaike's Information Criterion (AIC)	1064.211			1380.162		
Finite Sample Corrected AIC (AICC)	1064.902			1380.853		
Bayesian Information Criterion (BIC)	1086.161			1402.113		
Consistent AIC (CAIC)	1093.161			1409.113		

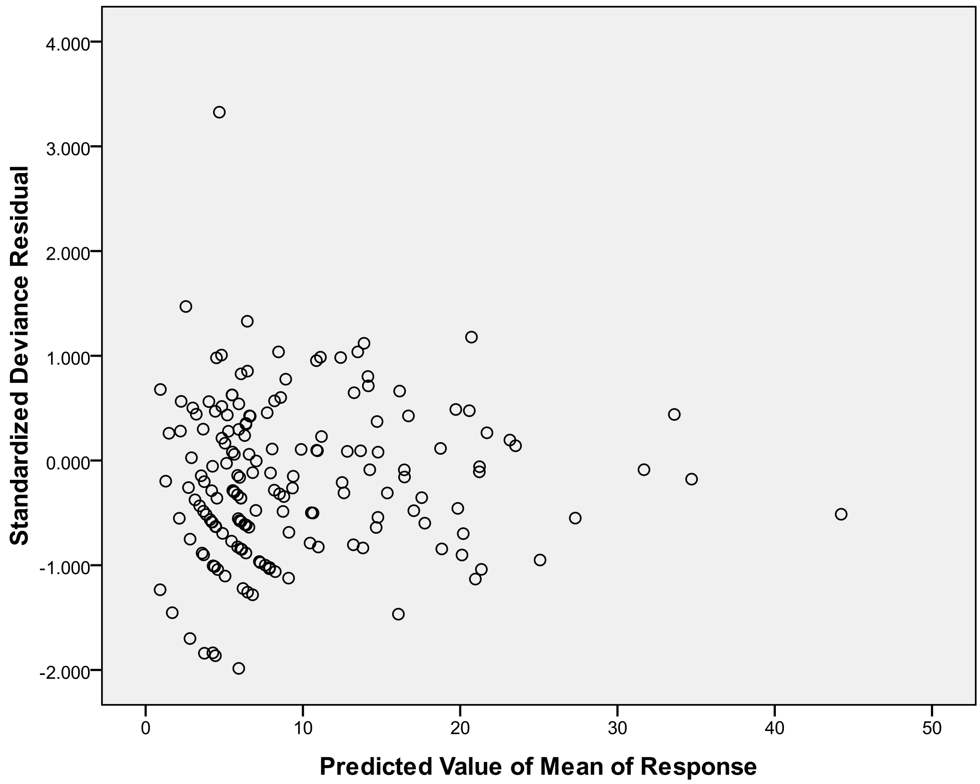
The results after applying the negative binomial regression are depicted in the following table. The independent variables were examined for their significance to the model. All the variables were significant at the 99% confidence as all probability values were <0.05 except LEDU. This variable was marginally significant and it was not eliminated from the model, because education plays a major role in EVs ownership. The highest the level of education. the more environmentally friendly behavior and increased concern for CO2 reduction people have.

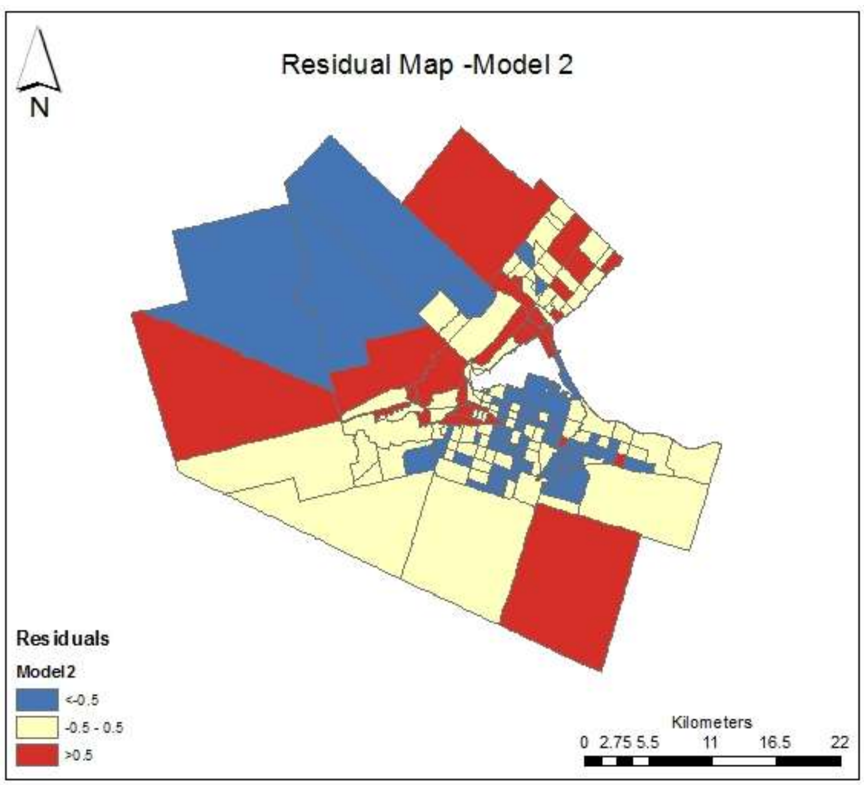
Table 10. Regression's results for Model 2

Parameters	B	St.Error	p-value
Model 2			
Intercept	4.167	0.8287	0.000
LEDU	-3.031	0.0157	0.051
[INC=1]	-0.984	0.4034	0.015
[INC=2]	-0.405	0.2325	0.081
[INC=3]	0	.	.
SINPAR	-1.532	0.0011	0.048
CWCHILD	2.161	0.0004	0.049
UNEMP	-3.334	0.1092	0.002

The independent variables were checked for their logical consistency and the signs of the coefficients were similar to the a priori expectation. The variable working adults was chosen to be represented by the variable UNEMP and it had a coefficient of -3.334, which is statistically significant. This means that for each unemployed person added, the expected log count of the number of EVs owned decreases by 3.334 cars. It is observed that the indirect indication of income level has a strong impact on the model. Relationship between single-parent households and number of EVs owned was also found. The analysis suggested that census tracts with a lower proportion of single-parent households were associated with a higher number of EVs ownership. Association was also ascertained between the number of couples that have children and the number of EVs registered in the census tracts.

For the second model the result of the Omnibus test was a likelihood ratio chi-square of 188.511, significant at the 99% confidence interval. Negative binomial regression was deemed adequate after the Lagrange Multiplier Test checking for overdispersion (chi-square for ancillary parameter was computed to be 68.200, significant at the 99% confidence interval). Subsequently, the graph illustrating the residuals against the predicted values was created. It was observed, that the model is predicting the values efficiently as the residuals were concentrated into the pursued range. The residuals map depicts where the difference between the predicted and the observed values is noticeable.


4.000
3.000
2.000
1.000
0.000
-1.000
-2.000
Standardized Deviance Residual
0
10
20
30
40
50
Predicted Value of Mean of Response


N
Residual Map -Model 2
Residuals
Model2
<-0.5
-0.5 - 0.5
>0.5
Kilometers
0 2.75 5.5 11 16.5 22

4.1.3 Model 3

For the third hypothesis, different variables were used in order to represent the same groups. Different combination took place in order to find the variables that don't add bias in the model. For example the household type was now described by the variable owning dwelling (ODWE) and the household structure by the variable apartments, duplex dwellings (DDWE). A new variable was introduced into the model as well – the average number of persons per household- because the size of households has been ascertained affecting vehicle ownership and along with high education the EVs ownership. Income along with the level of education were deemed as the most important variables across the studies (Haan et al., 2006; Curtin et al., 2009; Chu, 2002) with the latter being added again to model. This can be explained if we consider that income is described by household type indirectly, because when a household owns a house, it is probable that it can afford owning an EV. Furthermore, if the house structure is a single or detached house as well, there is availability of free parking in garages and space suitable to locate the charging infrastructure that EVs need. Age and gender were added as well. The gender did not follow the a priori expectations as it is common that males have the willingness to adopt new technologies and the variable of age was insignificant. The variables were tested for collinearity existence.

Table 11. Initial regression's results for Model 3

Parameters	B	St.Error	p-value
(Intercept)	9.231	3.3046	0.005
LEDU	-1.345	0.0157	0.000
ODWE	0.917	0.005	0.001
DDWE	-1.058	0.0206	0.005
NPPCF	-0.652	0.4637	0.066
MAL	-0.103	.0568	0.071
SEN	0.010	.0194	0.624

Poisson regression model was applied to the last model as well, with the same results. The ratio of deviance to degrees of freedom is 6.393 as seen in the results of Goodness of Fit test. The same ratio after implementing the Negative binomial regression was 0.853, the closest to 1 value of the three models assessed. All the other results from Goodness of Fit test indicate that the regression that was chosen to be applied was the most appropriate. In the second iteration the variables gender and age were excluded.

Table 12. Statistics for Model 3

Goodness of Fit[b]						
	Negative Binomial Regression			Poisson		
	Value	df	Value/df	Value	df	Value/df
Deviance	140.745	165	.853	1054.923	165	6.393
Scaled Deviance	140.745	165		137.690	165	
Pearson Chi-Square	146.685	165	.889	1264.158	165	7.662
Scaled Pearson Chi-Square	146.685	165		165.000	165	
Log Likelihood[a]	-126.79			-428.738		
Akaike's Information Criterion (AIC)	1093.932			1667.475		
Finite Sample Corrected AIC (AICC)	1094.297			1667.841		
Bayesian Information Criterion (BIC)	1109.611			1683.154		
Consistent AIC (CAIC)	1114.611			1688.154		

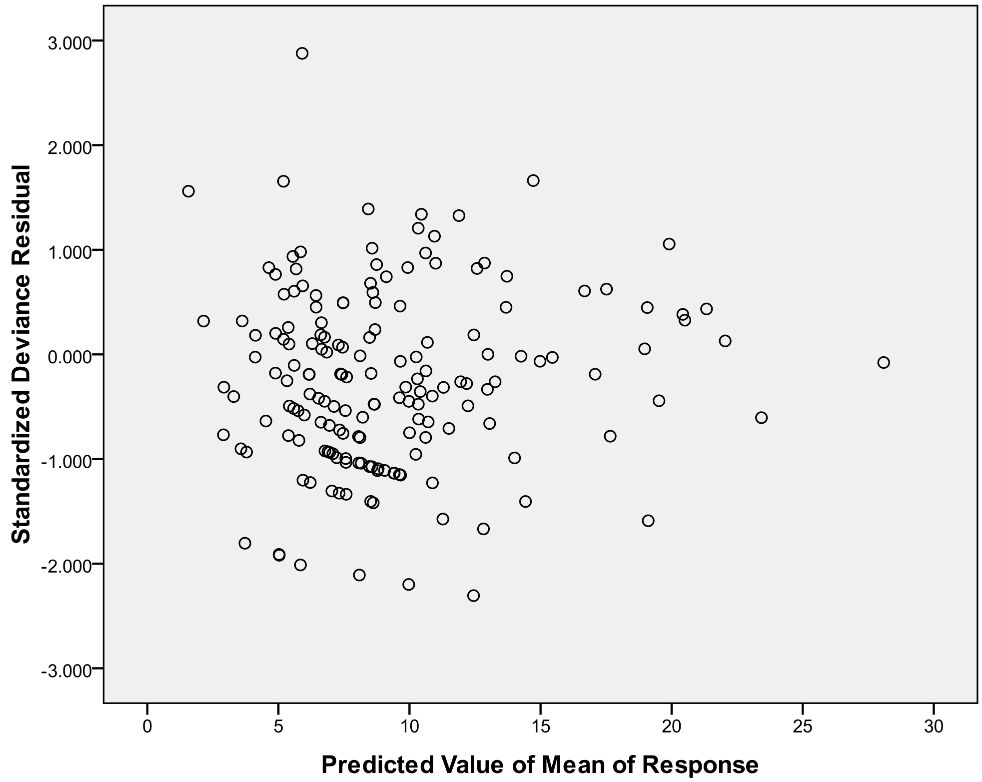
The results after implementing the regression model are illustrated in the following table. The independent variables were examined and were found significant to the model as probability values were all below 0.05. The independent variables were checked for their logical consistency. The size of the household was found to influence negatively the model. The variable household type was chosen to be described by the variable ODWE and it has a coefficient of 1.017, which is statistically significant. This means that for each one unit increase on owning dwellings, the expected log count of the number of HEVs owned increases by 1.017 cars. Relationship between apartments (household structure) and number of HEVs owned was also found. The analysis suggested that the highest incidence of HEVs counts was associated with the census tracts with a lower proportion of apartments (P=0.005).

Table 13. Final regression's results for Model 3

Parameters	**B**	**St.Error**	**p-value**
Model 3			
Intercept	6.355	1.5670	0.000
ODWE	1.017	0.005	0.001
DDWE	-0.958	0.0206	0.005
LEDU	-2.762	0.0157	0.000
NPPCF	-0.852	0.4637	0.066

For the last model the result of the Omnibus test was a likelihood ratio chi-square of 199.511, significant at the 95% confidence interval. Another way to check for overdispersion was the

Lagrange Multiplier Test (chi-square for ancillary parameter was computed to be 75.755, significant at the 95% confidence interval). Following this, the graph illustrating the residuals against the predicted values was created. It was observed, that the model is predicting the values efficiently as the residuals were concentrated into the pursued range [-3.3 to 3.3].



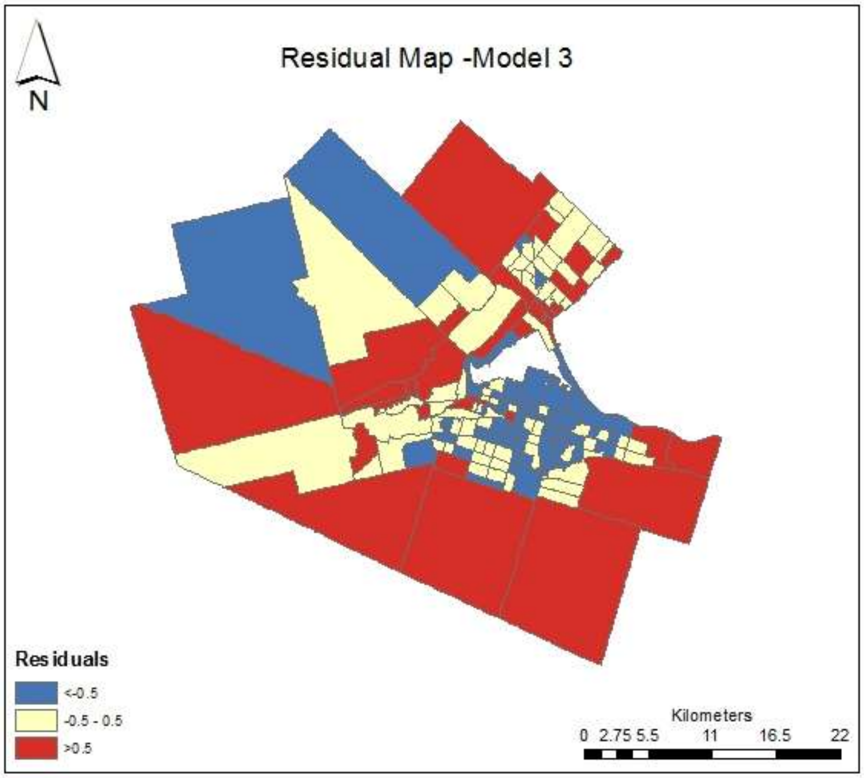


Table 17 in the appendix presents a summary of negative binomial distribution – based models. The predicted EV counts from each model were used along with the observed values in order to calculate the pseudo-R^2 values. These values provided an estimate on how the models fit the observed counts. The pseudo- R^2 values indicate that the best model out of the three can explain 44% the variation in HEV ownership.

Table 14. R^2 computation for the three Models

	Model 1	Model 2	Model 3
Chi-square	192.238	188.511	199.511
p-value	0.000	0.000	0.000
$LL(\beta_u)^2$	-126.742	-135.105	-126.79
$LL(\beta_R)^3$	-222.861	-229.361	-226.546
Pseudo R^2	0.4313	0.4109	0.4403
R^2	0.89	0.88	0.91

The correlation between the predicted values and the observed was examined with Pearson's correlation coefficient being 0.75 for Model 1, 0.78 for Model 2 and 0.62 for Model 3.

[2] Unrestricted Log likelihood
[3] Restricted log likelihood

Conclusions for the selected variables:

All models included variables that were either direct or indirect indication of income levels. Income was found to influence EVs possession along with the education level, a variable that demonstrates people's concern over environmental issues. The big size of the household does not indicate the need for more trips but people's adversity in affording a more expensive car. The gender was not a significant variable in any of the three models created. The same was indicated for the variable –licensed drivers as well. No relationship was observed between the number of licensed drivers and the number of EVs owned. The predicted values were used as weights in order to create the distribution patterns of EVs in 2021.

The observed along with the predicted values where then checked for spatial autocorrelation. The spatial patterns of each model are presented in the following maps. Clusters of high concentrations of EVs counts are depicted in Dundas, Ancaster and Burlington for the observed counts of EVs. The predicted values are restricted in Dundas and Ancaster after the statistical analysis of socioeconomic factors for Model 1, and in some census tracts of Burlington as well for Models 2 and 3 respectively. Downtown Hamilton concentrates groups of low number of EVs counts, while the rest of the study area is not statistically significant.

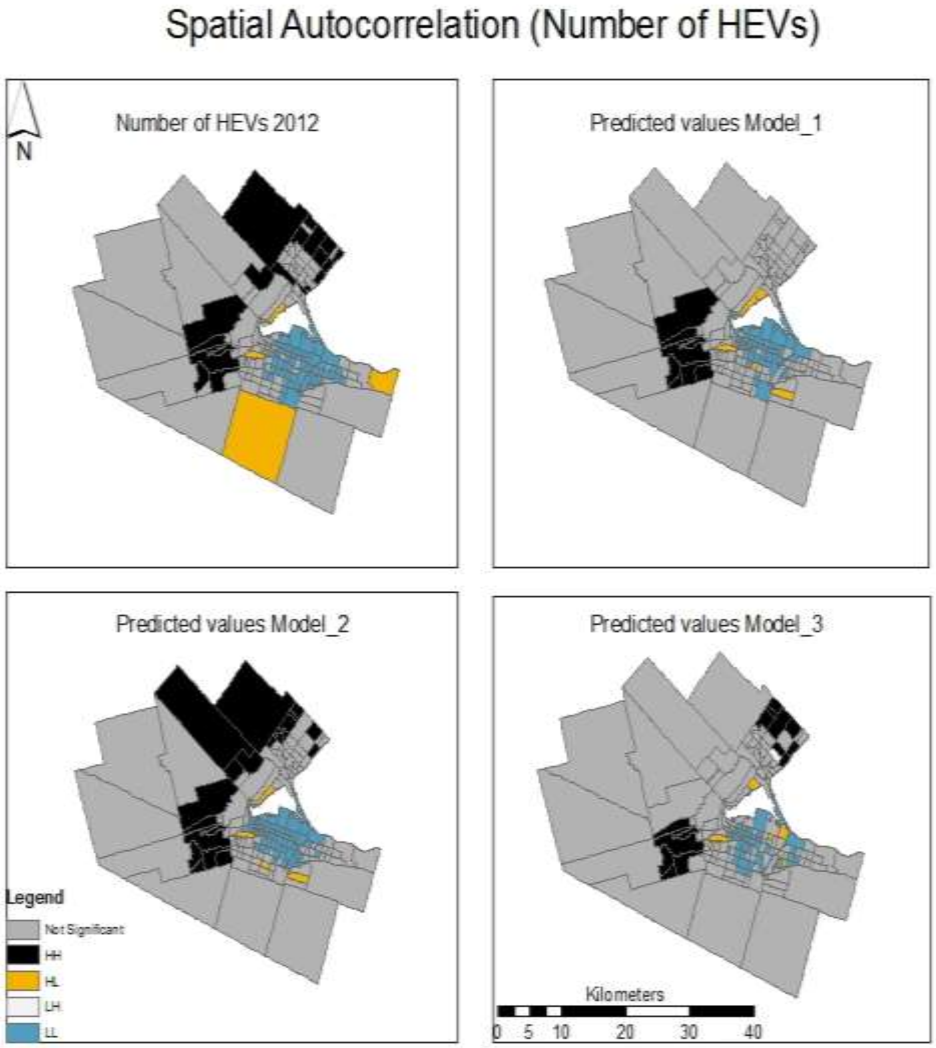


Table 15 illustrates the percent of census tracts that belong in each cluster (HH, HL, LH, LL) and the correlation between each model.

Table 15. HEV's clustering and correlation

Percentage of census tracts					
Clusters	HH	HL	LH	LL	Pearson Coefficient
NHEV12	11.63%	2.91%	0.00%	34.88%	1
Model_1	5.23%	3.49%	0.00%	27.91%	0.98359
Model_2	12.79%	2.91%	0.00%	34.88%	0.99932
Model_3	8.72%	4.07%	0.58%	22.67%	0.99734

Pearson's Coefficient indicates a very strong correlation between the observed values and Models 2 and 3.

4.2 Results

4.2.1 Scenario- based analysis

This study does not focus on analyzing the explanation behind each possible EVs penetration rate. Rather, it tries to evaluate the potential contribution of EVs in reducing GHG emissions. For that reason, different market share growth scenarios are introduced and the role of EVs is examined under each scenario. It should be also realized that the scenarios that are described and will be used in the thesis will not constitute a precise representation of the future, but they will inform on the various impacts that could be expected from EVs introduction in the coming decades.

For this thesis, the year 2006 was selected for the present scenario, as data for this year were available, and the year 2021 for the future scenario, as O-D matrices were estimated until this specific year. The future scenario incorporated the business-as-usual scenario (BAU) and three hypotheses with different penetration rates of EVs. Therefore the first hypothesis – Scenario 1- constitutes the most optimistic scenario, describing the distribution pattern after the introduction of 10% of EVs. Under the optimistic scenario we assume that an ambitious 10% (41899 vehicles) of vehicles will be replaced by EVs in 2021. Scenario 2 refers to moderate market growth of EVs which will result in attaining 5% (20950 vehicles) of market share by the end of 2021. Under the conservative scenario – Scenario 3- EVs will capture 2% of total vehicle fleet (8380 vehicles) by 202. Each hypothesis included three sub-models with different EVs distribution patterns combining various factors that influence EV ownership. Traffic emissions were estimated for January 1st (Day 1) and July 1st (Day 182) for the analysis which was conducted into two levels –the aggregate and the dissagregate.

4.2.2 EV O-D matrices validation

TRAFFIC and MOBILE 6.2C are designed to accommodate five main classes (passenger cars, light duty commercial vehicles, medium duty commercial vehicles, heavy duty commercial vehicles and bus transit vehicles) (CSpA, 2009). The models are not versatile in inducting new classes, hence, in order to introduce a new vehicle category, software modifications and validation of traffic assignment results should be avoided. In order to examine if this assumption is valid, the sum of all trips and the total vehicle kilometer travelled (VKT) must be equal across all models. The table indicates that the largest difference is detected in Model1_3 and Model2_3 (-0.04%) and confirms the effectiveness of the method used to introduce the new vehicle category.

Table 16. O-D matrices validation

Models	8am				5pm			
	EV	LDV	Total	Change	EV	LDV	Total	Change
BAU	2918.8	776606.3	779525.1	0.00%	2718.9	739925.7	742644.6	0.00%
Model1_1	89652.9	689713.7	779366.6	-0.02%	89408.4	653197.4	742605.8	-0.01%
Model1_2	90485.3	688867.4	779352.7	-0.02%	87861.5	654743.6	742605.1	-0.01%
Model1_3	95947.3	683279.8	779227.0	-0.04%	100309.4	642293.5	742602.9	-0.01%
Model2_1	44860.0	734469.5	779329.4	-0.03%	44710.5	697913.2	742623.8	0.00%
Model2_2	45134.2	734341.2	779475.4	-0.01%	43940.4	698682.6	742623.0	0.00%
Model2_3	47972.9	731232.7	779205.6	-0.04%	50150.9	692473.3	742624.3	0.00%
Model3_1	17888.0	761654.4	779542.5	0.00%	17880.7	724754.8	742635.5	0.00%
Model3_2	18055.1	761465.8	779520.9	0.00%	17573.1	725063.8	742636.9	0.00%
Model3_3	19174.0	760348.1	779522.1	0.00%	20061.5	722575.1	742636.6	0.00%

Models	Trips			
	EV	LCV	Total	Change
BAU	503.88	140318.25	140822.13	0.00%
Model1_1	15243.38	125578.75	140822.13	0.00%
Model1_2	15092.77	125729.36	140822.13	0.00%
Model1_3	16717.96	124104.17	140822.13	0.00%
Model2_1	7621.87	133200.26	140822.13	0.00%
Model2_2	7546.57	133275.56	140822.13	0.00%
Model2_3	8359.18	132462.95	140822.13	0.00%
Model3_1	3048.75	137773.38	140822.13	0.00%
Model3_2	3018.63	137803.50	140822.13	0.00%
Model3_3	3343.67	137478.46	140822.13	0.00%

4.2.3 Business-as-usual scenario

The scenario analysis starts with the business-as-usual scenario, continues with the most optimistic scenario and goes backwards to be ensured that a sensible ceiling is placed on penetration rates and prevent the percentage uptakes from running out of control as it is very common to continually push the upper limit upwards.

The first scenario is the business-as-usual scenario which assumes that future population and land use trends throughout the study region will be consistent with historical change. The method used to derive population projection for the BAU scenario was based on CSpA's report (CSpA, 2009) and relied on forecasting the number of newly developed residential dwellings and then multiplying it by the average number of persons per private household.

The assumption that 50220 new dwellings will be constructed in the period 2006-2021 was made. Regression models were also estimated in order to predict employment growth as well. In BAU scenario it was also assumed that no action or minimum policy controls will take place over the next couple of decades to reduce emissions. This scenario was applied in order to constitute the base with which all the EV market penetration models will be compared. The following tables illustrate the aggregate emission estimates per vehicle type for both 2006 and 2021 for rush hours 8 am and 5 pm of January 1st and July 1st. The last table shows the percent change in emissions between 2006 and 2021.

		2006						2021					
	Vehicle Type	HC[4]	CO	NOx	CO2	PM2.5	PM10	HC	CO	NOx	CO2	PM2.5	PM10
		8am						8am					
January 1st	EV	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.01	0.03
	HCV	1.01	39.68	23.56	2.05	2.15	2.38	0.84	33.56	20.22	1.73	1.81	2.01
	MCV	4.76	135.39	73.03	8.86	3.80	4.33	4.88	142.58	78.04	9.32	4.00	4.55
	LCPV	558.48	11711.93	712.06	133.81	96.38	108.00	648.21	14010.97	905.12	170.89	123.08	137.92
	Buses	0.62	8.71	6.24	0.99	0.51	0.57	0.66	9.25	6.62	1.05	0.54	0.61
July 1st	EV	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.01	0.03
	HCV	0.95	34.56	22.65	2.05	2.10	2.32	0.79	29.23	19.45	1.73	1.77	1.96
	MCV	4.49	116.22	69.60	8.85	3.74	4.25	4.59	122.38	74.39	9.31	3.93	4.47
	LCPV	613.23	8200.77	515.15	133.98	95.38	106.90	705.71	9804.66	655.23	171.10	121.81	136.52
	Buses	0.61	7.79	6.06	0.99	0.50	0.56	0.65	8.28	6.44	1.05	0.53	0.59

		2006						2021					
	Vehicle Type	HC	CO	NOx	CO2	PM2.5	PM10	HC	CO	NOx	CO2	PM2.5	PM10
		5pm						5pm					
January 1st	EV	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.02	0.03
	HCV	0.21	8.20	4.92	0.43	0.45	0.50	0.17	6.96	4.23	0.36	0.38	0.42
	MCV	1.36	38.91	21.27	2.58	1.11	1.26	1.43	42.08	23.34	2.78	1.19	1.36
	LCPV	287.54	7138.23	646.86	130.52	94.12	105.47	362.68	9128.71	824.19	164.90	118.92	133.27
	Buses	0.86	12.09	8.72	1.39	0.71	0.80	0.91	12.72	9.19	1.46	0.75	0.84
July 1st	EV	0.00	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.00	0.00	0.01	0.04
	HCV	0.21	8.02	4.67	0.43	0.44	0.49	0.17	6.81	4.01	0.36	0.37	0.41
	MCV	1.37	37.77	19.90	2.58	1.09	1.24	1.44	40.85	21.85	2.78	1.17	1.34
	LCPV	307.23	5811.21	452.06	129.21	91.99	104.40	388.26	7426.46	575.66	163.02	116.06	131.91
	Buses	0.90	12.03	8.38	1.39	0.70	0.79	0.95	12.66	8.83	1.46	0.73	0.83

[4] HC, CO, NOx, PM2.5, PM10 are in Kilograms(Kg) and CO2 in tones(t)

Table 17. Changes in emissions from 2006 to 2021 per vehicle type

vehicle type	HC	CO	NOx	CO2	PM2.5	PM10	HC	CO	NOx	CO2	PM2.5	PM10
	8am						5pm					
EV	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
HCV	-17.16%	-15.41%	-14.16%	-15.55%	-15.55%	-15.55%	-16.06%	-15.05%	-14.20%	-15.13%	-15.13%	-15.13%
MCV	2.50%	5.32%	6.86%	5.20%	5.20%	5.20%	5.21%	8.16%	9.73%	7.98%	7.98%	7.98%
LCPV	16.07%	19.63%	27.11%	27.71%	27.71%	27.71%	26.13%	27.88%	27.41%	26.34%	26.35%	26.36%
Buses	6.17%	6.23%	6.18%	6.08%	6.08%	6.08%	5.17%	5.27%	5.34%	5.23%	5.23%	5.23%
EV	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
HCV	-17.24%	-15.42%	-14.15%	-15.55%	-15.55%	-15.55%	-16.14%	-15.05%	-14.18%	-15.13%	-15.13%	-15.13%
MCV	2.37%	5.30%	6.88%	5.20%	5.20%	5.20%	5.01%	8.16%	9.76%	7.98%	7.98%	7.98%
LCPV	15.08%	19.56%	27.19%	27.71%	27.71%	27.71%	26.37%	27.80%	27.34%	26.16%	26.17%	26.36%
Buses	6.18%	6.23%	6.18%	6.08%	6.08%	6.08%	5.18%	5.27%	5.34%	5.23%	5.23%	5.23%

As the number of EVs is the same for 2006 and 2021, no change in emissions is depicted for this vehicle type. A decrease in emissions produced by heavy commercial vehicles is detected, which is justified by the projected development pattern of the Hamilton CMA for 2021 according to (CSpA, 2009). The employment growth model indicated a decline in manufacturing industries, wholesale trade resulting to decline in HCVs VKT and produced emissions. The BAU scenario produces an increase in emissions approximately 16 to 27 percentage points (for different pollutants) higher than base year levels. For the rest of the vehicle types an increase in emissions is represented as expected.

Emission estimates were simulated for 24 hours in 365 days in 2006 and 2021 but only morning and evening rush hours (8am and 5pm) for January 1st and July 1st were selected to evaluate the potential reduction in emissions.

4.3 Aggregated level

The table displays the percent change in emission estimates per pollutant for all the models created to introduce the different EV penetration rates. Aggregate emissions are the summations of emission estimates across all links in the road network. A reduction in traffic emissions is evident across all scenarios. Slight changes are observed between the different distribution models as well. For Models 2 and 3 the percent change is nearly the same for all pollutants. A conspicuous finding is that the percent abatement in HC and CO emissions in the morning for both January and July and the percent of EVs in the total fleet do not follow a linear trend. This fact can be explained by the high traffic volume observed that time of the day. At 8 am in the morning people commute using their private cars, thus congestion and low speeds are observed. It is noticed that HC and CO emissions reduces almost by half for the first scenario -as high HC and CO emissions are produced at low speeds- while NO_x follows a different trend. The difference is in the relationship of emission factors to link speed. On the contrary, as speeds in the evening are higher, HC and CO emissions change is lower. While for HC and CO the emission factors raise as average link speed decreases, NO_x emission factors tend to initially slightly decrease with speed, but then remain stable until about 30 mph, increasing with speed from then on. A significant difference between the three scenarios is observed in all pollutants. An essential change is also detected between models 1 and 3 for HC and CO at 5 pm for both January and July proving that the difference in EVs distribution can cause changes in emissions produced. It is deduced that even a modest adoption of EV technology may lead to significant reduction in traffic emissions.

Table 18. Percent aggregate emissions reduction compared to BAU for rush hours of January and July 1st

	January 1st							
	8am				5pm			
	HC	**CO**	**NO_x**	**CO_2**	**HC**	**CO**	**NO_x**	**CO_2**
Model1_1	-48.58%	-38.69%	-13.41%	-10.63%	-12.17%	-12.04%	-11.47%	-11.62%
Model1_2	-47.27%	-39.02%	-14.89%	-10.63%	-11.56%	-11.49%	-11.10%	-11.31%
Model1_3	-49.20%	-39.36%	-14.13%	-11.39%	-18.80%	-16.69%	-13.16%	-13.06%
Model2_1	-6.05%	-5.89%	-5.03%	-5.15%	-5.92%	-5.85%	-5.57%	-5.64%
Model2_2	-5.84%	-5.75%	-4.97%	-5.13%	-5.63%	-5.59%	-5.38%	-5.48%
Model2_3	-6.80%	-6.53%	-5.42%	-5.54%	-6.70%	-6.61%	-6.27%	-6.35%
Model3_1	-2.22%	-2.16%	-1.81%	-1.85%	-2.14%	-2.12%	-2.02%	-2.04%
Model3_2	-2.09%	-2.06%	-1.80%	-1.85%	-2.02%	-2.01%	-1.94%	-1.98%
Model3_3	-2.41%	-2.34%	-1.96%	-2.00%	-2.46%	-2.43%	-2.30%	-2.33%

	July 1st							
	8am				5pm			
	HC	**CO**	**NO_x**	**CO_2**	**HC**	**CO**	**NO_x**	**CO_2**
Model1_1	-52.32%	-38.75%	-12.92%	-10.63%	-12.24%	-12.03%	-11.31%	-11.62%
Model1_2	-51.03%	-39.20%	-14.60%	-10.63%	-11.57%	-11.48%	-14.44%	-11.32%
Model1_3	-52.93%	-39.42%	-13.62%	-11.39%	-20.02%	-16.68%	-13.01%	-13.05%
Model2_1	-6.12%	-5.88%	-4.89%	-5.15%	-5.96%	-5.84%	-5.49%	-5.63%
Model2_2	-5.91%	-5.73%	-4.82%	-5.13%	-5.64%	-5.58%	-5.31%	-5.48%
Model2_3	-6.90%	-6.52%	-5.26%	-5.54%	-6.75%	-6.60%	-6.19%	-6.35%
Model3_1	-2.25%	-2.15%	-1.76%	-1.85%	-2.15%	-2.12%	-1.99%	-2.04%
Model3_2	-2.10%	-2.05%	-1.74%	-1.85%	-2.02%	-2.01%	-1.91%	-1.98%

Model3_3	-2.45%	-2.34%	-1.90%	-2.00%	-2.48%	-2.43%	-2.27%	-2.33%

The exponential growth of HC emissions reduction can be seen in the following graph.

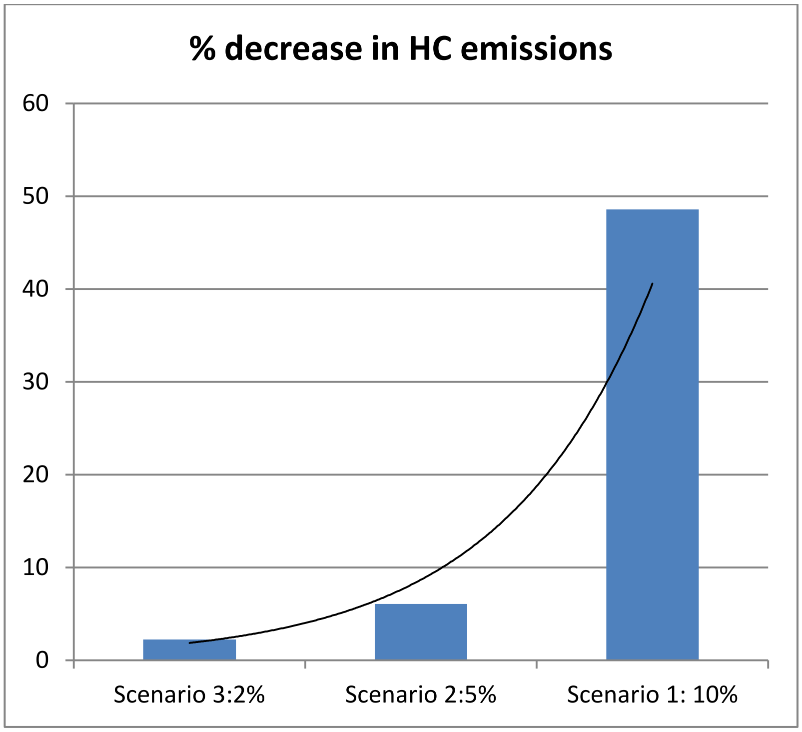


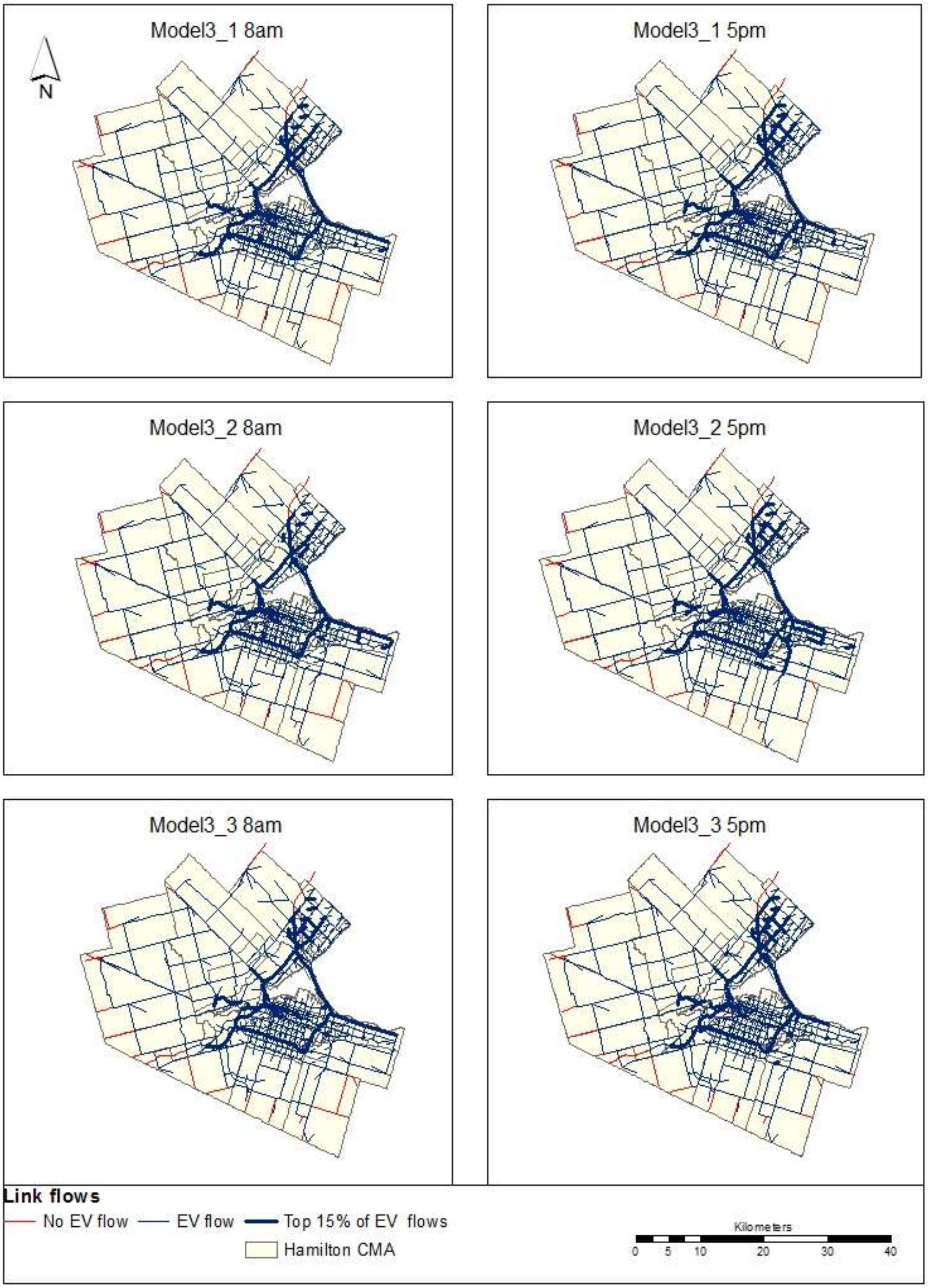
Figure 14. Emissions reduction after implementation of Scenarios

4.4 Disaggregated level

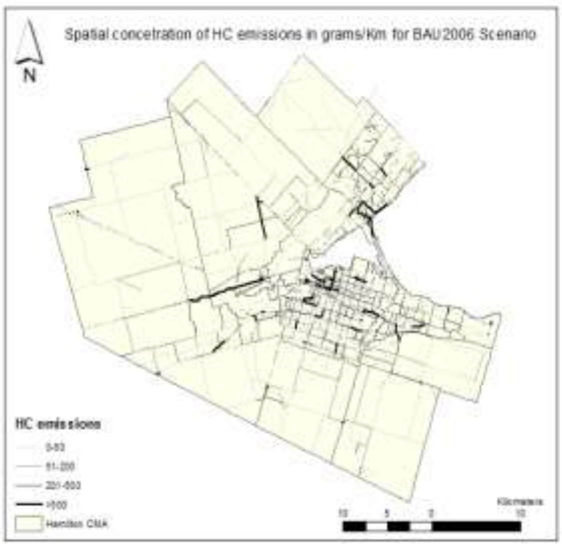
Before proceeding to the analysis of the spatial concentration of emissions at the link level, the links mostly traveled by EVs are presented.

The links –around 5%- that weren't travelled by electric vehicles were located at the edges of the study area as shown in the next figure applied for Model3. This can be explained by the traffic assignment model's function which can only calculate the intra-zonal trips and not trips out of the study area. As it is expected the most travelled links by EVs in all models were the major highways and the large arterial roads. The next figure displays -for both rush hours included in this study, 8am and 5pm- the EVs flows. The red lines represent the links with zero EV flows, while the thicker blue lines correspond to the top 15% of the highest EV flows. Similar spatial patterns are observed in general; slight differences are noticed though between 8 am and 5 pm.

EV flows


Model3_1 8am
Model3_1 5pm
Model3_2 8am
Model3_2 5pm
Model3_3 8am
Model3_3 5pm
N
Link flows
No EV flow
EV flow
Top 15% of EV flows
Hamilton CMA
Kilometers
0 5 10 20 30 40

This section is focused on the spatial concentration of emissions through a selected set of figures. The volume of emissions was normalized with regard to the length of links in order to be comparable. The following figures represent the spatial concentration of HC emissions for the BAU scenario for both 2006 and 2021 and the percent changes. The links with the highest traffic emissions per kilometer included sections of QEW in Burlington, Hwy 403, Main St West, King St West and major highways in general which is explained by the high volume of traffic and high vehicle flow in these specific roads during rush hours.



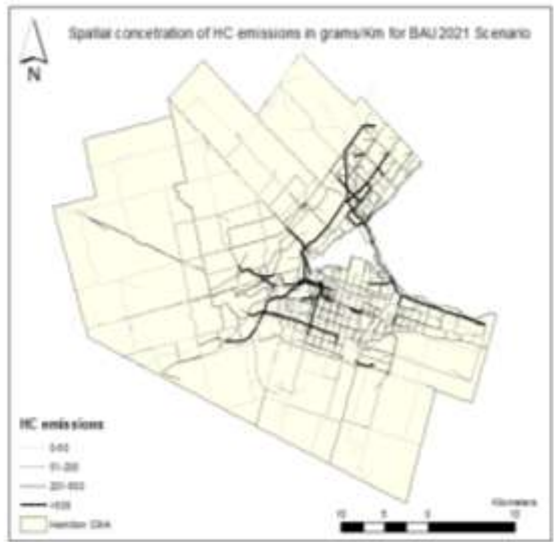
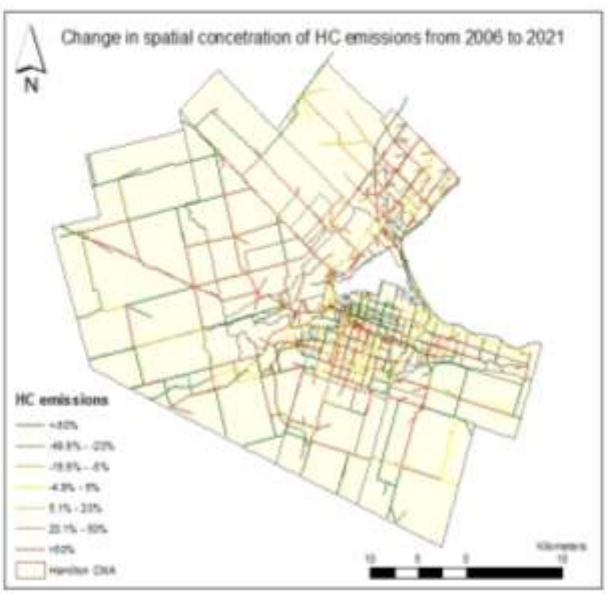


Table 19. #of links falling in each class of change



Classes	Links	Percent
<-50%	142	20.1%
-49.9%- -20%	41	5.8%
-19.9%- -5%	13	1.8%
-4.9%- 5%	74	10.5%
5.1%- 20%	19	2.7%
20.1%- 50%	140	19.7%
>50%	279	39.4%

Figure 15. Change in spatial concentration of HC emissions from 2006 to 2021

Seven classes were created to accommodate the changes in emissions between these years. No significant change is observed in the core of Hamilton (-4.9%-5%). The decrease in HC concentration occurs at links that heavy commercial vehicles and trucks used to traverse before the abatement in industrial sector. Table 2 depicts the percent of links, falling in each class of change for CO and CO_2 from 2006 to 2021. A similar trend is observed between the two pollutants.

Table 20. Changes in CO and CO_2 emissions from 2006 to 2021

Classes	CO	CO_2
<-50%	24%	23.6%
-49.9%- -20%	5.8%	6.1%
-19.9%- -5%	6.1%	6.4%
-4.9%- 5%	19.6%	20.2%
5.1%- 20%	7.1%	6.5%
20.1%- 50%	6.3%	6.4%
>50%	31.1%	30.8%

To compare the emissions produced by each model three ratios were obtained, dividing emissions from each model to the emissions of the BAU Scenario. Values close to 1 depict significant change in HC emissions, values between 0.8 and 0.9 illustrate a decrease and values less than 0.8 represent a massive HC emissions abatement. The following table displays HC ratio for the three models of the first scenario and accounts for the number of links falling in each category and the corresponding percentage. Most of the links belong to the second category, therefore there is an obvious decrease in emissions produced despite the model. While Model 1 and 2 share almost the same number of links in every category, Model 3 follows a different trend. The distribution of EVs, as dictated by Model 3, provokes a higher decrease in emissions. Only 27% of the links belong to the third category “significant change”, compared to the 40% of the other models and 466 links are concentrated on the second; meaning that most of the links did not remain stable but on the opposite the distribution of Model 3 made the emissions to decline considerably. Massive HC emissions decrease is not noticed as only 10% of the links are falling in the first category.

classes	number of links/percentage		
	Model 1	Model 2	Model 3
0-0.8	77 / 10.26%	80 / 10.67%	83 / 11.07%
0.8-0.9	365 / 48.67%	369 / 49.2%	466 / 62.13%
0.9-1.0	308 / 41.07%	301 / 40.13%	201 / 26.8%

The spatial variation of the three ratios is evident in Figure 11 which illustrates the hotspots of changes with regard to the BAU scenario for Scenario 1. Two main ‘hot-spot’ areas of maximum change compared to the BAU scenario can be identified in the HC emissions map below. The first one is evident across the three models and occurs at Burlington city including the major highways. These highways constitute main routes to the city of Toronto, a major employment centre for Hamilton’s residents. The second significant change occurs at Stoney Creek and it is observed only in the second model. Across all models the modest change compared to the BAU scenario is depicted in the core of Hamilton.

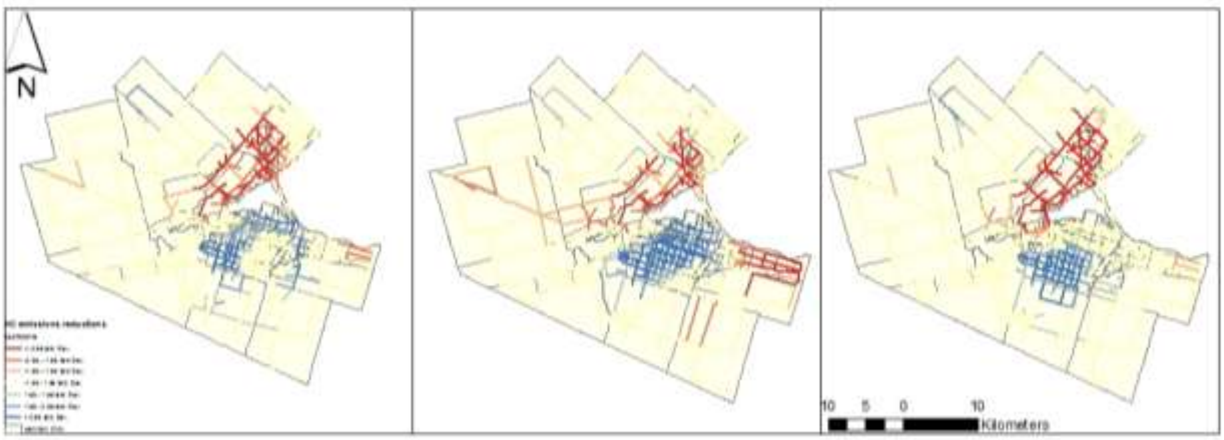


Figure 16. HC emissions changes hotspots for Model 1, Model 2 and Model 3 respectively

The next tables present the percent of links falling in each class for the rest of the pollutants and the Scenarios. It is remarkable that all pollutants have a similar behavior across all models. It can be observed that in the first scenario –with 10% EVs in the market- a major decrease in emissions of all pollutants can be seen, while around 40% of the links remain stable. Differences can also be noticed between the models as Model 3 concentrates the lowest proportion of links in the third category and more in the second meaning that there is a higher decrease in emissions when applying the distribution of EVs of this specific model. CO follows the same trend as HC for Scenario 1, while the other two pollutants do not present great change between the Models. For the rest of the scenarios higher proportions are concentrated in the third category, as the decrease in emissions is lower when fewer “green” vehicles are adopted in the fleet. The percentages in Scenarios 2 and 3 are similar since the links falling in the first category dropped to almost 9%, the links in the second were almost eliminated and these in the third Scenario vanished.

Table 21. Links' percentage falling in each ratio category for pollutants CO NOx and CO2

Scenario 1	CO			NO_x			CO_2		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
0-0.8	10%	10.67%	11.07%	9.87%	10.53%	10.80%	9.47%	10.13%	10.27%
0.8-0.9	48.13%	48.80%	61.60%	41.33%	46.40%	52.80%	44.40%	43.60%	57.60%
0-9-1.0	41.87%	40.53%	27.33%	48.80%	43.07%	36.40%	46.13%	46.27%	32.13%

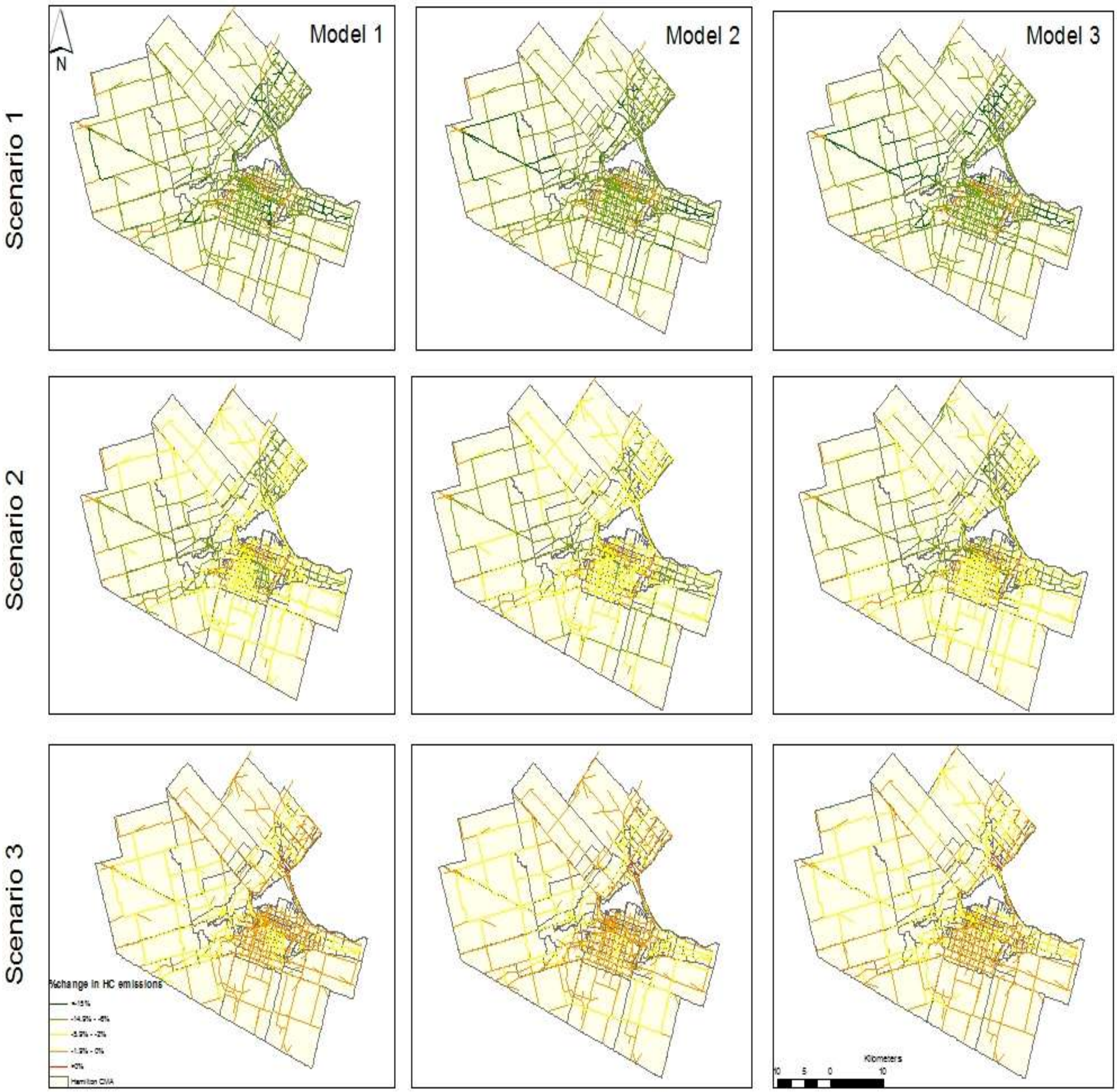
Table 22. Links' percentage falling in each ratio category for pollutants HC, CO NOx and CO2 for Scenario 2

Scenario 2	HC			CO			NO_x			CO_2		
	M 1	M 2	M 3	M 1	M 2	M 3	M 1	M 2	M 3	M 1	M 2	M3
0-0.8	8.67%	8.67%	8.67%	8.67%	8.67%	8.67%	8.67%	8.53%	8.67%	8.53%	8.53%	8.53%
0.8-0.9	1.20%	1.60%	2.13%	1.20%	1.60%	2.13%	0.90%	1.73%	1.73%	1.07%	1.60%	1.73%
0-9-1.0	90.13%	89.73%	89.20%	90.13%	89.73%	89.20%	90.40%	89.73%	89.60%	90.40%	89.87%	89.73%

Table 23. Links' percentage falling in each ratio category for pollutants HC, CO NOx and CO2 for Scenario 3

Scenario 3	HC			CO			NO_x			CO_2		
	M 1	M 2	M 3	M 1	M 2	M 3	M 1	M 2	M 3	M 1	M 2	M3
0-0.8	8.4%	8.53%	8.63%	8.59%	8.4%	8.53%	8.33%	8.47%	8.53%	8.53%	8.1%	8.53%
0.8-0.9	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
0-9-1.0	91.6%	91.47%	90.6%	91.41%	91.6%	91.47%	91.67%	91.53%	91.41%	91.41%	91.9%	91.47%

The next figure illustrates the spatial pattern of HC emissions reductions for each model for the three scenarios. Five classes were created to accommodate the change in percent emissions (change more than -15%, change between -6% and -15%, -2%- -6%, 0- -2% and changes over 0%). The largest reductions can be seen in the major highways which are travelled frequently. High traffic volume observed at rush hours leads to high values of HC, because of the low speeds that are developed. Introducing 10% of electric vehicles into the market fleet lead to a greater than 15% reduction in emissions of HC. It is remarkable that most of the links in the first Scenario fall in the second category, but in Scenario 2 the links are divided in the second and third class. The same can be seen for Scenario 3. Different distribution patterns produce different spatial patterns of traffic related emissions in the links. Each model creates another pattern with evident changes in downtown Hamilton and downtown Bulington.



The following graph depicts the number of links falling in each class of emission reductions. It is observed that for CO_2 as well the emissions can decrease more than 15% when applying Scenario 1 and 41899 vehicles enter the market. When applying Scenario 2 changes around 6-15% in CO_2 emissions are detected. Significant changes occur even when implementing Scenario 1 and 2% of vehicle fleet are electric. Small variations between the models can also be noticed. Model 3 in each scenario affects more the class with the highest decrease. For example, while in the classes '-2%-0' and '-15%- -6%' changes in emissions the links are almost evenly distributed across the three models, Model 3 influences more the emissions produced. Same impact has Model 3 on '-15%- -6%' class for Scenario 3 and on '-6%- -2%' for Scenario 3.

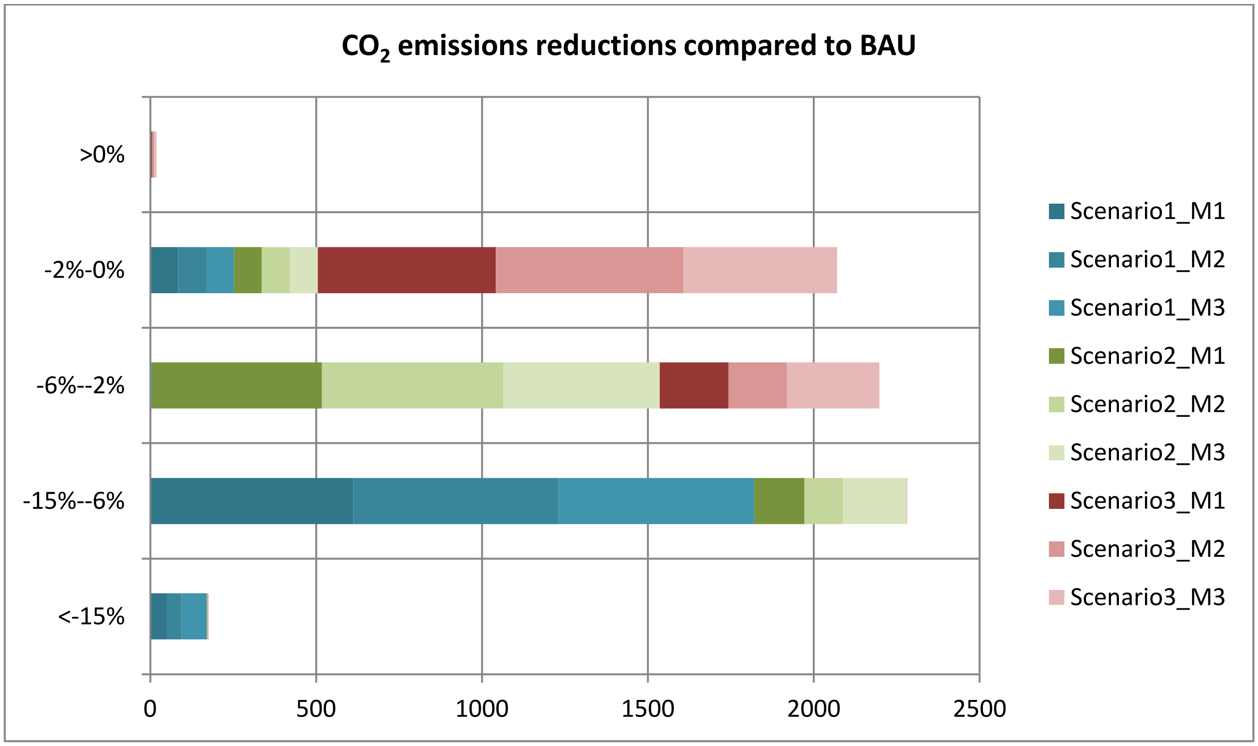


Table 8 illustrates the number of links that present reduction in traffic related pollution. The first part shows CO emissions abatement, while the second depicts reduction of the pollutant NO_x. What can be deduced from these tables is that in each scenario, Model 3 is the model that appears to influence more the emissions produced. Specifically model 3 concentrates most of the links falling in the class with the major decrease in emissions each time. CO and NO_x pollutants follow the same trend as observed for HC and CO_2.

Table 24. CO and NO_x emissions reduction

	CO									No_x								
Classes	**Scenario 1**			**Scenario 2**			**Scenario 3**			**Scenario 1**			**Scenario 2**			**Scenario 3**		
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
<-15%	58	51	89	2	2	2	1	1	1	50	47	70	2	2	2	1	1	1
-15%--6%	605	612	576	170	134	226	2	1	1	606	616	595	137	109	169	0	1	1
-6%--2%	2	2	0	493	529	437	230	192	311	9	2	0	526	554	492	191	158	261
-2%-0%	84	84	84	84	84	84	511	550	431	84	84	84	84	84	86	552	584	481
>0%	0	0	0	0	0	0	6	6	6	0	0	0	0	0	0	6	6	6

As the analysis has been focused at the link level in Hamilton CMA, it would be essential to mention not only the general pattern of links but also the links with the highest values of the pollutants.

Table 9 depicts the 10 links with the highest emissions production for pollutants CO_2, HC, NO_x and CO. Most of them are parts of the major highways, as higher speeds are developed and increase emissions production. The 9 links with the highest volume are the same for all pollutants in different order though and the last one is different for all. It is evident that the length of the link is not related with pollutants' values.

Table25. Top 10 links concentrating the highest volumes of traffic related pollution

TOP 10	LINKS ID	LENGTH	StreetName	CO_2[5]	HC	CO	NO_x
1	4490451	1.315618	HWY403	1.47634	2.161758	68.3714	7.779099
2	4510357	6.998608	HWY403	1.449276	2.124125	67.19023	7.636351
3	3570343	0.93886	QEW/403	1.350844	27.49395	372.3676	9.684859
4	2900297	1.434528	QEW	1.233215	1.793124	56.82594	6.583894
5	2970326	5.62885	QEW	1.233128	1.794166	56.87063	6.583471
6	4470449	1.874993	HWY403	1.13989	23.6281	319.7024	8.096006
7	2830290	1.678029	QEW	1.124351	1.640017	51.95966	5.975906
8	3420357	0.961316	QEW	1.099083	22.51845	304.8288	7.855726
9	3430315	1.95752	QEW/403	1.060731	1.53039	48.46022	5.725791
10	4870479	1.248222	Lincoln Alexander Expwy	0.888535			
10	4450446	0.188918	Main St		1.371972		
10	4570440	0.556836	HWY403			41.02175	
10	3150305	2.002319	QEW/403				4.736492

Most of the aforementioned links are parts of the major highways. The following figure illustrates the behavior of the pollutants in highways HWY403, QEW and Lincoln Alexander Expwy in total. It is obvious that higher values of HC, CO, NO_x and CO_2 are concentrated on the highways directing to Toronto, as people commute to work. Similar patterns are depicted for pollutants HC and CO. Lower volumes of emissions are noticed at QEW (at Stoney Creek side) as less congestion occurs at this specific section of the highway and higher speeds are developed. The higher speeds justify the higher emissions of NO_x and CO_2 at the same part.

[5] CO_2 in tones, HC, CO and NO_x in kg

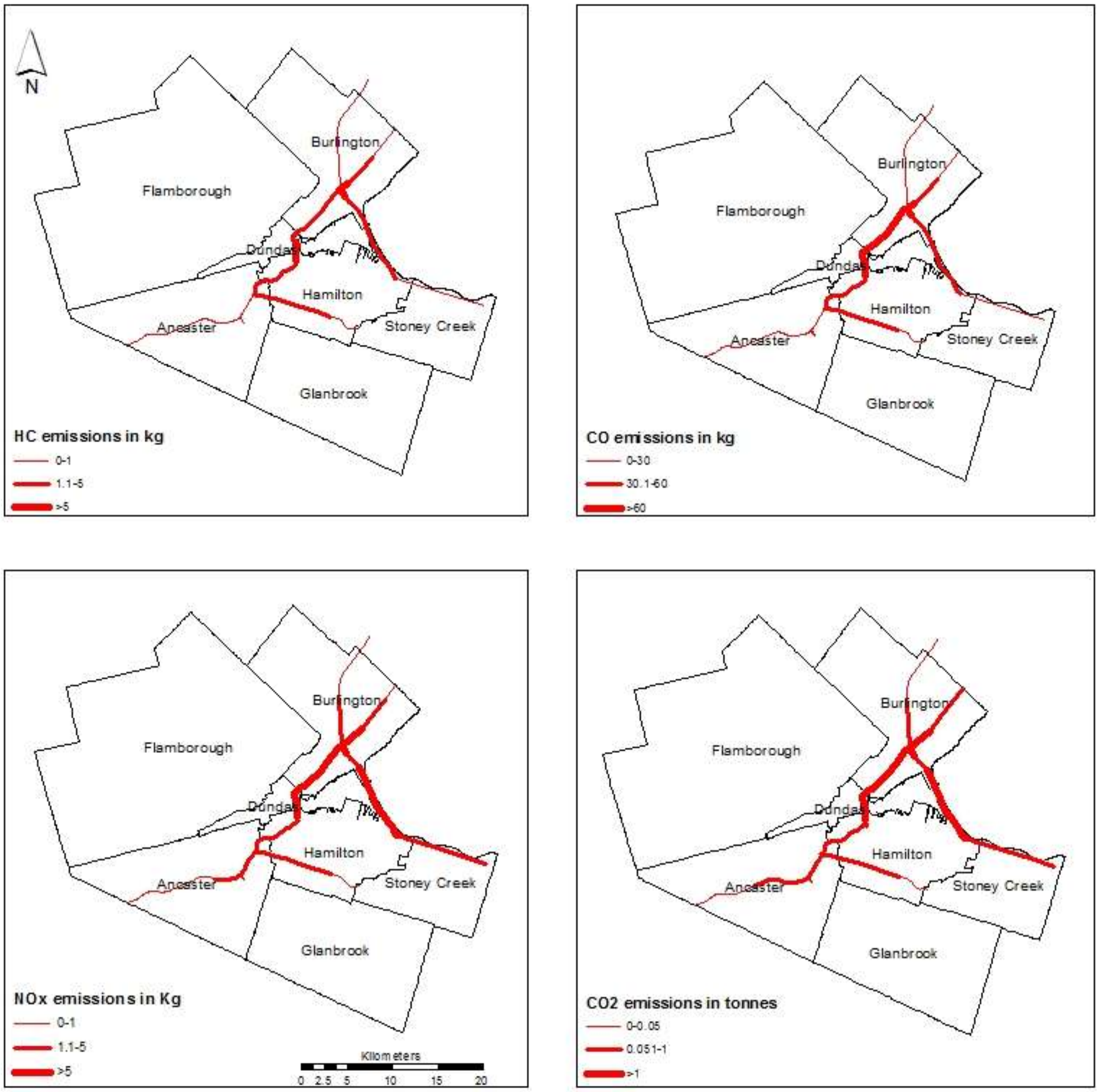


Figure 17. Emissions of pollutants on major highways

Figure 12 makes a classification of Hamilton CMA into subregions to illustrate the emissions on the highways. It is essential to analyze how socioeconomic factors from different subregions influence emissions and are related to them. Table 10 depicts the average emissions produced per subregion for the three different models for all four pollutants. Model 3 influences more the emissions produced as lower values of every pollutant is produced by the distribution of electric vehicles of Model 3. Figure 13 compares the difference between Models 1 and 2 with Model 3. The major differences are detected for HC and CO in Burlington in both the Models and in Dundas when comparing Model 2 with Model 3.

Table 26. Emissions produced by each model and pollutant on different subregions

	HC			CO			NOx			CO2		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Ancaster	0.1744	0.1774	0.1730	4.5413	4.6213	4.5050	0.4903	0.4947	0.4868	0.1086	0.1104	0.1078
Burlington	0.7977	0.8053	0.6630	14.7077	14.7852	12.9840	1.0785	1.0730	1.0498	0.2244	0.2266	0.2206
Dundas	0.5483	0.6473	0.5385	13.7120	14.1257	13.4756	1.4749	1.4186	1.4514	0.3331	0.3325	0.3274
Flamborough	0.1129	0.1125	0.1108	2.6930	2.6850	2.6436	0.2816	0.2795	0.2767	0.0708	0.0706	0.0696
Glanbrook	0.0477	0.0461	0.0472	1.1226	1.0867	1.1099	0.1140	0.1103	0.1128	0.0290	0.0280	0.0286
Hamilton	0.3706	0.3769	0.3669	7.3490	7.4205	7.2776	0.6751	0.6723	0.6696	0.1552	0.1557	0.1539
Stoney Creek	0.1764	0.1669	0.1744	4.2234	4.0111	4.1777	0.4357	0.4132	0.4312	0.1044	0.0991	0.1032

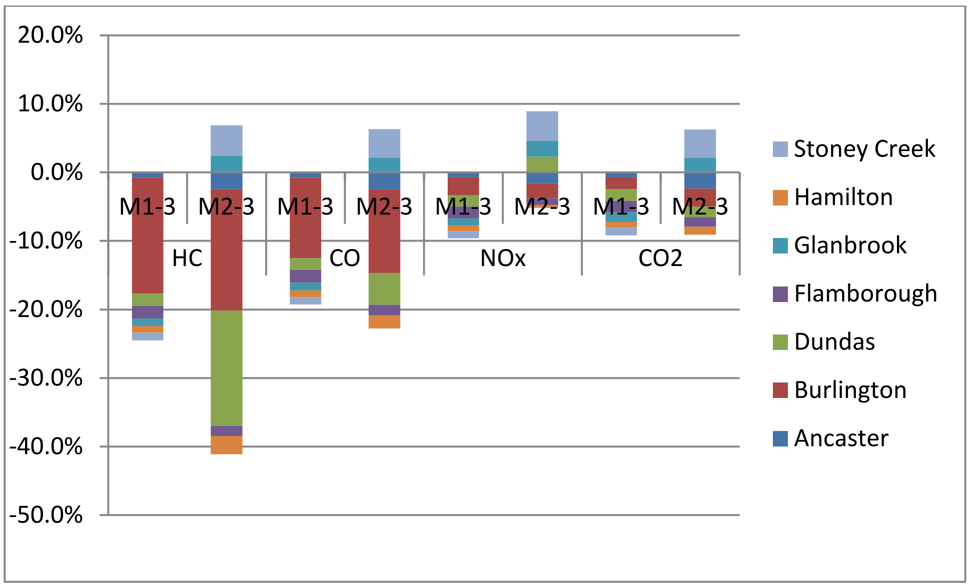


Figure 18. Comparison of the reduction percent between Models 1 and 2 with Model 3

Lastly, a hotspot analysis of HC, CO, NO_x and CO_2 pollutants is following. The analysis took place separately for every subregion in order to detect high and low volumes of emissions in every neighborhood. Slight differences are observed between the pollutants resulting to a similar total 'hotspot' pattern.

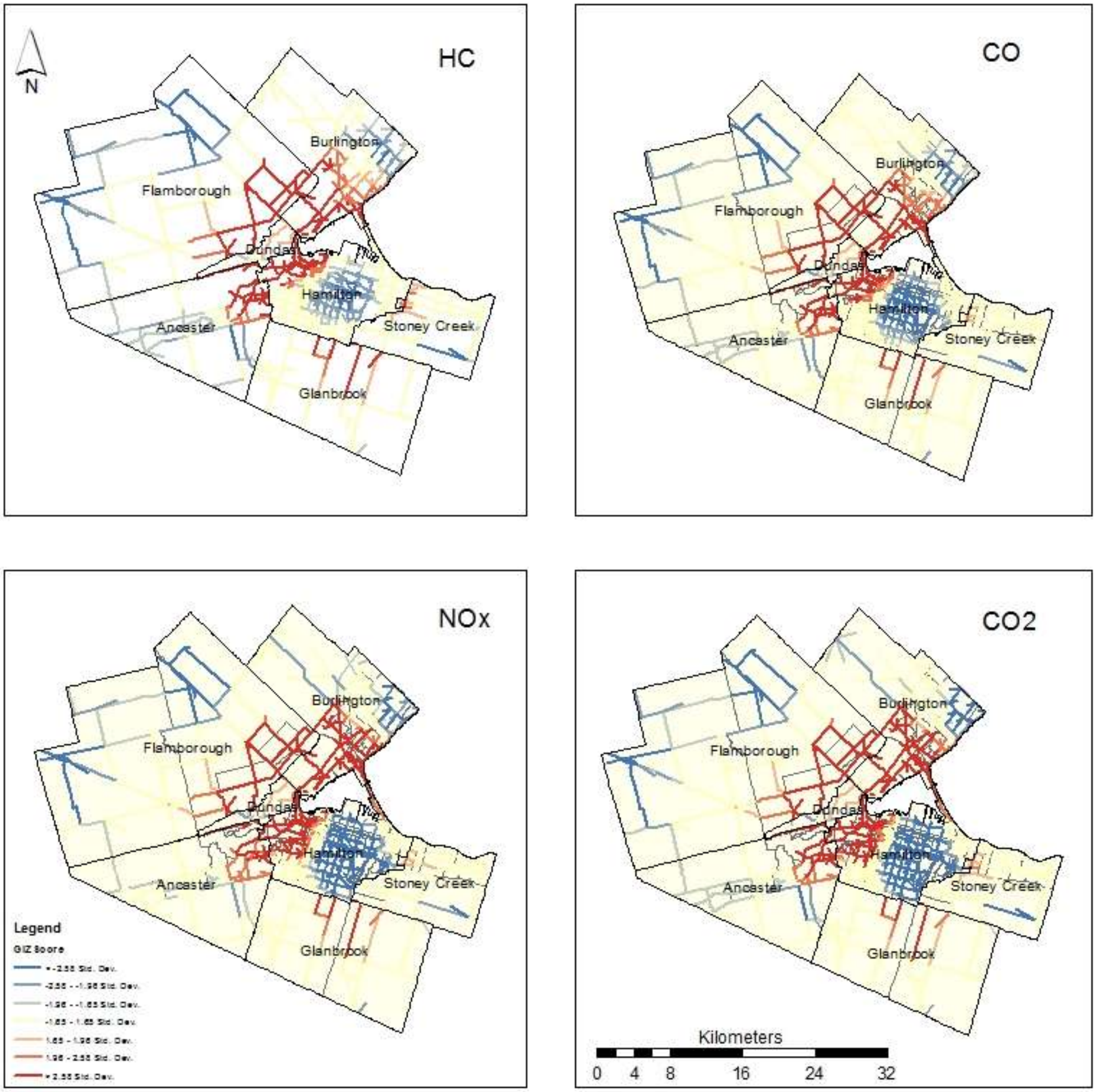


Figure 19. Hotspots of HC, CO, NOx and CO2 emissions by subregion

The hotspots as expected are detected on the major highways, where high values of emissions are concentrated, whilst low volumes are noticed at the core of Hamilton and at the edges of the study area.

4.5 Outcomes

The last phase of the analysis, after processing the data, consists of the summary of the most important points and the conclusions that can be drawn for the case study and the study area. In the case study we estimated the traffic related emissions reduction after the introduction of different rates of electric vehicles in the fleet. The process that was selected aimed to combine different spatial distribution patterns of EVs affected by socioeconomic factors with a set of integrated simulation models.

The analysis was first conducted at an aggregated level and then at a disaggregate level. In the beginning the O-D matrices were modified to accommodate the introduction of the new vehicle category according to the outputs from the regression analysis. The matrices were validated to examine if the VKT changes across the models. The results indicated that there is no significant change and confirmed that the reductions on traffic emissions were directly related to the differences of the tailpipe emissions between LDV and EVs.

After the simulation and the projection to 2021 the outputs were compared and the results detected an advantage of the EVs introduction over the BAU scenario. Under the first scenario a net reduction of 11% in CO2 emissions relative to BAU case could be achieved. Significant differences in emissions mitigation are noticed between 8 am and 5 pm for HC and CO. This finding proves what is already written in literature about high HC and CO emissions production at low speeds. The two pollutants were individually projected to decrease in the range 38-48% at 8 am and around 15% at 5pm. Full electrification of 10% of the passenger vehicle fleet by 2021 was found to be more effective stand alone strategy especially for HC and CO. An important finding was that the percent reduction in traffic emissions and the percent of EVs in the total fleet do not follow a linear trend. On the contrary, an exponential growth was detected in percent reductions at 8 am. NO_x emissions were estimated to decrease by 13% approximately under the first scenario. The rate of change in emissions between 2006 and 2021 for the second scenario was around 5-6% for each pollutant. Under the third scenario a mild abatement of 2% was detected for HC, CO, NO_x and CO_2.

At the disaggregate level more specific conclusions can be drawn for the links. To compare the emissions on each link, they had to be normalized with its length. Highest values of HC, CO, NO_x and CO_2 pollutants are detected at the major highways. These include HWY403, QEW and Lincoln Alexander Expwy. HWY403 connects Hamilton with Toronto and is the road with the greater emissions production. It is also the road, though, where the major decreases in emissions occurred after the implementation of electric vehicles. As mentioned earlier, depending on the type of emission, the speed at which the vehicle produces the minimum or the maximum amount of emissions changes. This can explain how the introduction of 10% of electric vehicles led to greater reduction of HC and CO.

Three ratios were obtained to compare the emissions produced by each model, dividing emissions from each model to the emissions of the BAU Scenario. Values close to 1 depict significant change in HC emissions, values between 0.8 and 0.9 illustrate a decrease and values less than 0.8 represent a massive HC emissions abatement. The results from the ratios computed lead to the conclusion that Model 3 provokes a higher decrease in emissions even though its distribution contained the lowest amount of electric vehicles before computing the weights.

The three models produced by the regression analysis created slightly different spatial patterns of emissions at the link level. In every case of comparison Model 3 revealed a greater reduction in emissions compared to the other two models. The combination of the variables education, number of persons in the household but also the household type, which is an indirect reference to income, proved to affect emissions production and mitigation after EVs implementation.

The next chapter offers an overview of the study, pointing out the benefits of EVs introduction in the market and the effectiveness of the selected methodological framework to achieve the objective of the research. Possibilities for the future are also discussed.

Chapter 5

5. Conclusions

Automobile has been the main mode for private transportation in Canada, leading to congestion, poor air quality and health problems. The last decade, auto manufacturers have started implementing electric vehicles as they produce no tail pipe emissions and constitute a 'greener' alternative of transportation. Although people in the beginning were reluctant to embrace the new technology, the idea has started to ripen according to Nemry and Brons (2010). Electric vehicles represent a conspicuous chance for pursuing a sustainable development not only of the transportation system but also of the whole world.

Previous research with regard to electric vehicles focused on the potential market uptake and acceptance from users, the reliability of batteries, the energy demand, the charging system and the GHG emissions reductions at an aggregate level. This study attempts to fill the gap in literature by offering insight on the relationship between the contributing socioeconomic factors that influence EVs market deployment and the decrease in GHG emissions at the link level.

In summary, chapter 1 constitutes an introduction to electric vehicles and justifies the need for research. Chapter 2 offers a critical review of the literature with respect to the potential market uptake, the reductions in emissions and the socioeconomic factors that impact EVs ownership. Afterwards we analyzed the analysis techniques that participated in the research. Chapter 3 describes the selected approach which is then implemented and the results drawn. The last chapter (Chapter 4) provides the final findings along with conclusions and directions for further research.

The geographical focus of attention has been the CMA of Hamilton, Ontario, Canada, but it has wide applicability. The modeling months were January and July to capture the peak and off-peak seasons for the various pollutants. The base year for this study was 2006 and the results were projected to year 2021. Three scenarios were created with regard to EVs market share (10%, 5% and 2%) after deeply analyzing the literature. A regression analysis was used to determine which socioeconomic characteristics influence mostly EV ownership. Three models were found to affect EV possession per census tract. The predicted values were used as weights to modify the O-D matrices, which participate in the simulation procedure. The trips were then assigned to the road network using TRAFFIC and combined with the estimated emission factors from MOBILE 6.2C. The emissions abatement was then computed. Lastly, the emissions reduction was quantified and evaluated.

The methodology was not designed only to predict pollutant concentrations resulting from EVs introduction. Rather, the methodology used the best available emission factors to estimate net changes in emissions compared to the BAU scenario.

The results indicate that the introduction of EVs exhibits advantage over the BAU case in every aspect of their emissions. The introduction of 10% of electric vehicles in the fleet may lead to almost 50% reduction in HC emissions in the morning rush hours (8am) and 12% in the evening (5pm). A similar trend is observed regarding CO pollutant with 40% decrease at 8am and 12% at 5pm for both January and July. The implementation of 5% of electric vehicles with the second scenario indicates a lower mitigation but still remarkable. For Scenarios 2 and 3 all four pollutants present the same rate of reduction.

We also confirmed findings in the literature that the probability of mitigating GHG emissions is influenced by personal and housing characteristics, such as income, education status, household size and type. We conclude that different distribution patterns of electric vehicles produce different spatial patterns of emissions in the links and variations in emissions reductions. The predicted values from all three models contributed to emissions decrease. Specifically, from the three models created by the regression analysis, the third one assisted to mostly mitigate the emissions produced at the aggregate level. The combination of the variables –Owned dwellings, detached dwellings, low level of education and average number of persons- created a distribution pattern of EVs sufficient enough to differentiate from the others two, whilst the spatial distributions from all models produced slightly different spatial patterns in the links.

This study represents a beginning in understanding and quantifying the impacts of market penetration for alternative vehicle technologies (electric) on regional vehicle emissions. As demonstrated in the body of this study, there are several factors affecting EVs penetration rates and future GHG emissions. Since these factors create uncertainty, it is difficult to accurately predict what the future holds for electric vehicles technologies. The effects of EVs on GHG emissions will depend on the rate of consumer adoption and the source of electricity used. Our focus on optimistic (10% market uptake), medium (5%) and conservative (2%) scenarios' results allows decision makers to implement policies amplifying EVs usage.

The results suggest that the procedure is effective and even a modest change in vehicle fleet could lead to traffic-related emissions reduction. Through TRAFFIC model, emissions are estimated at the link level. While the results are encouraging, they were based on the assumption that the electricity generated to charge the vehicles derived from renewable sources. Although only 5% of electricity in Ontario comes from burning coal, this percentage should be eliminated in order to benefit from the new technology. As a conclusion, the results obtained indicate that the time from the base year to the simulation year is sufficient for electric vehicles to acquire a significant share of the fleet and influence urban air quality.

Electric vehicles are a realistic alternative to conventional vehicles and can contribute to emissions reductions.

5.1 Discussion

Technology improvements alone will not be enough to improve air quality to the extent indicated by the study; behavioral change will also be crucial. Public transport, walking and cycling should be promoted in order to prevent rebound effects from excessive use of the new technology. Incentives should be given to people to minimize automobile's usage and on the contrary increase public transport's usage to reach sustainable transportation. Electric vehicles can contribute to emissions reductions only when used instead of conventional vehicles and the VMT remain constant.

It must also be emphasized that in order to achieve maximum benefit from electric vehicles, electricity should be acquired from renewable sources. Using the energy produced from coal-fired power stations may lead to just a small reduction in emissions or even increase. Nuclear power, hydroelectric, solar, wind and natural gas are some examples of renewable sources that every government, aiming to incorporate EVs as part of their transportation policies, should adopt to benefit from low "well-to-wheels" vehicle emissions.

5.2 Future Directions

There has been substantial interest in the transportation and planning literature on examining the factors contributing to EV ownership. To date, research over the demand for alternative fuel vehicles and HEVs has been conducted but not for electric vehicles. Thus, for this study, the scenarios were selected based on current demand for HEVs. A survey should take place to capture the tendency over EVs and consumer's preferences. Disaggregate data should also be collected in order to better outline consumer's behavior and willingness to afford another "greener" vehicle.

Canadian Nuclear Society (2013) reports that only 5% of electricity comes from burning coal in Ontario. The final cost-benefit analysis rests on whether renewable resources are used to generate the increased electricity demand. This study was based on the assumption that electricity is generated only by renewable sources of energy but is of great importance to include this detail in the research if even a small proportion of electricity comes from coal. An investigation over the energy costs after intense usage of electric cars and the way Ontario's government will respond to the growing electricity demand should also be embedded. Before policy makers introduce to the market share a large amount of electric vehicles organizing and planning is needed. The charging infrastructure and the possible locations of charging points could be a subject of future investigation.

Another recommendation that can be made with respect to future work is to develop more complex and realistic scenarios of market penetration based on analysis of data collected through stated preference surveys that should cover inter and intra-regional flows by vehicle type. Such scenarios should embed and integrate improvements in the characteristics of EVs (especially the range), a more widely available network of charging stations and the changing government policy towards incentives for the adoption of EVs.

The methods used in the study to introduce electric vehicles' class in place of LDPV and the conversion of LDPV and LDCV into LDV was possible only because these vehicles demonstrate the same passenger car equivalency values and share common characteristics. TRAFFIC module at the moment cannot simulate alternate vehicle technologies for an integrated analysis. In this study, EVs and HEVs should be considered and analyzed as two different and separate vehicle types. As the years pass, more vehicles become "greener" and alternative technologies are adopted by medium and heavy commercial vehicles as well. Therefore, an update to incorporate the changes should take place.

A last reference for future research would be to include not only Hamilton CMA but Toronto GTHA as well, as an overview of the benefits of electric cars on traffic related emissions reduction on a greater study area would assist to carry out integrated results.

Chapter 6

6. Bibliography

Acello R. (1997). Getting into Gear with the Vehicle of the Future. *San Diego Business Journal*.

Agresti A. (2002). Categorical data analysis. *Wiley and Sons*.

Balducci P. (2008). *Plug-In Hybrid Electric Vehicle Market Penetration Scenarios.* U.S Department of Energy.

Baptista P., Silva C., Gonçalves G., Farias T. (2009). Full life cycle analysis of market penetration of electricity based vehicles. *World Electric Vehicle Journal, 3*.

Beckmann J. (2010). Electric Mobility in Europe' s hilly heartland: The Swiss case. *Water, Energy and Transport*.

Bento A.M., CropperM.L., Mobarak A.M., Vinha K. (2005). The Impact of Urban Spatial Structure on Travel Demand in the United States. *Review of Economic and Statistics*, pp. 466-478.

BERR & DfT. (2008). *Investigation into the Scope for the Transport Sector to Switch to Electric Vehicles and Plugin Hybrid Vehicles.* UK: Department for Bussiness Enterprise & Regulatory Reform & Department for Transport.

Bhat C.R. and Pulugurta V. (1998). A Comparison of Two Alternative Behavioral Choice Mechanisms for Household Auto Ownership Decisions. *Transportation Research Part B*, pp.61-75.

Bhattacharjee A. (2012). India-One of the world's most exciting EV market. *Global Forum in Electric Mobility:Greening transport for sustainable development.* Rio de Janeiro: UN Department of Economic and Social Affairs: Division for Sustainable Development.

Bradley T.H., Frank A.A. (2009). Design, demonstrations and sustainability impact assessments for plug-in hybrid electric vehicles. *Renewable and Sustainable Energy Reviews, 13*(1), pp.115-128.

Brady J., O'Mahony M. (2011, March). Travel to work in Dublin. The potential impacts of electric vehicles on climate change and urban air quality. *Transportation Research Part D: Transport and Environment, 16*(2), pp. 188-193.

Bueno G. (2012, May). Analysis of scenarios for the reduction of energy consumption and GHG emissions in transport in the Basque Country. *Renewable and Sustainable Energy Reviews, 16*(4), pp. 1988-1998.

Butcher N. (2012, 07 25). *Greentechmedia.* Retrieved 05 02, 2013, from Guest Post: EV Myths and Realities, Part 2—Green as the Grid; Are electric vehicles really 'clean and green,' or are they just posing as such?: http://www.greentechmedia.com/articles/read/Guest-Post-EV-Myths-and-Realities-Part-2-Green-as-the-Grid

Cameron A.C. and Trivedi P.K. (1998). Regression analysis of count data. *Cambridge university Press*.

Canada's Action. (2010, 06 02). *Canada's Action on Climate Change*. Retrieved 12 17, 2012, from Governement of Canada: http://www.climatechange.gc.ca/default.asp?lang=En&n=97C0E131-1

Canadian Nuclear Society. (2013). *Electricity Sources*. Retrieved 2 6, 2013, from http://media.cns-snc.ca/ontarioelectricity/ontarioelectricity.html

Centre for Spatial Analysis (CSpA). (2009). *Mobile Emission Estimates for Toronto, Ontario, Canada.* Toronto: Mc Master University.

Choo S., Mokhtarian P.L. (2002). *The relationship of vehicle type choice to personality, lifestyle, attitudinal and demographic variables.* California: Institute of Transportation Studies University of California.

Chu Y.L. (2002). Automobile Ownership Analysis Using Ordered Probit Models. *Transportation Research Record*, pp. 60-67.

Climate Action. (2011, 01 06). *European Commission*. Retrieved 10 22, 2012, from http://ec.europa.eu/clima/policies/transport/index_en.htm

CSpA. (2009). *Mobile Emission Estimates for Hamilton, Ontario, Canada.* Hamilton: Mc Master University.

Cunningham J. (2009). *An Analysis of Battery Electric Vehicle Production Projections.* Massachusetts: MIT.

Curtin R., Shrago Y., Mikkelsen J. (2009). *Plug-in Hybrid Electric Vehicles.* Michigan: University of Michigan Transportation Research Institute.

Dagsvik J., W. D. (1996). *Potential Demand for Alternative Fuel Vehicles.* Statistics Norway.

Deloitte. (2010). *Gaining Traction: A Customer View of Electric Vehicle Mass Adoption in the US Automotive Market.*

Dempsey N. (2008). *Government announces plans for the electrification of Irish motoring.* Department of Transport. Dublin: Press Release.

Dijk M., Yarrime M. (2010). The emergence of hybrid-electric cars: Innovation path creation through co-evolution of supply and demand. *Technological Forecasting and Social Change, 77*(8), pp. 1371-1390.

Dobson A. J. (2002). An introduction to generalized linear models. *Chapan & Hall,CRC*.

Domencich and McFadden. (1975). *Urban Travel Demand: A Behavioral Analysis.* North-Holland Publishing Co.

Earley R., Kang L., An F., Green-Weiskel L. (2011). Electric vehicles in the context of sustainable development in China. *Commission on Sustainable Development.* New York: United Nations Department of Economic and Social Affairs.

EPA. (2003). *User's Guide to MOBILE 6.1 and MOBILE 6.2: Mobile Source Emission Factor Model.* USA: Environment Protection Agency.

EPRI and NRDC. (2007). *Environmental Assessment of Plug-in Hybrid Electric Vehicles.* U.S.A: Electric Power Research Institute Inc.

Fox J. (2008). Applied regression analysis and geeralized linear models. *Sage*.

Franke T., B. F. (2012). Enhancing sustainability of electric vehicles: A field study approach to understanding user acceptance and behavior. *Advances in Traffic Psychology*.

German advisory council on global change (WBGU). (2011). *World in transition: A Social Contract for Sustainability.* Berlin: WBGU.

Haan P., Peters A., Mueller M. (2006). Comparison of Buyers of Hybrid and Conventional Internal Combustion Engine Automobiles: Characteristics, Preferences and previously Owned Vehicles. *Transportation Research Record*, pp. 106-113.

Hadley S., Tsvetkova A. (2008). *Potential Impacts of Plug-in Hybrid Electric Vehicles on Regional Power Generation.* Oak Ridge, Tennessee, U.S.A: Oak Ridge National Laboratory.

Hardin J.W. & Hilbe J.M. (2007). Generalized linear models and extensions. *College Station*.

Hauer E. (2001). Overdispersion in modeling accidents on road section and in empirical Bayes estimation. *Accident Analysis and Prevention* , pp.799-808.

Hesss D.B., Ong P.M. (2002). Tradiotional Neighborhoods and Automobile Ownership. *Transpotation Research Record*, pp. 35-44.

Hilbe J.M. (2007). *Negative binomial regression.* Cambridge University Press.

Hoffman J.P. (2004). Generalized linear models: An applied approach. *Allyn & Bacon*.

Huo H., Zhang Q., Wang M., Streets D., He K. (2010, May). Environmental Implication of Electric Vehicles in China. *Environmental Science technology, 44*, pp.4856-4861.

Hybrid Auto Market Analysis. (2007, March 10). Retrieved December 4, 2012, from Marketing & Advertising: http://w303.com/354/hybrid-auto-market-analysis/

Ian Hobday. (2013, 05 28). *Liberty Electric Cars*. Retrieved 01 20, 2014, from http://www.liberty-ecars.com/home/the-company

Intergovernmental Panel on Climate Change (IPCC). (2011). *Renewable Energy Sources and Climate Change Mitigation.* Cambridge: Cambridge University Press.

Ito N., T. K. (2011). *Willingness to pay for the infrastructure investments for alternative fuel vehicles.* Japan: Policy Studies of Environment and Economy.

Ji S., Cherry C., Bechle M., Wu Y., Marshall J. (2011). Electric Vehicles in China: Emissions and Health Impacts. *Environmental Science and Technology, 46*, pp. 2018-2024.

Kanaroglou P.S and Buliung R.N. (2008). Estimating the contribution of commercial vehicle movement to mobile emissions in urban areas. *Transportation Research Part E: Logistics and Transportation Review*, pp. 260-276.

Koutsopoulos K. (2006). *Spatial Analysis: Theory, Methodology and Techniques.* Athens: Diinekes.

Krems J., F. T. (2010). Research methods to assess the aceptance of EVs-experiences from an EV user study. *Human Interface Design for Intelligent Transport Systems* (pp. pp. 445-453). Berlin, Germany: Humanist Publications.

Kromer, M. A. (2007). *Electric Powertrains: Opportunities and Challenges in the U.S. Light-Duty Vehicle Fleet.* Cambridge, Massachusetts: MIT Laboratory for Energy and the Environment.

Land K.C., M. P. (1996). A Comparison of Poisson, negative binomial and semi-parametric mixed Poission regression models-with empirical applications to criminal careers data. *Socio-logical Methods and Research*, pp. 387-442.

Lane B. (2005). *Car buyer research report:Consumer attitudes to low carbon and fuel-efficient passenger cars.* UK: Low Carbon Vehicle Partnership.

Lave, Charles A. et al. (1980). Market Share of Imported Cars: A Model of Geographic and Demographic Determinants. *Transportation Research*, pp. 379-387.

Lord D., Mannering F.L. (2010). The statistical analysis of crash-frequency data:a review and assessment of methodological alternatives. *Transportation Research Part A*, pp. 291-305.

Mc Manus W., Senter R. (2009). *Market Models for Predicting PHEV Adoption and Diffusion.* University of Michigan Transportation Research Institute.

Ministry of Transportation. (2010). *A plan for a Greener Ontario*. Retrieved 10 20, 2012, from Ontario Ministry of Transportation: http://www.mto.gov.on.ca/english/dandv/vehicle/electric/plan-greener-ontario/index.shtml

Ministry of Transportation. (2011, 12 7). *Ontario*. Retrieved 2 21, 2013, from http://www.mto.gov.on.ca/english/dandv/vehicle/electric/ev-green-plates.shtml

MIT. (2008). *On the Road in 2035: Reducing Transportation's Petroleum Consumption and GHG Emissions.* Massachusetts, U.S.A: Laboratory for Energy and the Environment.

National Research Council. (2010). *Transitions to Alternative Transportation Technologies--Plug-in Hybrid Electric Vehicles.* Board on Energy and Environmental Systems.

Natural Resources Canada. (2009). *Natural Resources Canada*. Retrieved May 8, 2013, from http://www.nrcan.gc.ca/energy/publications/sources/oil-gas-review-outlook/1229

Nemry F., Brons M. (2010). *Plug-in Hybrid and Battery Electric Vehicles: Market penetration scenarios of electric drive vehicles.* Luxembourg, Europe: JRC-IPTS.

OECD. (2007). *Environmental Data, Compendium.* Paris: OECD.

Parks K., Denholm P. and Markel T. (2007). *Costs and Emissions Associated with Plug-in Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory.* U.S.A: National Renewable Energy Laboratory.

Perujo A., Ciuffo B. (2010). The introduction of electric vehicles in the private fleet: Potential impact on the electric supply system and on the environment. A case study for the Province of Milan, Italy. *Energy Policy 38*, pp. 4549-4561.

Potoglou D., K. P. (2007, June). Household demand and willingness to pay for clean vehicles. *Transportation Research Part D: Transport and Environment, 12*(4), pp.264-274.

Potoglou D., Kanaroglou P. (2008). Modelling car ownership in urban areas:a case study of Hamilton, Canada. *Journal of Transport Geography*, pp.42-54.

Primer, P. (2010). *The Pembina Institute*. Retrieved 10 25, 2012, from http://www.pembina.org/pub/2072

Santarius T. (2012). Green Growth Unravelled. How rebound effects baffle sustainability targets when the economy keeps growing. *Heinrich Böll Foundation and Wuppertal Institute for Climate, Environment and Energy*, 22.

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt,. (2007). Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. *Cambridge University Press*.

Statistics Canada. (2008). *Summary tables for Hamilton Census Metropolitan Area.* Retrieved from http://www40.statcan.ca/l01/met01/met109-eng.htm

Stuben J., Sterman J.D. (2008). Transition Challenges for Alternative Fuel Vehicles and Transportation Systems. *Environment and Planning B: Planning and Design*, pp.1070-1097.

Tesla. (2014). *Electric Vehicles Incentives around the World*. Retrieved from http://www.teslamotors.com/incentives

The Boston Consulting Group. (2009). *The Comeback of the Electric Car? How real, how soon and what must happen next.* Boston.

Thiel C., Perujo A., Mercier A. (2010, November). Cost and CO2 aspects of future vehicle options in Europe under new energy policy scenarios. *Energy Policy, 38*(11), pp. 7142-7151.

Transport Canada. (2011). *User Guide For Urban Transportation Emissions Calculator.* Canada: IBI Group.

TTS. (2006). *Data Management Group: Transportation Tomorrow Survey 2006.* Retrieved Nov. 2012, from Joint Program in Transportation, University of Toronto: http://www.dmg.utoronto.ca/

US Environmental Protection Agency . (2003). *User's Guide to MOBILE 6.1 and MOBILE 6.2 (Mobile Source Emission Factor Model).* Washinghton D.C: United States Envrironmental Protection Agency .

World Business Council for Sustainable Development. (2004). *Mobility 2030: Meeting the challenges to sustainability.* Geneva, Switzerland: WBCSD.

Wu G., Yamamoto T., Kitamura R. (1999). Vehicle ownership model that incorporates the causal struvture underlying attitudes toward vehicle ownership. *Transportation Research*, pp.61-67.

WWF. (2012). *Greenhouse Gas Reduction Potential of Electric Vehicles: 2025 Outlook Report.* WWF Climate Change and Energy Program.

Zehner O. (2013). *Unclean at any Speed.* Berkeley, California: IEEE Spectrum.

Appendices

Table 27. EVs distribution in 2008, 2012 and predicted values

Cencus tracts	Observed values		Predicted Number of EVs			
	NHEV08	NHEV12	Model 1	Model 2	Model 3	VHHLD
5370001.01	1	4	4	6	8	2182
5370001.02	2	5	5	9	9	3162
5370001.04	5	11	17	15	9	3392
5370001.05	2	9	8	8	12	2333
5370001.06	6	7	15	15	6	2940
5370001.07	1	1	4	6	6	1652
5370001.08	4	8	15	15	7	3446
5370001.09	0	5	11	14	10	2286
5370002.01	2	2	4	9	8	2794
5370002.02	4	19	35	21	9	5092
5370002.03	2	6	9	8	10	1665
5370002.04	1	5	13	13	6	2762
5370003.01	9	14	15	11	14	2851
5370003.02	2	2	7	6	7	1871
5370003.03	2	4	4	7	8	1427
5370003.04	3	10	9	7	8	2822
5370004.01	0	4	5	6	7	1903
5370004.02	1	4	6	6	6	2092
5370005.01	2	7	12	9	7	3059
5370005.02	0	3	5	6	6	1913
5370005.03	0	2	7	8	8	2289
5370006	4	4	7	6	5	2672
5370007	1	2	8	6	8	1725
5370008	2	2	14	7	10	1305
5370009	0	0	5	6	5	1723
5370010	1	3	6	6	7	1733
5370011	3	5	7	6	11	1319
5370012	1	2	3	5	5	709
5370013	7	12	8	8	11	1719
5370014	2	7	7	7	12	1618
5370015	3	2	14	8	19	917
5370016	0	1	4	3	5	107
5370017	16	29	26	16	20	1931

Scenario 1: 10% EVs (41899 vehicles)

Scenario 2: 5% EVs (20950 vehicles)

Scenario 3: 2% EVs (8380 vehicles)

5370019	3	6	6	7	7	2072
5370020	0	2	4	6	7	2144
5370021	3	1	5	5	6	2325
5370022	0	3	5	4	6	2495
5370023	1	3	5	6	8	1370
5370024	4	9	5	6	7	1454
5370025	0	2	6	4	10	1679
5370026.01	2	1	8	7	7	1726
5370026.02	2	1	14	6	7	868
5370026.03	1	4	14	9	14	1375
5370026.04	1	1	5	4	11	905
5370026.05	2	3	7	6	10	2258
5370026.06	1	3	4	6	5	2484
5370027	0	2	3	1	9	701
5370028	1	2	6	4	7	1636
5370029	0	2	6	4	7	2271
5370030	1	8	5	5	8	2239
5370031	1	5	4	4	4	1053
5370032	0	1	7	4	4	1225
5370033	3	6	4	5	2	1296
5370034	1	4	2	2	4	1942
5370035	1	0	2	3	4	1129
5370036	14	18	15	14	19	1630
5370037	1	3	3	3	7	860
5370038	4	9	5	3	5	1337
5370039	2	3	3	4	6	2133
5370040	3	5	4	3	4	876
5370041	1	4	7	6	7	828
5370042	8	11	5	5	6	1474
5370043	3	10	6	5	5	1585
5370044	3	8	10	6	7	2079
5370045	12	26	23	11	13	1563
5370046	7	7	8	8	10	1373
5370047	5	12	8	5	7	1878
5370048	1	2	2	3	8	591
5370049	1	6	3	5	5	942
5370050	0	5	5	3	6	1227
5370051	1	1	3	3	4	1276
5370052	1	3	2	2	2	1391
5370053	0	1	4	4	3	1322
5370054	0	1	3	4	9	1211

5370055	0	2	4	4	9	1940
5370056	0	0	5	4	10	1899
5370057	0	0	5	4	12	1434
5370058	0	1	1	2	8	1001
5370059	2	4	3	4	5	1419
5370060	0	2	5	4	8	1032
5370061	1	2	4	4	6	1991
5370062	0	2	5	6	5	1326
5370063	3	0	2	4	6	1311
5370064	10	9	7	6	11	872
5370065	2	2	2	3	7	1417
5370066	2	7	6	4	9	2218
5370067	0	1	3	5	9	1072
5370068	1	0	2	2	5	743
5370069	0	0	3	1	8	702
5370070	0	2	4	3	14	2352
5370071	2	3	7	4	7	2798
5370072.01	1	4	2	3	3	1606
5370072.02	1	3	5	5	7	1771
5370072.03	2	6	8	9	5	2680
5370072.04	1	2	5	7	9	1820
5370073	4	2	2	1	3	1002
5370080.01	1	4	11	10	10	2018
5370080.03	4	12	9	11	6	3030
5370080.04	5	7	22	20	7	4686
5370080.05	7	9	18	18	12	3580
5370081	3	6	6	6	5	1482
5370082	3	5	7	6	6	2077
5370083	1	2	3	4	3	1402
5370084.01	1	2	5	8	9	1822
5370084.02	2	3	6	7	8	1905
5370084.03	0	2	11	8	11	1434
5370084.04	2	7	4	4	11	2354
5370084.05	3	6	8	11	13	1937
5370085.01	9	9	14	13	10	2954
5370085.02	3	6	16	21	8	4219
5370085.03	5	10	10	7	10	3629
5370086	9	28	15	22	13	6059
5370100	8	16	13	15	9	8209
5370101	23	32	15	13	10	8591
5370120.01	23	29	25	35	17	5865

5370120.02	4	4	12	11	11	1475
5370121	11	11	7	10	6	1216
5370122.01	6	13	17	14	13	3810
5370122.02	17	29	32	32	19	4433
5370123	23	27	38	24	14	4730
5370124	7	20	28	21	19	2496
5370130.02	15	32	22	21	21	2774
5370130.03	10	14	40	16	15	2239
5370131	17	29	20	14	10	3110
5370132	9	13	8	6	6	1897
5370133	27	55	45	21	15	6203
5370140.02	11	25	14	17	11	6915
5370140.03	4	9	8	20	13	2991
5370140.04	3	10	9	17	13	2395
5370141	12	21	13	15	9	3298
5370142.01	4	18	4	9	9	4178
5370142.02	3	15	4	9	9	3259
5370143	5	2	10	16	9	912
5370144	15	15	11	27	10	4548
5370200	5	7	15	19	18	2002
5370201	10	14	13	13	9	2757
5370202	15	36	20	14	12	3615
5370203	6	12	19	11	23	1804
5370204	4	10	4	6	6	2728
5370205.01	11	14	15	8	17	2810
5370205.02	6	14	11	6	6	2241
5370206	28	44	6	5	6	3239
5370207.01	12	27	15	14	8	4364
5370207.02	5	12	9	18	7	4235
5370207.03	6	6	10	11	10	2681
5370207.04	4	8	4	5	7	1653
5370208	0	4	4	6	7	1929
5370209	0	5	9	5	9	1144
5370210	1	2	4	5	9	1504
5370211	2	7	4	5	5	2319
5370212	3	6	10	6	7	934
5370213	18	20	8	6	5	2285
5370214	1	7	8	7	10	1615
5370215	5	8	6	9	11	1720
5370216	20	31	18	20	18	2783
5370217.01	4	10	9	6	5	3340

5370217.02	3	15	17	14	15	2909
5370218	17	29	15	12	11	5728
5370219	16	28	19	23	21	3194
5370220	9	21	11	8	10	3900
5370221	5	6	8	9	10	2048
5370222	13	21	18	19	14	6460
5370223.01	5	8	7	6	7	2286
5370223.02	3	10	6	12	6	4197
5370223.05	4	5	8	21	12	2036
5370223.06	7	8	9	25	10	2816
5370223.07	6	15	10	16	12	3065
5370223.09	10	26	12	44	28	4656
5370223.1	2	12	8	20	20	2643
5370223.11	32	49	25	34	20	8691
5370223.12	14	25	6	11	22	7383
5370224	5	24	11	13	11	5108
Total	**848**	**1622**	**1626**	**1634**	**1596**	**418994**

Table 28. Weights

	Scenario 1			Scenario 2			Scenario 3		
Cencus tracts	Model1	Model 2	Model3	Model1	Model 2	Model3	Model1	Model 2	Model3
5370001.01	4.72%	7.05%	9.63%	2.36%	3.53%	4.81%	0.94%	1.41%	1.93%
5370001.02	4.07%	7.30%	7.47%	2.04%	3.65%	3.74%	0.81%	1.46%	1.49%
5370001.04	12.91%	11.34%	6.97%	6.46%	5.67%	3.48%	2.58%	2.27%	1.39%
5370001.05	8.84%	8.79%	13.50%	4.42%	4.40%	6.75%	1.77%	1.76%	2.70%
5370001.06	13.15%	13.08%	5.36%	6.57%	6.54%	2.68%	2.63%	2.62%	1.07%
5370001.07	6.24%	9.31%	9.53%	3.12%	4.66%	4.77%	1.25%	1.86%	1.91%
5370001.08	11.22%	11.16%	5.33%	5.61%	5.58%	2.67%	2.24%	2.23%	1.07%
5370001.09	12.40%	15.70%	11.48%	6.20%	7.85%	5.74%	2.48%	3.14%	2.30%
5370002.01	3.69%	8.26%	7.52%	1.84%	4.13%	3.76%	0.74%	1.65%	1.50%
5370002.02	17.71%	10.58%	4.64%	8.86%	5.29%	2.32%	3.54%	2.12%	0.93%
5370002.03	13.93%	12.32%	15.77%	6.96%	6.16%	7.88%	2.79%	2.46%	3.15%
5370002.04	12.13%	12.07%	5.70%	6.06%	6.03%	2.85%	2.43%	2.41%	1.14%
5370003.01	13.56%	9.89%	12.89%	6.78%	4.95%	6.45%	2.71%	1.98%	2.58%
5370003.02	9.64%	8.22%	9.82%	4.82%	4.11%	4.91%	1.93%	1.64%	1.96%
5370003.03	7.22%	12.58%	14.72%	3.61%	6.29%	7.36%	1.44%	2.52%	2.94%
5370003.04	8.22%	6.36%	7.44%	4.11%	3.18%	3.72%	1.64%	1.27%	1.49%
5370004.01	6.77%	8.08%	9.66%	3.39%	4.04%	4.83%	1.35%	1.62%	1.93%
5370004.02	7.39%	7.35%	7.53%	3.70%	3.68%	3.76%	1.48%	1.47%	1.51%
5370005.01	10.11%	7.54%	6.01%	5.05%	3.77%	3.00%	2.02%	1.51%	1.20%
5370005.02	6.74%	8.04%	8.23%	3.37%	4.02%	4.12%	1.35%	1.61%	1.65%
5370005.03	7.88%	8.96%	9.18%	3.94%	4.48%	4.59%	1.58%	1.79%	1.84%
5370006.00	6.75%	5.76%	4.91%	3.38%	2.88%	2.46%	1.35%	1.15%	0.98%
5370007.00	11.95%	8.92%	12.18%	5.98%	4.46%	6.09%	2.39%	1.78%	2.44%
5370008.00	27.64%	13.75%	20.12%	13.82%	6.88%	10.06%	5.53%	2.75%	4.02%
5370009.00	7.48%	8.93%	7.62%	3.74%	4.46%	3.81%	1.50%	1.79%	1.52%
5370010.00	8.92%	8.88%	10.60%	4.46%	4.44%	5.30%	1.78%	1.78%	2.12%
5370011.00	13.68%	11.66%	21.89%	6.84%	5.83%	10.95%	2.74%	2.33%	4.38%
5370012.00	10.90%	18.08%	18.51%	5.45%	9.04%	9.26%	2.18%	3.62%	3.70%

5370013.00	11.99%	11.93%	16.80%	6.00%	5.97%	8.40%	2.40%	2.39%	3.36%
5370014.00	11.15%	11.09%	19.47%	5.57%	5.55%	9.74%	2.23%	2.22%	3.89%
5370015.00	39.34%	22.37%	54.39%	19.67%	11.19%	27.20%	7.87%	4.47%	10.88%
5370016.00	31.33%	27.41%	43.07%	15.66%	13.71%	21.54%	6.27%	5.48%	8.61%
5370017.00	34.70%	21.25%	27.19%	17.35%	10.62%	13.60%	6.94%	4.25%	5.44%
5370019.00	7.46%	8.66%	8.87%	3.73%	4.33%	4.43%	1.49%	1.73%	1.77%
5370020.00	4.81%	7.18%	8.57%	2.40%	3.59%	4.29%	0.96%	1.44%	1.71%
5370021.00	5.54%	5.51%	6.77%	2.77%	2.76%	3.39%	1.11%	1.10%	1.36%
5370022.00	5.16%	4.11%	6.31%	2.58%	2.06%	3.16%	1.03%	0.82%	1.26%
5370023.00	9.40%	11.23%	15.33%	4.70%	5.62%	7.67%	1.88%	2.25%	3.07%
5370024.00	8.86%	10.58%	12.64%	4.43%	5.29%	6.32%	1.77%	2.12%	2.53%
5370025.00	9.21%	6.11%	15.64%	4.60%	3.05%	7.82%	1.84%	1.22%	3.13%
5370026.01	11.94%	10.40%	10.65%	5.97%	5.20%	5.32%	2.39%	2.08%	2.13%
5370026.02	41.56%	17.72%	21.17%	20.78%	8.86%	10.59%	8.31%	3.55%	4.23%
5370026.03	26.24%	16.78%	26.73%	13.12%	8.39%	13.37%	5.25%	3.36%	5.35%
5370026.04	14.24%	11.33%	31.91%	7.12%	5.67%	15.95%	2.85%	2.27%	6.38%
5370026.05	7.99%	6.81%	11.63%	3.99%	3.41%	5.81%	1.60%	1.36%	2.33%
5370026.06	4.15%	6.19%	5.28%	2.07%	3.10%	2.64%	0.83%	1.24%	1.06%
5370027.00	11.03%	3.66%	33.71%	5.51%	1.83%	16.85%	2.21%	0.73%	6.74%
5370028.00	9.45%	6.27%	11.23%	4.73%	3.13%	5.62%	1.89%	1.25%	2.25%
5370029.00	6.81%	4.52%	8.09%	3.40%	2.26%	4.05%	1.36%	0.90%	1.62%
5370030.00	5.75%	5.73%	9.38%	2.88%	2.86%	4.69%	1.15%	1.15%	1.88%
5370031.00	9.79%	9.74%	9.97%	4.89%	4.87%	4.99%	1.96%	1.95%	1.99%
5370032.00	14.72%	8.37%	8.57%	7.36%	4.19%	4.29%	2.95%	1.67%	1.71%
5370033.00	7.95%	9.89%	4.05%	3.98%	4.95%	2.03%	1.59%	1.98%	0.81%
5370034.00	2.65%	2.64%	5.41%	1.33%	1.32%	2.70%	0.53%	0.53%	1.08%
5370035.00	4.56%	6.81%	9.30%	2.28%	3.41%	4.65%	0.91%	1.36%	1.86%
5370036.00	23.71%	22.02%	30.60%	11.86%	11.01%	15.30%	4.74%	4.40%	6.12%
5370037.00	8.99%	8.94%	21.37%	4.49%	4.47%	10.68%	1.80%	1.79%	4.27%
5370038.00	9.64%	5.75%	9.82%	4.82%	2.88%	4.91%	1.93%	1.15%	1.96%
5370039.00	3.62%	4.81%	7.38%	1.81%	2.40%	3.69%	0.72%	0.96%	1.48%
5370040.00	11.77%	8.78%	11.99%	5.88%	4.39%	5.99%	2.35%	1.76%	2.40%
5370041.00	21.78%	18.58%	22.19%	10.89%	9.29%	11.10%	4.36%	3.72%	4.44%
5370042.00	8.74%	8.70%	10.69%	4.37%	4.35%	5.34%	1.75%	1.74%	2.14%
5370043.00	9.75%	8.09%	8.28%	4.88%	4.04%	4.14%	1.95%	1.62%	1.66%
5370044.00	12.39%	7.40%	8.84%	6.20%	3.70%	4.42%	2.48%	1.48%	1.77%
5370045.00	37.92%	18.05%	21.84%	18.96%	9.02%	10.92%	7.58%	3.61%	4.37%
5370046.00	15.01%	14.94%	19.12%	7.51%	7.47%	9.56%	3.00%	2.99%	3.82%
5370047.00	10.98%	6.83%	9.79%	5.49%	3.41%	4.89%	2.20%	1.37%	1.96%
5370048.00	8.72%	13.02%	35.54%	4.36%	6.51%	17.77%	1.74%	2.60%	7.11%
5370049.00	8.21%	13.61%	13.93%	4.10%	6.81%	6.97%	1.64%	2.72%	2.79%
5370050.00	10.50%	6.27%	12.84%	5.25%	3.13%	6.42%	2.10%	1.25%	2.57%
5370051.00	6.06%	6.03%	8.23%	3.03%	3.01%	4.11%	1.21%	1.21%	1.65%
5370052.00	3.70%	3.69%	3.77%	1.85%	1.84%	1.89%	0.74%	0.74%	0.75%
5370053.00	7.80%	7.76%	5.96%	3.90%	3.88%	2.98%	1.56%	1.55%	1.19%
5370054.00	6.38%	8.47%	19.51%	3.19%	4.23%	9.76%	1.28%	1.69%	3.90%
5370055.00	5.31%	5.29%	12.18%	2.66%	2.64%	6.09%	1.06%	1.06%	2.44%
5370056.00	6.78%	5.40%	13.82%	3.39%	2.70%	6.91%	1.36%	1.08%	2.76%
5370057.00	8.98%	7.15%	21.97%	4.49%	3.58%	10.98%	1.80%	1.43%	4.39%
5370058.00	2.57%	5.12%	20.98%	1.29%	2.56%	10.49%	0.51%	1.02%	4.20%
5370059.00	5.45%	7.23%	9.25%	2.72%	3.61%	4.63%	1.09%	1.45%	1.85%
5370060.00	12.48%	9.94%	20.35%	6.24%	4.97%	10.18%	2.50%	1.99%	4.07%
5370061.00	5.18%	5.15%	7.91%	2.59%	2.58%	3.96%	1.04%	1.03%	1.58%
5370062.00	9.72%	11.60%	9.90%	4.86%	5.80%	4.95%	1.94%	2.32%	1.98%
5370063.00	3.93%	7.82%	12.01%	1.97%	3.91%	6.01%	0.79%	1.56%	2.40%
5370064.00	20.69%	17.64%	33.12%	10.34%	8.82%	16.56%	4.14%	3.53%	6.62%
5370065.00	3.64%	5.43%	12.97%	1.82%	2.71%	6.48%	0.73%	1.09%	2.59%
5370066.00	6.97%	4.62%	10.65%	3.49%	2.31%	5.33%	1.39%	0.92%	2.13%

5370067.00	7.21%	11.96%	22.04%	3.61%	5.98%	11.02%	1.44%	2.39%	4.41%
5370068.00	6.94%	6.90%	17.67%	3.47%	3.45%	8.83%	1.39%	1.38%	3.53%
5370069.00	11.01%	3.65%	29.92%	5.51%	1.83%	14.96%	2.20%	0.73%	5.98%
5370070.00	4.38%	3.27%	15.63%	2.19%	1.64%	7.81%	0.88%	0.65%	3.13%
5370071.00	6.45%	3.67%	6.57%	3.22%	1.83%	3.28%	1.29%	0.73%	1.31%
5370072.01	3.21%	4.79%	4.90%	1.60%	2.40%	2.45%	0.64%	0.96%	0.98%
5370072.02	7.28%	7.24%	10.38%	3.64%	3.62%	5.19%	1.46%	1.45%	2.08%
5370072.03	7.69%	8.61%	4.90%	3.85%	4.31%	2.45%	1.54%	1.72%	0.98%
5370072.04	7.08%	9.86%	12.98%	3.54%	4.93%	6.49%	1.42%	1.97%	2.60%
5370073.00	5.14%	2.56%	7.86%	2.57%	1.28%	3.93%	1.03%	0.51%	1.57%
5370080.01	14.05%	12.71%	13.01%	7.02%	6.35%	6.50%	2.81%	2.54%	2.60%
5370080.03	7.65%	9.31%	5.20%	3.83%	4.65%	2.60%	1.53%	1.86%	1.04%
5370080.04	12.10%	10.94%	3.92%	6.05%	5.47%	1.96%	2.42%	2.19%	0.78%
5370080.05	12.96%	12.89%	8.80%	6.48%	6.45%	4.40%	2.59%	2.58%	1.76%
5370081.00	10.43%	10.38%	8.86%	5.22%	5.19%	4.43%	2.09%	2.08%	1.77%
5370082.00	8.68%	7.41%	7.58%	4.34%	3.70%	3.79%	1.74%	1.48%	1.52%
5370083.00	5.51%	7.32%	5.62%	2.76%	3.66%	2.81%	1.10%	1.46%	1.12%
5370084.01	7.07%	11.26%	12.97%	3.54%	5.63%	6.48%	1.41%	2.25%	2.59%
5370084.02	8.12%	9.42%	11.02%	4.06%	4.71%	5.51%	1.62%	1.88%	2.20%
5370084.03	19.77%	14.31%	20.14%	9.88%	7.15%	10.07%	3.95%	2.86%	4.03%
5370084.04	4.38%	4.36%	12.27%	2.19%	2.18%	6.13%	0.88%	0.87%	2.45%
5370084.05	10.64%	14.56%	17.62%	5.32%	7.28%	8.81%	2.13%	2.91%	3.52%
5370085.01	12.21%	11.28%	8.89%	6.11%	5.64%	4.44%	2.44%	2.26%	1.78%
5370085.02	9.77%	12.76%	4.98%	4.89%	6.38%	2.49%	1.95%	2.55%	1.00%
5370085.03	7.10%	4.95%	7.23%	3.55%	2.47%	3.62%	1.42%	0.99%	1.45%
5370086.00	6.38%	9.31%	5.63%	3.19%	4.66%	2.82%	1.28%	1.86%	1.13%
5370100.00	4.08%	4.69%	2.88%	2.04%	2.34%	1.44%	0.82%	0.94%	0.58%
5370101.00	4.50%	3.88%	3.06%	2.25%	1.94%	1.53%	0.90%	0.78%	0.61%
5370120.01	10.98%	15.30%	7.61%	5.49%	7.65%	3.80%	2.20%	3.06%	1.52%
5370120.02	20.96%	19.12%	19.58%	10.48%	9.56%	9.79%	4.19%	3.82%	3.92%
5370121.00	14.83%	21.09%	12.95%	7.42%	10.54%	6.48%	2.97%	4.22%	2.59%
5370122.01	11.50%	9.42%	8.96%	5.75%	4.71%	4.48%	2.30%	1.88%	1.79%
5370122.02	18.60%	18.51%	11.25%	9.30%	9.26%	5.63%	3.72%	3.70%	2.25%
5370123.00	20.70%	13.01%	7.77%	10.35%	6.51%	3.89%	4.14%	2.60%	1.55%
5370124.00	28.91%	21.57%	19.98%	14.45%	10.79%	9.99%	5.78%	4.31%	4.00%
5370130.02	20.44%	19.41%	19.87%	10.22%	9.71%	9.94%	4.09%	3.88%	3.97%
5370130.03	46.04%	18.32%	17.59%	23.02%	9.16%	8.79%	9.21%	3.66%	3.52%
5370131.00	16.57%	11.54%	8.44%	8.29%	5.77%	4.22%	3.31%	2.31%	1.69%
5370132.00	10.87%	8.11%	8.30%	5.43%	4.06%	4.15%	2.17%	1.62%	1.66%
5370133.00	18.69%	8.68%	6.35%	9.35%	4.34%	3.17%	3.74%	1.74%	1.27%
5370140.02	5.22%	6.30%	4.18%	2.61%	3.15%	2.09%	1.04%	1.26%	0.84%
5370140.03	6.89%	17.15%	11.41%	3.45%	8.57%	5.71%	1.38%	3.43%	2.28%
5370140.04	9.68%	18.20%	14.25%	4.84%	9.10%	7.13%	1.94%	3.64%	2.85%
5370141.00	10.16%	11.66%	7.16%	5.08%	5.83%	3.58%	2.03%	2.33%	1.43%
5370142.01	2.47%	5.52%	5.66%	1.23%	2.76%	2.83%	0.49%	1.10%	1.13%
5370142.02	3.16%	7.08%	7.25%	1.58%	3.54%	3.63%	0.63%	1.42%	1.45%
5370143.00	28.25%	44.99%	25.91%	14.13%	22.49%	12.95%	5.65%	9.00%	5.18%
5370144.00	6.23%	15.22%	5.77%	3.12%	7.61%	2.89%	1.25%	3.04%	1.15%
5370200.00	19.31%	24.34%	23.60%	9.65%	12.17%	11.80%	3.86%	4.87%	4.72%
5370201.00	12.15%	12.09%	8.57%	6.08%	6.05%	4.29%	2.43%	2.42%	1.71%
5370202.00	14.26%	9.93%	8.71%	7.13%	4.97%	4.36%	2.85%	1.99%	1.74%
5370203.00	27.14%	15.64%	33.47%	13.57%	7.82%	16.74%	5.43%	3.13%	6.69%
5370204.00	3.78%	5.64%	5.77%	1.89%	2.82%	2.89%	0.76%	1.13%	1.15%
5370205.01	13.76%	7.30%	15.88%	6.88%	3.65%	7.94%	2.75%	1.46%	3.18%
5370205.02	12.65%	6.87%	7.03%	6.32%	3.43%	3.51%	2.53%	1.37%	1.41%
5370206.00	4.77%	3.96%	4.86%	2.39%	1.98%	2.43%	0.95%	0.79%	0.97%
5370207.01	8.86%	8.23%	4.81%	4.43%	4.11%	2.41%	1.77%	1.65%	0.96%
5370207.02	5.48%	10.90%	4.34%	2.74%	5.45%	2.17%	1.10%	2.18%	0.87%

5370207.03	9.61%	10.52%	9.79%	4.81%	5.26%	4.90%	1.92%	2.10%	1.96%
5370207.04	6.24%	7.76%	11.12%	3.12%	3.88%	5.56%	1.25%	1.55%	2.22%
5370208.00	5.34%	7.98%	9.53%	2.67%	3.99%	4.76%	1.07%	1.60%	1.91%
5370209.00	20.27%	11.21%	20.65%	10.14%	5.60%	10.33%	4.05%	2.24%	4.13%
5370210.00	6.85%	8.52%	15.71%	3.43%	4.26%	7.85%	1.37%	1.70%	3.14%
5370211.00	4.44%	5.53%	5.66%	2.22%	2.76%	2.83%	0.89%	1.11%	1.13%
5370212.00	27.59%	16.47%	19.68%	13.79%	8.24%	9.84%	5.52%	3.29%	3.94%
5370213.00	9.02%	6.73%	5.74%	4.51%	3.37%	2.87%	1.80%	1.35%	1.15%
5370214.00	12.76%	11.11%	16.26%	6.38%	5.56%	8.13%	2.55%	2.22%	3.25%
5370215.00	8.99%	13.42%	16.79%	4.49%	6.71%	8.39%	1.80%	2.68%	3.36%
5370216.00	16.67%	18.43%	16.98%	8.33%	9.21%	8.49%	3.33%	3.69%	3.40%
5370217.01	6.94%	4.61%	3.93%	3.47%	2.30%	1.97%	1.39%	0.92%	0.79%
5370217.02	15.06%	12.34%	13.54%	7.53%	6.17%	6.77%	3.01%	2.47%	2.71%
5370218.00	6.75%	5.37%	5.04%	3.37%	2.69%	2.52%	1.35%	1.07%	1.01%
5370219.00	15.33%	18.46%	17.26%	7.66%	9.23%	8.63%	3.07%	3.69%	3.45%
5370220.00	7.27%	5.26%	6.73%	3.63%	2.63%	3.37%	1.45%	1.05%	1.35%
5370221.00	10.07%	11.27%	12.82%	5.03%	5.63%	6.41%	2.01%	2.25%	2.56%
5370222.00	7.18%	7.54%	5.69%	3.59%	3.77%	2.84%	1.44%	1.51%	1.14%
5370223.01	7.89%	6.73%	8.04%	3.95%	3.37%	4.02%	1.58%	1.35%	1.61%
5370223.02	3.68%	7.33%	3.75%	1.84%	3.67%	1.88%	0.74%	1.47%	0.75%
5370223.05	10.13%	26.45%	15.47%	5.06%	13.22%	7.74%	2.03%	5.29%	3.09%
5370223.06	8.24%	22.76%	9.32%	4.12%	11.38%	4.66%	1.65%	4.55%	1.86%
5370223.07	8.41%	13.39%	10.28%	4.20%	6.69%	5.14%	1.68%	2.68%	2.06%
5370223.09	6.64%	24.23%	15.79%	3.32%	12.12%	7.89%	1.33%	4.85%	3.16%
5370223.10	7.80%	19.40%	19.87%	3.90%	9.70%	9.93%	1.56%	3.88%	3.97%
5370223.11	7.41%	10.03%	6.04%	3.71%	5.02%	3.02%	1.48%	2.01%	1.21%
5370223.12	2.09%	3.82%	7.82%	1.05%	1.91%	3.91%	0.42%	0.76%	1.56%
5370224.00	5.55%	6.53%	5.65%	2.77%	3.26%	2.83%	1.11%	1.31%	1.13%

Table 29. A summary of negative binomial distribution – based models.

Model 1				**Model 2**				**Model 3**			
Parameters	**B**	**St. Error**	**p-value**	**Parameters**	**B**	**St.Error**	**p-value**	**Parameters**	**B**	**St.Error**	**p-value**
Intercept	3.19	0.73	0	***Intercept***	4.17	0.829	0	***Intercept***	6.35	1.57	0
LEDU	-2.04	0.02	0.006	***LEDU***	-3.03	0.016	0.051	***ODWE***	1.02	0.01	0.001
[INC=1]	-1.78	0.35	0	***[INC=1]***	-0.98	0.403	0.015	***DDWE***	-0.96	0.02	0.005
[INC=2]	-0.93	0.2	0	***[INC=2]***	-0.41	0.233	0.081	***LEDU***	-2.76	0.02	0
[INC=3]	0[a]	.	.	***[INC=3]***	0	.	.	***NPPCF***	-0.85	0.46	0.066
SEN	1.06	0.01	0	***SINPAR***	-1.53	0.001	0.048				
PWSCT	2.3	0.01	0.001	***CWCHILD***	2.16	0.001	0.049				
				UNEMP	-3.3	0.109	0.002				

Table 30. Abbreviations

Abbreviations	Variables
CTN	cencus tract name
CTUID	cencus tract id
POP	total population 2006
AREA	land area in sq.Km 2006
POP_DEN	Population density
CHILD	total number of children 0 to 19 years
ADUL	total number of adults 20 to 64 years
SEN	total number of seniors over 65 years
MAL	males per c.t 2006
FEM	females per c.t 2006
CNCHILD	Married couples Without children at home
CWCHILD	Married couples With children at home
SINPAR	Total lone-parent families
DWE	Total number of occupied private dwellings by structural type of dwelling - 100% data
SIDDWE	Total number of occupied private dwellings by structural type of dwelling - 100% data / Single-detached house
DDWE	Total number of occupied private dwellings by structural type of dwelling - 100% data / Apartment, duplex
ADWE	Total number of occupied private dwellings by structural type of dwelling - 100% data / Apartments
ODWE	Total number of occupied private dwellings by housing tenure - 20% sample data / Owned
RDWE	Total number of occupied private dwellings by housing tenure - 20% sample data / Rented
HHLD	Total number of households
NCPCF	Average number of children at home per census family
NPPCF	Average number of persons per census family
NPPHHLD	Average number of persons in private households
HINC30	Household income in 2005 of private households - 20% sample data / Under $30,000
HINC80	Household income in 2005 of private households - 20% sample data / Under $80,000
HINCO80	Household income in 2005 of private households - 20% sample data / Over $80,000
AHINC	Average household income $
ATAXINC	Average after tax income $
VHHLD	vehicles per hhld 2006
NHEV	number of Hybrid Electric Vehicles POLK data 2012
LHHLD	licences per cencus tract 2006
FTEMPL	full time employers per cencus tract 2006
PTEMPL	part time workers per cencus tract 2006
HWORK	home workers cencus tract 2006
UNEMP	unemployed per cencus tract
LEDU	Total population by lowest level of education (including high school certificate, apprenticeship or trades certificate, college, CeGep or other non-university certificate or diploma)

MEDU	Total population be medium level of education (including university certificate, below bachelor level, bachelor's degree, above bachelor level, degree in medicine, dentistry, otometry)
HEDU	Total population by highest level of education (including master's degree, earned doctorate)
PWSCT	Usual place of work (same census subdivision of residence)
PWDCT	Usual place of work (different census subdivision of residence)