STRUCTURAL EFFECTS OF THE BUILT ENVIRONMENT ON VEHICLE GREENHOUSE GAS EMISSIONS: EVIDENCE FROM VANCOUVER, CANADA

by

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ABSTRACT

This thesis summarizes efforts to estimate fundamental relationships among built environment characteristics, activity patterns and vehicle use in order to assess their relative influences on vehicle GHG emission generation in Metro Vancouver, Canada. Activity-based structural equation models were specified in a cross-sectional study design using local travel survey data and highly detailed urban form data. Structural equation analysis permitted explicit modeling of the indirect effects between built environment variables and vehicle emissions as mediated through activity patterns and vehicle use. Modeling travel at the activity-tour level allowed for a deeper understanding of the relative contributions of local and regional built environment variables in explaining tour complexity, vehicle use and emissions. Controlling for pertinent socio-economic and demographic variables, standardized parameter coefficients show the built environment to be a significant predictor of vehicle-related GHG emissions across all models, although the strength and magnitude of these effects vary by activity tour type. The local built environment is a stronger predictor of vehicle use and related emissions for non-work/school tours, while regional accessibility measures yielded larger effects on the carbon-intensity of work and school tours. Vehicle accessibility yielded significantly large effects on vehicle use and emissions across all models, suggesting that policy directions beyond promoting more compact, walkable and regionally connected development to curb emissions are required. Additional strategies may include those that address vehicle use in a more direct manner, including higher taxation, insurance or parking fees. Future research would benefit by incorporating travel and residential preferences to control for self-selection, assessing the affect of the work and school built environment on activity patterns and undertaking a more holistic assessment of the links between the built environment and total household emissions and energy use (including building, transportation, etc).

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF ACRONYMS

CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
GHG	Greenhouse gas(es)
HBO	Home-based other activity tour
HBWS	Home-based work/school activity tour
OLS	Ordinary least-squares regression
SEM	Structural equation model(ing)
VKT	Vehicle kilometers traveled
VMT	Vehicle miles traveled

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1. INTRODUCTION

1.1. Background and Context

1.1.1. Travel and Emission Trends in Canada

Rising levels of private vehicle use are becoming increasingly widespread across Canada's urban regions. Between 1992 and 2005, the proportion of adults who regularly traveled by car – as either a driver or passenger – rose from 68% to 74%. At the same time, the share of adults nationwide who made at least one daily trip by bicycle or on foot declined from 26% in 1992 to 19% in 2005 (Turcotte, 2008). These trends have significant implications for nationwide greenhouse gas (GHG) levels. Transportation emissions, largely attributable to household vehicle travel, are now the largest single sector contributor to local anthropogenic GHG levels across Canada, currently accounting for approximately 190 $MtCO_2e$ (carbon dioxide equivalent[1]) or 25% of total emissions. If left unabated, it is predicted that these levels will rise by 18% to over 230 $MtCO_2e$ by 2020, still maintaining the single largest component of Canada's CO_2 emissions (Natural Resources Canada, 2006).

Increasing GHG levels contribute to global climate change by perpetuating the greenhouse effect: the process whereby gases of carbon dioxide, methane, nitrous oxide and water vapour trap heat in the earth's atmosphere that would otherwise radiate back to space (Intergovernmetal Panel of Climate Change, 2007). Worldwide, a changing climate and an increasing global mean temperature is leading to rising sea levels, more sporadic growing seasons, ecosystem degradation, and disease outbreaks, all of which may have potentially devastating effects on both humans and other species (Cazenave et al., 2007; Cox et al., 2000; Parmesan and Yohe, 2003; Haines et al., 2006). Therefore, it is important to analyze the nature of anthropogenic GHG emission sources and find ways to reduce their production in order to mitigate against potentially deleterious impacts on the biophysical environment for future generations.

[1] Carbon dioxide equivalent is a metric measure used to compare the emissions from various greenhouse gases based upon their global warming potential (GWP), using carbon dioxide as the reference (Abler, 2003).

Most research and policy focused on minimizing travel-related GHG emissions is concentrated on technological fixes such as vehicle and fuel efficiency (United Nations Framework Convention on Climate Change, 2003). Recent work suggests, however, that slow market penetration of alternative fuels and efficiency standards, coupled with continued strong growth in population and travel demand, may offset any emission reduction achievements made by technology into the future (Greening, 2004; National Research Council, 2008). As a result, strategies focused on reducing vehicle travel demand may yield more significant decreases in travel-related GHG emissions in the longer term.

1.1.2. Linkages Between Built Environment, Travel and Emissions

A large and ever-increasing body of empirical work consistently demonstrates that the physical design of the places where people live and work is related with and likely influences daily travel demand. More compact, walkable and transit-oriented development patterns characterized by higher densities and mixing of land uses, street connectivity, quality urban design elements, and pedestrian-scale street design have been shown to be associated with decreased per capita vehicle travel (fewer miles and trips) and increased use of alternative modes such as transit, walking and cycling (see reviews of the literature by Crane, 2000; Ewing and Cervero, 2001; Badoe and Miller, 2000; Frank and Engelke, 2001; Frank, 2000; Saelens et al., 2003). Although strengths of association vary between studies, findings have been confirmed in a variety of geographic scales - from the regional level of major population and employment centres, to local street and neighbourhood design. These relationships persist even when controlling for socio-economic characteristics and other potentially confounding factors. More recent research shows a positive relationship between urban form and travel patterns when accounting for residential self-selection, suggesting a causal nature of the built environments influence on travel behaviour (Handy et al., 2006; Vance and Hedel, 2007; Cao et al., 2009; Frank et al., 2007a).

Empirical studies focused on explicitly exploring the connections between the built environment and travel-related GHG emissions are sparse, but growing (see review by

Ewing et al., 2008). Findings from this emerging work demonstrate that negative associations exist between more compact, well-connected and accessible land use patterns and levels of travel-related GHG emissions. As a result, improving the built environment to make it easier for people to use alternatives modes of travel, like walking, cycling, and public transit is seen as an essential component toward reducing vehicle demand and mitigating rising GHG emissions related to personal travel (Nolon and Bacher, 2007).

1.2. Problem Statement

Despite these findings, this thesis contends that a detailed understanding of the strength of effect that the built environment has on vehicle emissions remains underdeveloped. Two perceived limitations in the current body of work are identified and addressed in the current study. The first issue concerns approaches to empirically assessing this relationship. Urban form impacts vehicle emissions indirectly through mediating travel variables such as broader activity patterns, mode choice, and distance traveled (Anderson et al., 1996; Naess et al., 1995). Teasing out the independent effects of the built environment on travel-related emissions is extremely difficult unless appropriate analytical frameworks are employed. Current attempts to articulate the link between urban form and travel GHG emissions struggle to capture this complex set of interactions, due in large part to data limitations and model misspecification. Effects of the built environment on GHG emissions are examined here in a structural equations model (SEM) framework to overcome this weakness and clarify relationships. SEM is a set of simultaneous regression equations specifying the direct links (paths) between sets of variables (Kaplan, 2000). The second issue relates to the appropriate representation and measurement of travel and emissions. Daily travel patterns and their subsequent emission levels are a function of broader activity participation decisions and trip chaining or touring patterns (Shiftan, 2008). Only limited research has explored how these decisions interact with the built environment and household demographics to influence emission generation (Frank et al., 2005a). In this research, travel and emission levels are measured at the daily activity scale to better assess how transportation decisions are made and estimate implications for GHG emissions generation.

1.3. Research Objectives and Questions

This thesis represents an attempt to enhance the current state of knowledge surrounding the linkages between urban form and vehicle emissions by adding new dimensions to the analytical approach in order to more accurately estimate different effects. The geographic focus of this study is on Metro Vancouver, British Columbia, Canada. Specifically, this research will:

- Investigate the associations between the built environment, daily activity patterns, vehicle use, and associated GHG emissions;
- Develop a methodological framework that isolates individual linkages in a pathway from urban form to travel to emissions; and
- Highlight policy and regulatory implications for local and regional government on how reduction in vehicle use and related GHG emissions can potentially be achieved through changes in land use policy.

Out of these research objectives, the following questions will be investigated:

- Are variations in self-reported vehicle use and vehicle GHG emission estimates statistically associated with different built environment and regional accessibility characteristics in Metro Vancouver?
- What are the relative structural (regression) effects of different built environment and regional accessibility characteristics as opposed to individual and household socio-economic variables on per-capita vehicle GHG emissions?
- Do the structural (regression) effects of local built environment characteristics and regional accessibility measures on vehicle related GHG emissions vary by activity tour type?
- Which land use and transportation strategies may be most effective at supporting a reduction in vehicle GHG emissions in Metro Vancouver?

1.4. Thesis Organization

The remaining chapters are structured as follows: Chapter 2 discusses pertinent literature related to two key themes: travel and activity pattern measurements and modeling techniques used in systems having multiple sets of relationships and endogenous (dependent) variables. Chapter 3 details the conceptual framework and modeling methodology used in this analysis. Also included is a description of the data sources, variables and measurements used to populate the analytical models. Chapter 4 introduces the study area and outlines results from a descriptive analysis of the sample population. In Chapter 5, empirical results are presented and the implications of the findings are discussed. Finally, Chapter 6 summarizes the research and discusses the study's limitations and directions for future research.

2. LITERATURE REVIEW

2.1. Overview

Relevant literature pertaining to this thesis falls within two methodological themes: 1) measuring daily travel and emissions, and 2) frameworks for assessing multivariate statistical problems. This chapter reviews the current analytical procedures employed to study linkages between urban form, travel, and GHG emissions against applicable methodological improvements that have evolved within and beyond the transportation research field. It will be demonstrated how key analytical advancements can be applied to enhance our understanding of the relationships between urban form, travel and emissions.

2.2. Measuring Travel Behaviour and GHG Emissions

2.2.1. Trip-Scale Modeling

Central to any assessment of the spatial patterns of travel-related emissions are appropriately measured travel variables with which to derive emission estimates. By far the most popular measure used in this effort is distance traveled by mode (Ewing et al., 2008). This is not surprising as common distance-based and mode-specific emission factors can be easily applied to these variables (Van Wee et al., 2005; Stead, 2000). In an assessment of the relationship between urban density and travel-related CO_2 in the Netherlands, Grazi et al (2008) estimate emissions using commute distance by travel mode measures. Statistically significant negative relationships were found between urban density, measured private vehicle use, total commuting distance, distance traveled by mode, and total daily CO_2 emissions. Frank et al (2005a) estimated per-capita travel emissions in King County Washington from a measure of total daily vehicle miles traveled while accounting for travel speed, fleet characteristics and vehicle occupancy. Statistically significant relationships between a number of detailed neighbourhood urban form measures and per-capita daily travel CO_2 emissions were found while controlling for pertinent socio-economic and demographic factors. Households in areas with higher levels of land use mix, residential density, retail availability, and street connectivity generated fewer vehicle miles traveled (VMT) and lower per-capita CO_2 emissions. Frank et al (2009) undertook additional comparative analyses on the relative influence of local urban form and regional accessibility measures on vehicle CO_2 emissions in the Puget Sound region. VMT and CO_2 were estimated in daily totals. Findings suggested that neighborhood scale urban form factors, such as land use mix and street connectivity, while significant, were weaker predictors than regional accessibility.

VandeWeghe and Kennedy (2007) used travel data from Toronto's 2001 Transportation Tomorrow Survey, in combination with the City's EMME/2 travel demand modeling software to estimate aggregated daily travel distance (i.e. summation of all individual trip distances over the course of a day) and GHG emissions related to travel. The study compared both building and travel emissions across Toronto's census metropolitan areas to determine the impact of urban form on greenhouse gas causing activities. Results demonstrated that the per-capita generation of transportation related greenhouse gas emissions were highest in low-density suburban areas of the city where distance traveled by vehicle were highest.

A common thread between these studies is the scale at which distance traveled and subsequent emission levels are calculated and analyzed. In most cases, these variables are aggregated to daily trip-based totals. Research suggests, however, that representing and analyzing daily travel in this manner may produce two related limitations. The first concerns discounting the complexity and pattern language of daily travel. Travel is often organized into tours, or trip-chains to accomplish a set of activities in an efficient manner while minimizing time use and costs (Primerano et al., 2008). For instance, an individual may accomplish their daily errands in the return trip from work so as to avoid leaving home again in the evening. These patterns are not discernable using aggregated, trip-based travel measures (Krizek, 2003a). The second drawback is that aggregated travel variables provide only limited insight into the broader forces that generate and influence activity decisions and travel demand (Shiftan, 2008; Buliung and Kanaroglou, 2007). Travel decisions are a function of many factors, including activity type, the location of destinations, available travel modes, and intra-household decision processes (Timmermans and Zhang, 2009). The influence of these mechanisms on travel and emissions are not explicitly modeled in current empirical studies related to travel emissions. It is often concluded that modeling and analytical frameworks assessing travel and related impacts that inappropriately account for these dynamics may yield to spurious correlations between urban form, travel, and, ultimately, emissions (Handy, 1996; Shiftan and Suhrbier, 2002).

2.2.2. Activity Tour Modeling

Activity or tour-level modeling of travel addresses the aforementioned limitations and has proven to yield more insight into the mechanisms driving activity and travel decisions (Shiftan et al., 2003; Miller et al., 2005; Davidson et al., 2007). Activity modeling organizes daily travel into sets of home or work-based “activity tours” or “activity chains” that link individual trips together to include both the outbound and return trips and all stops made along the way (Bowman and Ben-Akiva, 2001). Tours can be classified based on their primary tour purpose (e.g. subsistence, maintenance, or discretionary) and their complexity (number of stops) (Krizek, 2003a; Kuppam and Pendyala, 2001; Lee et al., 2009). Distance traveled, mode choice, and emission estimates can then be estimated for an entire tour or set of tours. Buliung and Kanaroglou (2007) provide a comprehensive overview of additional activity-based concepts, model and analysis specification, and simulation modeling.

Considerable effort has been extended to understanding the links between tour complexity and socio-economic and demographic, travel time, and travel cost variables (Hanson and Hanson, 1981; McGuckin and Murakami, 1999; Jang, 2003; Jang and Hwang, 2009). Notable findings include parents and guardians in households with younger children tend to engage in more activity tours, likely the result of the need to make extra shopping trips and trips to pick up and drop off children at school (Lu and Pas, 1999). Older adults and retired individuals are more likely to have simple daily travel patterns (i.e. fewer trips per tour) due to limited direct responsibilities for others (e.g. younger children) (Golob and Hensher, 2007).

More recent work has explored the spatial properties of activity tours. Households located in more compact, accessible areas complete more simple tours with stops closer to home per tour while households in lower density environments are related to more complex, multi-stop tours (Krizek, 2003a; Noland and Thomas, 2007; Buliung and Kanaroglou, 2006). Analysis at the activity-tour type level has also yielded significant results. Frank et al (2007b), using nested logit modeling, found an inverse relationship between the level of mixed use, density, and street connectivity where people live and work and the amount of stops made to and from work during home-based work tours in the Seattle region. Using similar travel data from the Puget Sound (Seattle) region, Krizek (2003b) demonstrated that tour frequency increases, while the number of stops per tour decreases across all tours with heightened neighbourhood accessibility. Unlike the Frank et al study, however, Krizek is unable to find a significant relationship between complex work tours and neighbourhood accessibility.

The effect of interactions between socio-economic characteristics, urban form and activity patterns on distance traveled and mode choice are important, especially from a GHG emissions perspective. Strathman and Duecker (1994) observe that complex activity patterns may lead to an increase in vehicle use given the flexibility afforded by a vehicle for such activity patterns. Crane (1996) suggests that more accessible neighbourhoods will tend to generate more tours and, subsequently, more vehicle use. Maat and Timmermans (2006) found that more compact neighbourhoods may induce higher activity frequencies as shorter trips that can save time may result in more available time for other low priority activities that may be impossible otherwise. Frank et al (2007b) demonstrated that less complex tours with stops closer to home might be more easily accomplished using alternative modes like transit, walking and cycling. These results suggest a time-based trade-off between the location of stops and tour complexity. Those living in places where destinations are close can complete single destination trips easily using less carbon intensive modes. Conversely, those in sprawling, single-use locations tend to chain their activities to save time and may not be inclined to make as many home based simple tours. Higher rates of vehicle use are also expected given the likely increases in distance between destinations.

Observations from the activity tour-level analysis literature point to important modeling implications for study directed at assessing the influence of urban form and travel behaviour on GHG emissions. The ability to capture daily activity pattern characteristics in combination with traditional measures, like distance traveled and mode choice, is demonstrated to provide a better approximation of how activity patterns vary over space (Davidson et al., 2007, Vovsha and Bradley, 2005). These improved estimates of differences in key travel variables provide the basis for the development of more accurate estimate of potential GHG emission reductions resulting from the implementation of more compact, walkable and regionally connected neighbourhood design strategies.

No pertinent studies have explored the influence of urban form and travel behaviour on GHG at the tour-level. Frank et al (2005a) suggest doing so would offer a greater understanding of how different land use and regional accessibility characteristics like transit service and distance to major employment centres, relative to other socio-economic and demographic variables, influence travel emissions at unit of analysis that more accurately depicts travel choice. The current study aims to fulfill this research gap.

2.3. Analytical Frameworks and Techniques

The set of interactions between variables influencing the generation of travel-related GHG emissions in urban areas is complex. Many studies have demonstrated that a variety of socio-demographic, urban form and transportation systems/networks, and travel behaviour characteristics all have the ability to affect travel behaviour and activity patterns (Crane, 2000; Ewing and Cervero, 2001; Badoe and Miller, 2000; Saelens et al., 2003). These variables all have a subsequent influence on daily travel-related GHG emissions. Complexity arises from the influence that different factors have on each other and from the nature of their individual and combined effects on travel emissions (Naess et al., 1995). For example, only travel variables like mode choice, distance traveled, vehicle occupancy, speed, and engine operating temperature have a direct influence on vehicle emissions (Van Wee et al., 2005; Stead, 2000). Conversely, the influence of urban form, transportation systems, socio-demographics, and broader activity patterns on emissions is an indirect one and is only realized through their direct effects on the intervening travel behaviour variables (Anderson et al., 1996; Mindali et al., 2004). The nature of these interactions affects the ability to accurately estimate potential effects of the built environment on emissions if inappropriate analytical frameworks are employed.

2.3.1. Single Equation Modeling

The use of single-equation modeling techniques, such as ordinary least-squares (OLS) regression, logit, and multivariate regression analysis, are commonplace in much the empirical transportation literature (see reviews Ewing and Cervero, 2001, Boarnet and Crane, 2001; Handy, 1996). As illustrated in Figure 2.1.a, these methods use several predictor (independent x) variables to predict the strength and nature of effect on one criterion measure (dependent y). Their use is also ubiquitous in work assessing the linkages between urban form and travel emissions. Frank et al (2009) used single-equation regression models to quantify the interactions between urban form, travel and related CO_2 emissions in Puget Sound, Washington. Models specified that travel-related CO_2 per capita (dependent variable) would be equally and directly influenced by all independent socio-economic, urban form, regional accessibility, and travel behaviour characteristics. Frank et al (2000) also used ordinary least-square regression techniques to connect urban form characteristics around where people live with vehicle miles traveled and criteria air pollutants like nitrous oxide, volatile organic compounds, ozone, and particulate matter. Grazi et al (2008) employed separate instrumental variable and ordinary least-square models to assess the effect of urban density, certain socio-economic and demographic variables, and commuting patterns (independent variable) on total daily travel-related CO_2 emissions (dependent variable) in a sample from the Netherlands.

Single-equation analytical frameworks used in the above studies are limited in their ability to model the multifaceted interaction between urban form, travel behaviour and GHG emissions. Primary shortcomings of these efforts include a lack of control for assessing relationships with multiple equations and multiple endogenous variables and the inability to account for and estimate both direct and indirect effects between measures (Washington et al., 2003; Kline, 2005). The limitations of single-equation models in this context are a key motivation for the current research.

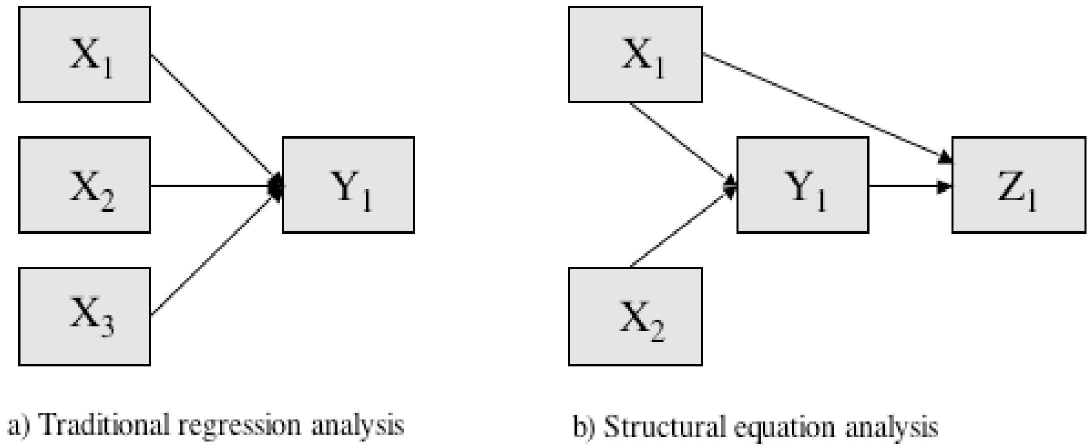


FIGURE 2.1. Traditional regression vs. structural equation techniques. In (b), the researcher is able to examine the ability of more than one predictor variable to explain multiple dependent, possibly mediating, variables.

2.3.3. Structural Equation Modeling

Advancements in computing and statistical analysis techniques have allowed for more comprehensive, structural relationships between socio-demographics, activity participation, travel behaviour and urban form using diverse modeling methods (Bhat, 2005, Bhat and Guo, 2007, Habib and Miller, 2008; Misra et al., 2003; Cervero, 2003; Jang and Hwang, 2009). Structural equation modeling (SEM), originally developed for use in psychological studies, has emerged as a valuable analytical framework for assessing complex, multivariate transportation research problems (Golob, 2003).

SEM offers several improvements over traditional single-equation approaches and addresses many of the analytical realities of the research problem in this study. SEM allows for the simultaneous prediction of multiple variables and equations in one model (Tomarken et al., 2005; Kline, 2005). That is, variables that are dependent in one set of equations may be explicitly specified as explanatory in another. This research involves multiple relationships among a set of variables and meets the requirements for application of SEM. For example, while built environment characteristics influence travel behaviour and activity patterns, it is these behaviours that then influence the generation of GHG emissions related to travel. An additional advantage of SEM includes the ability to separately estimate direct (i.e. x impacts y) and indirect (i.e. x impacts z though y) relationships (Kaplan, 2000) (see Figure 2.1.b). SEM can estimate the magnitude of the influence of each variable on the other. This is necessary in order to determine the total and independent effects of these variables on travel emissions.

SEM has been employed in many transportation-related analysis studies (see review by Golob, 2003). Common to this body of work are problems centred on complex, multi-equation issues. Popular applications include assessing the relative influence of attitudinal and lifestyle predispositions (also known as self-selection) and residential neighbourhood type on travel behaviour (Jang et al., 2009; Cao et al., 2007). Bagley and Mokhtarian (2002) developed and employed a nine-equation structural model system to tease out the direct, indirect and total effects of attitudes and preferences and local urban form characteristics on daily person trips and daily distance traveled by mode. Ory and Mokhtarian (2009a) modeled the direct and indirect interrelationships among reported amount of travel and perceptions, affections and desire for travel using ten structural equation models. Other applications include activity-based travel demand modeling where frameworks are needed to study direct relationships between activity demand and need to travel, or interrelationships between participation in different activities (Jang, 2003; Golob, 2000; Gould et al., 1998; Fujii and Kitamura, 2000). Kuppam and Pendyala (2000) developed structural equation models to explore the relationships between activity duration and generation, duration of in-home and out-of-home activities, and activity frequency and trip chain generation in Washington, D.C. An emerging group of application includes modeling the mediating pathways linking built environment and travel behaviour to secondary outcomes like obesity (Stafford et al., 2007).

A perusal of the literature located only one study that has applied a structural equation modeling framework in the context of assessing the travel emission impacts associated with different land use patterns and travel behaviour. Bailey et al (2008) use SEM within a cross-sectional research design to test the hypothesis that public transportation availability interacts with land use patterns to influence travel patterns in urban areas. The authors deduce that those individuals in compact places with higher bus and rail transit accessibility travel less by vehicle and, as a result, reduce their overall petroleum use and carbon footprint. The SEM confirms this theory by demonstrating that public transit availability is negatively associated with vehicle miles traveled. Estimated levels of GHG emissions are not included in the SEM model. Instead, the total effect of transit availability on fuel use and GHG emissions is determined using an ad hoc process outside of the SEM model. As such, the study does not explicitly model what aspects of urban form, transit availability, and travel behaviour might lead to a reduction in travel-related GHG emissions.

2.4. Summary

The literature reviewed in this chapter suggests that the use of structural equation modeling frameworks and activity-level travel behaviour measurements are appropriate analytical elements that may help to increase our understanding of the interrelationships between urban form, travel decisions and emissions. Their limited application in assessing these linkages offers a unique research opportunity. Pertinent studies completed to date exploring the effects on urban form and travel behaviour and GHG emissions highlighted in this chapter provide both a theoretical and methodological foundation for future studies. The research in this thesis will build upon this previous work and utilize a more robust analytical procedure in order to tease out the independent effects of urban form, travel behaviour and socio-economics and demographic characteristics on travel-related GHG.

3. MODELING METHODOLOGY & DATA SET

3.1. Overview

A leading objective of this research is to develop a series of empirical models to help better isolate and quantify fundamental relationships among built environment characteristics, activity patterns and vehicle use, in order to assess their relative influences on vehicle GHG emissions. Structural equation and activity-tour modeling approaches are utilized in this effort. This chapter begins with an extensive overview of the conceptual framework used to guide model development, an explanation of postulated effects, and a technical synopsis of the procedure followed to develop the structural equation models. This is followed by a detailed summary of the data used to populate the models. Methods employed to operationalize both exogenous and endogenous variables are presented. Also outlined is the process for organizing individual trips into activity tours.

3.2. Conceptual Framework

The conceptual framework used to guide model specification and analysis in this research is illustrated in Figure 3.1. The framework was developed based on previous modeling efforts described in the literature and logical inferences among variable categories (see Chapter 2). Four sets of variables known to relate with the generation of travel emissions are included in the conceptual framework: (1) socio-economic and (2) built environment characteristics are specified as exogenous (independent) variables; (3) activity patterns, (4) vehicle use as endogenous (dependent) variables. Vehicle GHG emissions are specified as the final and ultimate endogenous measure. Each variable category includes a number of individual measures described in greater detail in Section 3.3. Daily travel characteristics and emission levels are modeled at the activity tour scale in the conceptual framework.

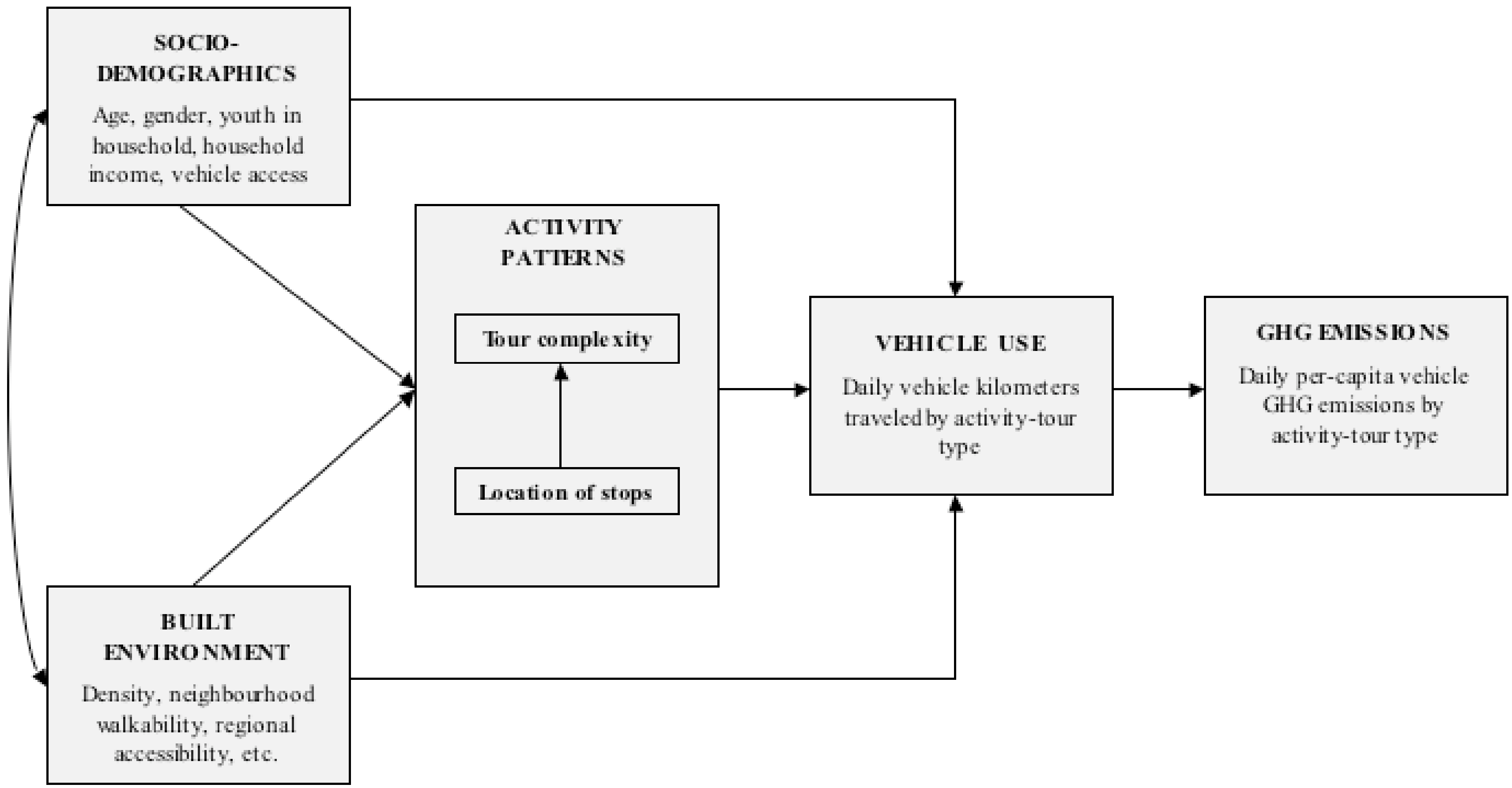


FIGURE 3.1. Conceptual modeling framework.

3.2.1. Activity Patterns

Daily activity patterns are specified as one of two mediating sets of variables between urban form and travel-related GHG emissions in the conceptual framework. Activity patterns are defined as the sequence and combination of daily trips and destinations (Jones et al., 1990). In the current research, these characteristics are represented by two variables: complexity of activity tours undertaken (i.e. number of stops made in a given home-based activity tour) and the spatial distribution of activities (i.e. location of stops in a given tour). Activity tour patterns have been previously demonstrated to be a direct function of both individual socio-economic and demographic characteristics (Hanson and Hanson, 1981; Golob, 2000; Hensher and Reyes, 2000; McGuckin and Murakami, 1999) and the built environment where individuals reside (Krizek, 2003a; Noland and Thomas, 2007; Frank et al., 2007b; Maat and Timmermans, 2006). These relationships are reflected in the conceptual model and serve as a starting point for the structural model estimation procedure.

The framework in Figure 3.1 also anticipates a time-based trade-off between tour complexity and the location of stops, modeled as a direct effect between the location of stops and tour complexity. It is expected that a greater share of daily destinations located near home will be associated with more simple tour patterns (Frank et al., 2007b). Conversely, destinations spread throughout a city or region may encourage trip-chaining to save time (Noland and Thomas, 2007).

This research measures only the prospective associations between the home urban environment and daily activity patterns. Urban form and regional accessibility characteristics of the work location have been demonstrated to yield statistically significant links with work-related tour complexity (Krizek, 2003b) and midday work-based tours (Frank et al., 2007b). This research did not develop measures or account for mid-day work based other tours (i.e. work → lunch → shopping → work), which occurred in some instances in the sample population. Such tours may impact the frequency and complexity of other tours during the day (i.e. if an individual can perform maintenance or discretionary activities during lunch then these may not be required either on the way to or from work or in the evening) (Frank et al., 2007b). Total daily vehicle use and emission implications associated with these decisions could potentially be significant. That work location urban form variables and mid-day work tours were not included in the analysis is a drawback of the research.

The specified variables and linkages chosen to define the structure of daily activity patterns in this research are an over-simplification of how these decisions are actually made in reality. Additional variables including individual attitudes and preferences regarding travel (Khattak and Rodriguez, 2005), travel-time considerations (Mohktarian and Chen, 2004), and detailed household decision-making processes and trade-offs (Vovsha, et al., 2004) have been demonstrated to yield significant influence over activity scheduling and patterns. These are absent here due to data limitations. Nevertheless, the anticipated linkages are assumed to be reasonable given the scope of the current study.

3.2.2. Vehicle Use

Vehicle use is specified as the second mediating variable between urban form and travel GHG emissions and is measured by vehicle kilometers traveled (VKT). Variables related to other modes of travel (i.e. share of daily travel made or traveled by walking, cycling and transit) are excluded in the models, as this study is not directed at explicitly exploring the connections between urban form and broader mode choice behaviour. Because all individuals in the sample reported travel, it is assumed that those traveling zero kilometers by vehicle are, instead, using alternative, less carbon intensive modes like transit, cycling, and walking. The reader is encouraged to explore studies described in Chapter 2 that pursue mode choice modeling within an activity-based framework, or local research linking urban form and mode choice in the Metro Vancouver region (Devlin et al., 2009).

The conceptual model reflects research demonstrating that vehicle travel is likely a direct function of socio-economic and demographic dispositions (Crane, 2000), the built environment characteristics near home (Frank and Pivo, 1994; Holtzclaw et al., 2002), and daily activity patterns (Krizek, 2003a). Built environment and socio-economic characteristics on travel are also anticipated to have an indirect (or mediating) effect on vehicle use through their influence on daily activity patterns.

3.2.3. GHG Emissions

Vehicle GHG emissions are specified as the final endogenous variable in the model; that is all structural relationships previously identified are modeled to influence how much vehicle GHG emissions related to activity tours are generated daily. Empirical analyses of GHG emission impacts associated with urban form are found in several studies identified in Chapter 2. These single-equation approaches demonstrate GHG emissions to be a function of distance traveled, built environment characteristics, travel preferences and attitudes, and socio-demographic dispositions (Grazi et al., 2008; Frank et al., 2009). The conceptual framework reflects these findings in theory; however, it explicitly specifies that only vehicle kilometers traveled have a direct influence on emissions. The effects of built environment characteristics like density, neighbourhood walkability, and regional access on emission levels operate indirectly through activity patterns and vehicle use. This idea of the built environment as an enabler or disabler for less carbon intensive travel patterns is consistent with observations in the literature (Anderson et al., 1996; Mindali et al., 2006). The complexity of these expected relationships highlights the need for multiple-equation models capable of estimating direct, indirect and total effects.

3.3. Model Structure

The literature reviewed in Chapter 2 suggests that structural equation modeling is a useful technique for analyzing the relationships specified in the conceptual framework, namely due to its ability to isolate and separately estimate direct, indirect, and total effects between variables. Path analysis, a special type of SEM that estimates effects between observed measures only, is employed in this research. Kaplan (2000) defines a typical structural equation model without latent variables (i.e. path analysis) as having the form (Equation 3.1):

$$Y = a + BY + TX + e \qquad \text{(EQUATION 3.1)}$$

Where Y = a vector holding *p* observed endogenous variables

X = a vector holding *q* observed exogenous variables

B = a coefficient matrix that related endogenous variables to each other (*p* x *p*)

T = a coefficient matrix that relates endogenous variables to other exogenous variables (*p* x *q*)

e = a vector of error terms associated with the endogenous variables

a = a vector of structural intercepts

The elements B and T in Eq 3.1 represent the structural relationships among the variables. For example, returning to the conceptual framework in Figure 3.1, an element of B would be the path relating activity patterns to travel behaviour. An element of T would be the path relating travel behaviour to the built environment. Structural equation models are estimated using structural covariance analysis; whereby parameter estimates are obtained by minimizing the difference between the observed sample covariance matrix (i.e. natural co-variances between variables in the sample) and the theoretical covariance matrix implied by the model (Kline, 2005).

3.4. Model Development

The effect of physical environment measures, like regional accessibility or local urban form on travel behaviour, has been demonstrated to vary by trip or activity types (Cervero and Duncan, 2006; Chatman, 2005; Handy, 1992; Cervero and Radisch, 1996). Exploring all activity tours, regardless of main purpose in the same model, may mask nuanced effects of certain physical environment variables on vehicle use and/or emissions. Separate structural equation models were developed to explain the effect of the built environment on per-capita travel behaviour and emissions related to both home-based work/school (HBWS) and home-based other (HBO) activity tours. HBWS tours are classified as those that include a work or school stop, regardless of the presence of other stops. HBO tours are specified as those including only non-work or school stops like shopping, recreation, or picking up a passenger. The process used to operationalize activity-tours is described in detail in Section 3.6. Previous work on activity-tour modeling has employed similar classifications of tours to assess built environment influences (Bowman and Ben-Akiva, 2001; Kuppam and Pendyala, 2001; Lee et al., 2009, Frank et al., 2007b; Krizek, 2003b).

3.5. Modeling Procedure

3.5.1. Model Specification

The conceptual framework in Figure 3.1 guided development of the initial structural equation models for each activity-type (work/non-work). The AMOS 16.0 software extension of SPSS 17.0 was utilized in this effort. AMOS allows for the graphical specification of SEMs by way of path diagrams, using boxes to represent variables and arrows to represent nature and direction of effect. After specifying each initial model, exploratory modeling is performed in order to reach a model that best reproduces the variances between variables in the sample. This included variable transformation (described below) and, where appropriate, removal of cases or variables. Model estimation results summarized in Chapter 5 detail the specification processes used to finalize each activity type model.

3.5.2. Model Identification

An SEM is identifiable when the number of data points inputted into the model is sufficient to estimate the specified parameters. Kaplan (2000) and Golob (2003) suggest that the necessary condition for a model to be identifiable be that the number of variance and covariance terms (observable variables) is larger than the number of parameters to be estimated (including regression weights, covariance terms, and variance terms), resulting in zero or positive degrees of freedom. Zero degrees of freedom imply a just identified model. Positive degrees of freedom denote a model that is over-identified while a negative value equates with an under-identified model. An under-identified model denotes unique values that cannot be estimated from the model. Over-identified models indicate that the value for each parameter in the model can be obtained in multiple ways from the observed data (Hoyle, 1995). Achieving an over-identified model is ideal as it suggests that more appropriate models may exist. A just-identified model will always fit perfectly, making an assessment of fit meaningless. AMOS includes a degrees of freedom calculation in its model output and this was utilized to assess model identification for each SEM.

3.5.3. Model Estimation

Maximum likelihood (ML) estimation, the standard method of estimating parameters in structural equation models, is employed in the current study. This procedure establishes the probability that the observed correlations in the sample data are function of the specified parameters in the model (Johnson and Wichern, 2002). ML estimation is an iterative procedure, whereby the AMOS software makes an initial deduction on the value of the specified parameters and then improves the initial estimate step-by-step through a series of model runs (Blunch, 2008).

Multivariate normality is a key assumption in structural equation modeling employing the ML estimation approach. If violated, estimated effects and model fit measures may be rendered inaccurate. Meeting this condition is a difficulty in many studies (Tomarken, et al., 2005), with the presence of outliers being especially problematic (Hoyle, 1995). The current study tested for multivariate distribution for each specified SEM in order to achieve the best-suited distribution for each model using the Mardia statistic. The Mardia statistic assesses multivariate normality based on the model's skewness and kurtosis functions. A Mardia statistic with a critical ratio greater than 1.96 signifies a departure from multivariate normality with 95% confidence (West et al., 1995; Blunch, 2008). Where significant non-normality in a model was observed, variables exhibiting the highest degree of skew and kurtosis were transformed using the natural log or square root method. Such transformations have been found to be potentially effective in normalizing distributions (West et al., 1995). Models were then re-estimated using the newly transformed variables. If the critical ratio of the revised model's Mardia statistic still exceeded 1.96, statistically outlying cases were identified and removed until a reliable degree of normality in the model was achieved. The Mahalanobis distance generated by AMOS for each case in the SEM was used to identify outliers in the sample. The

Mahalanobis distance variable establishes a single mean calculation for all independent variables in the model and assesses how far away each case in the sample (i.e. in this case, the person) is from that mean value relative to all remaining cases (Everitt, 1993). The greater the Mahalanobis distance, the greater contribution said case adds to the non-normality of the data. Where an individual case was removed in one activity type model, the corresponding case in the other model was also removed, if applicable, in order to maintain a more realistic account of total daily per-capita emission levels. A detailed summary of the corrective actions used in each model is summarized in the results in Chapter 5. This approach to achieving multivariate normality is consistent with the methods described in the literature (Blunch, 2008).

A number of alternative estimation approaches have been developed that do not require multivariate normality in the model dataset, most notably the asymptotic distribution free (ADF) or weighted-least square (WLS) function. Estimation using these techniques was considered for models exhibiting extreme non-normality. The literature suggests, however, that ADF/WLS does not perform well on small datasets (i.e. less than 2,500) or on models with a large number of variables (Curran et al. 1996; Hoogland and Boomsma, 1998; Ory and Mohktarian, 2009b). ADF/WLS results have also been found to be subject to parameter overestimation and inflated fit indices (Olsson et al., 2000). For these reasons, this research avoids the use of ADF/WLS estimation techniques and, where appropriate, strives to achieve multivariate normal datasets using the steps described above.

3.5.4. Effect Decomposition

Structural equation models are sets of simultaneous linear regression equations. The estimated parameter effects are the regression coefficients produced by the interaction between specified exogenous and endogenous variables (Kaplan, 2000; Golob, 2003). Direct, indirect, and total regression effects between variables are explicitly calculated for each activity type model. Direct effects of an exogenous/endogenous variable on an endogenous variable are simply the regression coefficient between the two variables. Indirect effects are those between two variables occurring through one or more mediating variables. For instance, if x has a direct effect on y, and y has a direct effect on z, then x is said to have an indirect effect on z through y. Indirect effects are calculated by summing the product of any associated regression coefficients that link the variables in the particular structural chain. Total effects between variables are obtained by summing all direct and indirect regression effects between the variables of interest. It should be noted that, where occurring, direct and indirect effects between two variables might be of different signs (positive (+) or negative (-)). A focus only on either the direct or indirect effects, then, may lead to inconsistent conclusions in some cases. As such, it is important to ground final model deductions in the estimated total effect. By doing so, an understanding of how variables of interest influence the system as a whole (e.g. specified model) is gained. This is a key motive for employing SEM in the current research context.

3.5.5. Assessing Model Fit

Measures of model fit assess the ability of an identified model to reproduce the correlations of a given data set. Dozens of measures have been developed for assessing the fit of an SEM (Golob, 2003; Bollen and Long, 1993). However, little agreement exists regarding the best measures to employ for assessing model fit given sensitivity to differences in sample size and model complexity (Bentler, 2007; Yuan, 2005). Debate concerning appropriate value cut-off points for fit indices is also prevalent in the literature (Chen et al., 2008). In this context, the reliance on a single index to accept/reject model fit is considered imprudent, with many suggesting the use of multiple indices (Kaplan, 2000, Bentler, 2007; Hooper et al., 2008). A total of five indices are used to measure the fit of each activity type model in this research. Absolute fit measures, those that assess how well an a priori model reproduces the sample data, include chi-square (X^2), relative chi-square (X^2/df), residual mean square error of approximation (RMSEA), and the standard root mean square residual (SRMR). The comparative fit index (CFI) and Tucker-Lewis index (TLI), both incremental fit measures, are selected to assess the adequacy of the target model against an alternative, baseline model specified by the SEM analysis program (i.e. a “null” or “independent” model). These measures are chosen over other indices as they have been found to be the most insensitive to sample size, model misspecification and parameter estimates (Hooper et al., 2008). Table 3.1 summarizes these goodness-of-fit measures and the common acceptable threshold values for a well-fitted model in the literature.

TABLE 3.1. Summary of model fit indices.

Measure	Description	Acceptable Thresholds	Comments
Chi-square (X^2)	Assess the magnitude of discrepancy between the sample and model-fitted covariances	Insignifcant p value (ie. greater than 0.05)	Extremely sensitive to sample size and model complexity, almost always rejects models for large sample sizes (ie. > 1000); the more complex a model the higher likelihood for better fit; included here to recognize "traditional" fit assessment
Relative chi-square (X^2/df)	Chi-square test which controls for sample size	Less than 5 acceptable; less than 3 denotes good model fit	Gaining popularity given limitations with traditional chi-square test; still sensitive to complex models
Root mean square error of approximation (RMSEA)	Assess the magnitude of discrepancy between the sample and model-fitted covariances	Good fit = 0.00 - 0.05; fair fit = 0.05 - 0.08; mediocre fit = 0.08 - 1.0	Favours parsimony, models with fewer parameters, therefore may be infalted by complex models
Standardized root mean square residual (SRMR)	Average, standardized difference between observed and estimated covariance matrices	Close to zero, less than 0.05 suggests good fit	
Comparative Fit Index (CFI)	Compares the covariance matrix predicted by the model to the observed covariance matrix in the sample; controls for sample size	Greater than 0.9	
Tucker-Lewis Index (TLI)	Compares the X^2 value of the specified model to the X^2 of the null model	Greater than 0.9	Like RMSEA, sensitive to model complexity; favour simple models

3.6. Data Sources and Attributes

Four data sources were utilized to calculate and operationalize variables for the models in this research: self-reported daily travel data, regional parcel-level land and urban form data, regional transit network data, including roadway and transit networks, and locally-developed GHG emission factors for each transportation mode type in the region. These data characteristics are described below.

3.6.1. Daily Travel Data

The 1999 TransLink Travel Diary Survey provided detailed travel, person and household level socio-economic and demographic data used in this research. This survey included 7,063 individuals in 2,990 households across Metro Vancouver who reported approximately 22,000 trips during the course of one 24-hour period. Collected trip characteristics included postal code or intersection location of all reported origins and destinations, modes of travel and purpose for each trip segment. Socio-economic and demographic characteristics included age, gender, household income, and persons per household. Recruitment and data collection was conducted between September and October 1999. Detailed data collection methods are described in detail elsewhere (TransLink, 2003) and not included in this research for reasons of brevity.

In order to get a complete daily emission profile for each individual in the travel survey, individual respondents who did not provide all origin and destination points (i.e. valid postal code, street intersection, address) for all reported trip ends were omitted from the sample. For instance, if an individual took a total of 5 vehicle trips but recorded the origin and destination points of only 2 of those trips then that individuals total GHG emission estimates would be under-reported and inaccurate. Individuals reporting incomplete socio-economic data were also removed from the full sample. Additionally, only those individuals identified as adults (age 18 and older) were selected for study. Adults are generally considered more independent than children and youth. Indeed, studies have shown travel in youth to be less autonomous and often interlinked with the behaviour and preferences of their parents (McDonald, 2006; Copperman and Bhat, 2007). After the validation process, a sample of 2,690 individuals reporting 5,464 trips within 3,746 tours remained for analysis. Although considerably smaller than the full travel diary survey, this action was required in order to utilize realistic daily emission profiles.

3.6.2. Local Urban Form Data

The Metro Vancouver walkability index developed at the University of British Columbia by Dr. Lawrence Frank and colleagues was used as the source for the urban form measures in the analysis. The walkability index is a high-resolution, spatial database that utilizes land use data from the British Columbia Assessment office, street network data from CanMap, and census data integrated within a Geographic Information System (GIS) to measure the urban form characteristics of the immediate neighbourhoods around each postal code centroid in Metro Vancouver. Neighbourhoods are defined as a buffer created by drawing a road-network based polygon traveling 1-km from the centroid of each postal code (see Figure 3.2). A 1-kilometer buffer represents the distance that can generally be covered in a 10-minute walk along the road network. Findings suggest that this distance is the most reasonable scale for investigating how the general population's travel patterns relate with neighbourhood urban form (Moudon et al., 2006; Lee and Moudon, 2006).

The land area within each network buffer is categorized by use (e.g. commercial, parks, multi-family residential, etc.). The buffer area, land use categories, and census data were used to develop four measures of urban form: net residential density, the ratio of retail floor area to retail ground area, land use mix and street connectivity. These four characteristics are the most common measures of urban form in the existing travel behaviour literature and have demonstrated significant correlations with travel behaviour and choices (Cervero, 2002; Frank and Pivo, 1994; Cervero and Kockelman, 1997; Greenwald and Boarnet, 2000; Saelens et al., 2003). An overall measure of neighbourhood walkability is calculated for each postal code using these four urban form variables. Section 3.7.2.2 offers a detailed description of the methods used to operationalize these variables.

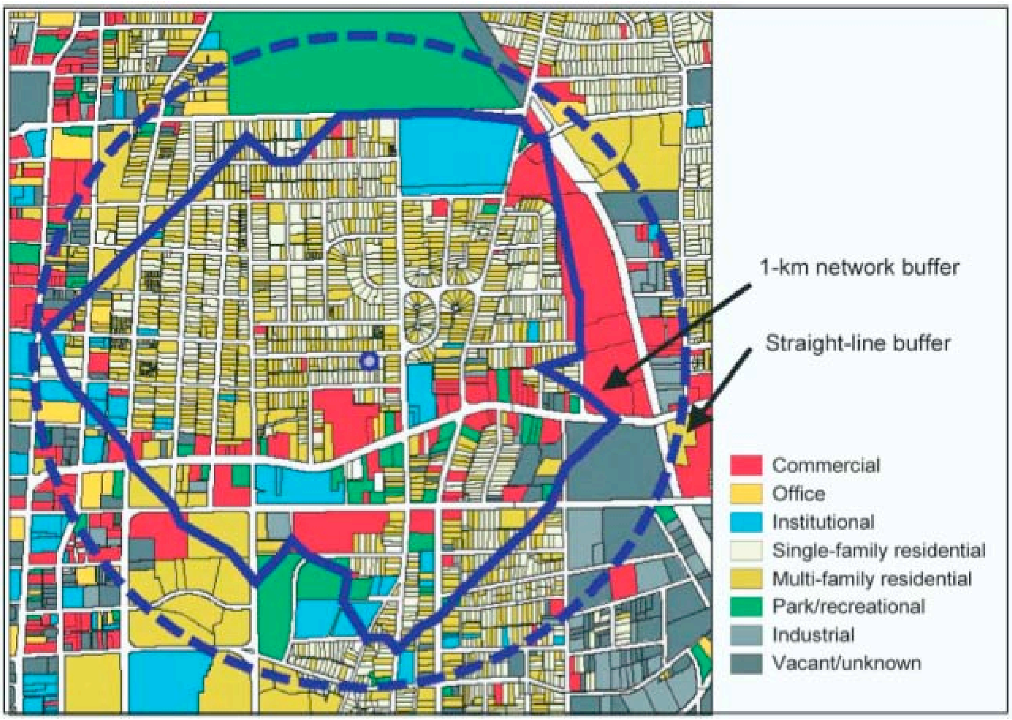


FIGURE 3.2. Defining a neighbourhood and measuring urban form. The blue dot in the centre of the neighbourhood buffer boundaries represents a household. Source: Frank et al., 2005. Reproduced with permission.

3.6.3. Regional Transit Network Data

TransLink, Metro Vancouver's regional transportation authority, provided spatial data on the region's transit routes and stop locations. Route and stop data was provided for all transit modes in the region, including Bus, SkyTrain, SeaBus, handyDart, and West Coast Express. The data was date stamped, and is accurate as of, March 2009.

3.6.4. Travel GHG Emissions Data

TransLink also provided mode-specific GHG emissions estimates for both vehicle and transit modes in the region (TransLink, 2009). Emissions are measured in gCO_2e/km (equivalent carbon dioxide per kilometer) but were transformed to $kgCO_2$/km for the purposes of this study. An equivalent carbon dioxide value is a universal standard of measuring GHG emission effects using the functionally equivalent amount of carbon dioxide as the reference (Abler, 2003). Self-reported vehicle occupancy for all auto trips in the 1999 Travel Diary Survey were used to develop detailed per-capita emission estimates for each individual reporting vehicle travel.

3.7. Variables

A total of 18 variables were tested and inputted into the structural equation models in this research, of which 13 were classified exogenous (independent) and 5 specified as endogenous (dependent). Detailed descriptions of the methods used to operationalize each measure are included in this section.

3.7.1. Exogenous Variables

3.7.1.1. Socio-Demographic Characteristics

Socio-demographic characteristics were one of two sets of exogenous (independent) variables in the analytical models. Individual and household level socio-demographic variables were self-reported and obtained from the 1999 TransLink Travel Diary Survey. Previous studies have found that socio-demographic variables like age, gender and income are strongly associated with travel behaviour (Murakami and Young, 1997; Lu and Pas, 1999). The current study controls for five socio-demographic variables: age (AGE), gender (FEMALE), persons in household under 18 years of age (PERSONS<18), vehicle access (VEHCL ACCESS), and household income (HH INCOME). Age was measured in years as a continuous variable. Gender was coded as dichotomous dummy variable (0 = Male, 1 = Female). Persons in household under 18 years of age was also coded as a dummy variable (0 = no, 1 = yes). Household income was measured as an ordinal variable with four categories (less than $30,000, $30,000 to $59,000, $60,000 - $90,000, and more than $90,000). As a categorical variable, 4 categories were assumed to be sufficient to be included in the SEM (Skrondal and Rabe-Hesketh, 2005). Vehicle access was calculated by dividing the number of vehicles in a household by the number of licensed drivers.

3.7.2.2. Local and Regional Built Environment

Built environment measures included local neighbourhood urban form characteristics and regional accessibility measures such as distance to nearest town centres and/or distance to work or school. Variables were specified as observed (measurable) exogenous (independent) variables in the structural equation. These variables were taken from or calculate using the Metro Vancouver walkability index.

Net Residential Density (NRD): Net residential density is the number of household units per residential acre within each 1-km network buffer. This measure was calculated by summing the total number of households in the buffer and the total acres of residential land base in each buffer. A simple ratio is then used (Equation 3.2):

$$NRD = h/a \qquad \text{(EQUATION 3.2)}$$

Where NRD is the net household density per acre; h is the number of households in the buffer area, and a is the residential land area in acres (calculated as the total area associated with the centroids of the housing unit).

Intersection Density (INTDEN): Intersection density is defined as the number of intersections per square km within each postal code network buffer. This measure is obtained from street network files by summing the total number of intersections in the buffer, and dividing by the total buffer area in km^2. This variable is calculated as (Equation 3.3):

$$INTDEN = i/a \qquad \text{(EQUATION 3.3)}$$

Where INTDEN is the intersection density, i is the number of intersections, and a is the area of the buffer, in km^2 for region x. Intersection density provides a measure of connectivity for a given neighbourhood. The greater the number of intersections over a given area, the more direct a route is likely to be from any randomly selected destination to any other, due in part to smaller blocks and streets that cross at frequent intervals.

Land Use Mix (MIX): The measure of land use mix captures the evenness of the distribution of square footage of development across 5 categories of land use deemed to contribute to walkability (Kockelman, 1997). These categories include (a) single family residential; (b) multi-family residential; (c) entertainment (comprised of entertainment, restaurant, and fast food land uses); (d) retail (comprised of small and large neighborhood retail, large retail, grocery and convenience store land uses, and excepting super large retail); and (e) office buildings (comprised of office and office building land uses). The land use mix index did not include agricultural, institutional, industrial, and parking classifications, as these are not considered to encompass walkable areas. The final land use mix measure is calculated as follows (Equation 3.4):

$$\begin{aligned} MIX = [&(\text{area (a)/total area})^* \ln(\text{area (a)/ total area})^* \\ &(\text{area (b)/ total area})^* \ln(\text{area (b)/total area})^* \\ &(\text{area (c)/ total area})^* \ln(\text{area (c)/ total area})^* \\ &(\text{area (d)/ total area})^* \ln(\text{area (d)/total area})^* \\ &(\text{area (e)/ total area})^* \ln(\text{area (e)/ total area})] / \ln(5); \end{aligned} \qquad \text{(EQUATION 3.4)}$$

Where area is the building floor area for the buffer in ft^2, a=single family residential, b= multi-family residential, c= entertainment, d=retail, and e=office, and total area is the sum of all of a-e. The final land use mix measure is an entropy index with values ranging from zero to one. A land use measure of zero represents a single-use environment and one represents a highly mixed built environment.

Retail Floor Area Ratio (RFA): The RFA represents the proportion of the retail parcel area in the buffer which is occupied by retail buildings. This measure was operationalized by summing the building floor area for all retail uses within the buffer, as well as the total parcel area for retail uses. In this case, retail use includes grocery stores, small and large neighbourhood retail as well as large retail, but not the super large retail areas. This variable is the ratio of (Equation 3.5):

$$RFA = rba/ ra \qquad \text{(EQUATION 3.5.)}$$

Where RFA is the ratio of retail floor area, rba= total building area for retail in ft^2, and ra is the retail land area, also in ft^2. RFA is a ratio and has no units. FAR provides an indicator of the degree to which pieces of land is covered in surface parking or where store-fronts are set up close to the sidewalk providing easy pedestrian access. A ratio of greater than one indicates the building contains more surface area than the land area it occupies. A low ratio indicates that the building covers very little of the parcel it is on and, given the commercial nature of the use, is likely to be surrounded by parking and expected to encourage automobile rather than pedestrian access.

Composite measure of neighbourhood walkability (NEIGHBRHD WALK): Measures of urban form (connectivity, household density, land use mix, and retail floor area) are often correlated (Frank et al., 2005b; Saelens et al., 2003; Leslie et al., 2007): areas with higher residential densities also tend to have a higher mixture of land uses and a more interconnected street pattern. Table 3.2 demonstrates that similar trends are noted in the Metro Vancouver urban form data.

TABLE 3.2 Bivariate correlations between individual urban form measures.

Urban Form Measure		Net residential density (NRD)	Intersection density (INTDEN)	Retail floor area ratio (RFA)	Land use mix (MIX)
Net residential density (NRD)	Correlation	1.000	0.175	0.533	0.300
	p -value	-	0.000	0.000	0.000
Intersection density (INTDEN)	Correlation	0.175	1.000	0.283	0.297
	p -value	0.000	-	0.000	0.000
Retail floor area ratio (RFA)	Correlation	0.533	0.283	1.000	0.365
	p -value	0.000	0.000	-	0.000
Land use mix (MIX)	Correlation	0.300	0.297	0.365	1.000
	p -value	0.000	0.000	0.000	-

Source: Metro Vancouver walkability index. Author's own analysis.
n = 61,580 postal code centroids.

The inclusion of all neighbourhood design variables in a regression model could produce spurious results (Ben-Akiva and Lerman, 1985). A walkability index was created that integrates these variables in order to avoid potential multicolinearity problems in data analysis. A normalized distribution (z-score) was taken for each urban form variable within a buffer, and the four normalized scores were then combined to create an overall walkability index for each buffer. The walkability index was created using the following formula (Equation 3.6):

$$\begin{aligned}\text{NEIGHBRHD WALK} = {} & \text{z-score}\,(\text{INTDEN}_x) + \\ & \text{z-score}\,(\text{NRD}_x) + \text{z-score}\,(\text{NRD}_x) + \\ & \text{z-score}\,(\text{MIX}_x) + \text{-score}\,(\text{RFA}_x)\end{aligned} \qquad \text{(EQUATION 3.6)}$$

Where $INTDEN_x$ is intersection density, NRD_x is household density, MIX_x is land use mix, and RFA_x the ratio of retail floor area for a given buffer zone x. Correlation analyses were run using the neighbourhood urban form measures of the sample population to obtain the degree of association between these individual variables and the walkability index. These results are presented in Table 3.3. As expected, it is observed that all urban form variables show strong positive correlation with the walkability index. The Metro Vancouver walkability surface is illustrated in Figure 3.3.

TABLE 3.3. Bivariate correlations between individual urban form measures and local neighbourhood walkability index value.

Urban Form Measure		Walkability Value (NEIGHBRHD WALK)
Net residential density (NRD)	Correlation	0.636
	p -value	0.000
Intersection density (INTDEN)	Correlation	0.783
	p -value	0.000
Retail floor area ratio (RFA)	Correlation	0.763
	p -value	0.000
Land use mix (MIX)	Correlation	0.634
	p -value	0.000

Source: Metro Vancouver walkability index. Author's own analysis.
n = 61,580 postal code centroids.

Distance to nearest town centre (DIST TO CENTRE): Recent research has demonstrated varying degrees of effect between local urban form and regional accessibility characteristics on travel behaviour (Cervero and Duncan, 2006) and travel emissions (Frank et al., 2009). In addition to local urban form variables, this research includes regional-scale characteristics like access to major shopping and employment areas. The shortest network distance to the nearest centre as identified in the Metro Vancouver Livable Region Strategic Plan (LRSP) was calculated for each postal code in the region (see Figure 3.4). A 1.5 km network buffer was drawn around a central postal code in each centre using ArcGIS 9.1 software. The distance is measured from the home postal code to the edge of the buffer using the Network Analyst extension in ArcGIS 9.1. Three levels of centres are defined in the LRSP: metropolitan core, regional centres and municipal town centres (Greater Vancouver Regional District, 1996). The metropolitan core includes downtown Vancouver and the Broadway corridor and is characterized by the

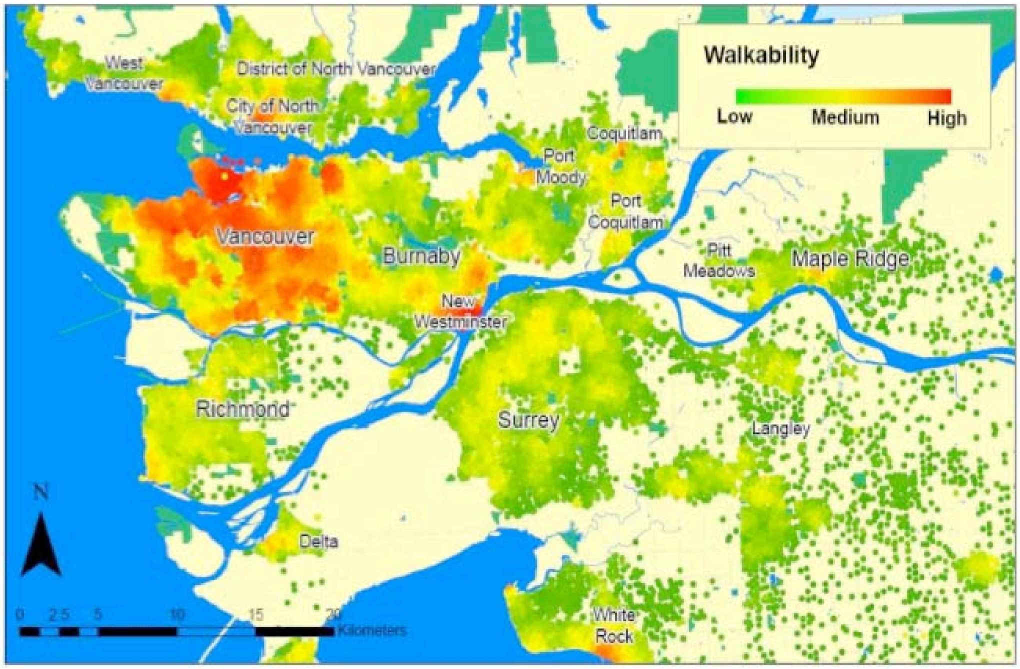


FIGURE 3.3. Metro Vancouver walkability surface. Each dot represents one postal code centroid. Red postal codes measured as most walkable. Green postal codes measured as least walkable.

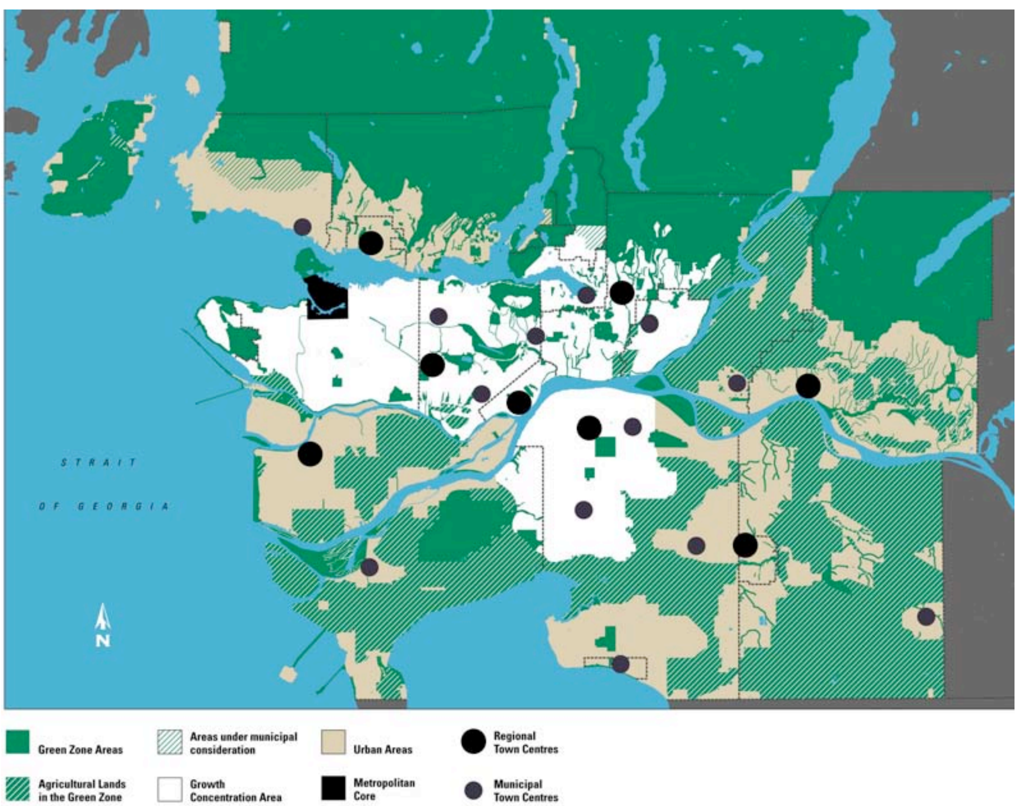


FIGURE 3.4. Metro Vancouver town and regional centres. Source: Greater Vancouver Regional District, 1996. Reproduced with permission.

highest densities of amenities, businesses, residential uses and transit service in the region. Regional centres are highly dispersed and accommodate a significant but lesser share of the region's current and future residential, commercial, business and transit service relative to the metropolitan core. Town centres provide for a smaller number of business and community facilities and act to support the larger regional centres. It is acknowledged that the scale of amenities and services varies by type of centre and that this may have implications on the relative degree of regional accessibility measured in this research.

Distance to work or school (DIST TO WRK/SCHL): Operationalized as the shortest network distance between an individual's home postal code to their self-reported place of employment or school. The distance is measured using the Network Analyst extension in ArcGIS 9.1. For individuals reporting both work and school tours, the distance between home and these destinations were averaged.

Transit Route Availability (TRANSIT AVLBLTY): Measured as the number of transit routes within and bisecting each 1-km postal code network buffer. This variable acts as a proxy measure of transit level-of-service for each local neighbourhood in Metro Vancouver.

3.7.2. Endogenous Variables

3.7.2.1. Daily Activity Tours

This analysis assesses the relationships between built environment measures and vehicle emissions as mediated by activity tour patterns and vehicle use. Self-reported daily travel from the 1999 GVRD Trip Diary Survey is aggregated to the activity-tour level as this scale provides a more realistic account of how travel decisions are made and, as a result, is less likely to lead to spurious correlations regarding emission generation (Shiftan et al., 2003). Custom designed algorithms developed in SPSS 17.0 were utilized to aggregate individual trips into one of two home-based tour types: 1) Home-based Work or School (HBWS), and 2) Home-based Other (HBO). Work/school tours are classified as those that include a work or school stop, regardless of the presence of other stops. Non-work tours are specified as those including only non-work or school stops like shopping, recreation, or picking up a passenger. A home-based tour includes all trips made between leaving home and arriving back at home again. Similar classification of activity patterns and tours has been used in previous research (Bowman and Ben-Akiva, 2001; Frank et al., 2007b). Tours were sorted by complexity (defined by number of stops on a tour). Simple tours are identified as those with only one destination before returning home (i.e. home → shopping → home). Complex tours include those with more than one destination before returning home (i.e. home → work → dinning → shopping → home).

Complex tours with several intermediate destinations can have more than one purpose and mode at individual locations and for individual trip segments. It was assumed that not all reported purposes and modes are the main choices for such a tour. A hierarchy of purposes was used in order to categorize complex tours for descriptive purposes. A tour's main purpose (i.e. work or non-work) is based on the following prioritized order of reported activity patterns (Frank et al., 2007b):

1 – Work
2 – Work-related
3 – School
4 – Personal Business
5 – Shopping
6 – Recreation and social
7 – To pick up or drop off passenger
8 – Dining and restaurants
9 – Other

This ordering of tour priorities is similar, although more detailed, to previous efforts at classifying travel activity (Krizek, 2003b; Strathman and Dueker, 1995). Note that subsistence (income producing) and maintenance travel is given priority while more discretionary activities are given the least amount of weight. Any tour containing a work trip or school trip was categorized as a HBW tour. Tours containing neither a work or school trip were classified as HBO tours.

A main travel mode was also assigned to each tour for descriptive analysis purposes. Home-based tours with only one mode were assigned the reported mode. For multi-mode tours, the main travel mode was assigned by considering which mode would be a controlling consideration in planning daily activities. At the trip level, travel modes affected by schedules (e.g. transit) and availability (e.g. vehicle, bicycle) have a greater degree of influence than the mode with neither of these constraints – walking (Frank et al., 2007b). The mode priority order based on the modes available for each trip constituting a tour is as follows:

1 – Drive to Transit
2 – Walk to Transit
3 – Auto Shared Ride
4 – Auto Drive Alone
5 – Bicycle
6 – Walk

Activity-tour variables: Three variable types were developed to capture daily activity pattern characteristics for each tour type: fraction of daily stops by tour type located within 1-km of home (suitable walking distance) (% STOPS NEAR HOME), and fraction of daily tours by type specified as simple (one stop) (% TOURS SIMPLE). A third tour complexity variable was operationalized, average number of stops per activity tour (TOUR CMPLXTY), and employed in models where a disproportionate number of individuals in the dataset reported taking only a single tour (i.e. expected for the work/school model, given the one-day nature of the travel survey).

3.7.2.2. Daily Vehicle Kilometers Traveled by Activity Type

A measure of vehicle kilometers traveled (VKT) is used to characterize the daily vehicle use arising from the complexity and location of activity participation. Total VKT for each home-based tour type was determined by calculating the shortest network distance along the roadway between each postal code centroid corresponding to the self-reported origin and destination point for all vehicle trips in ArcGIS's Network Analyst extension. Total distance traveled by walking, cycling and transit was also calculated for descriptive purposes. The same method was used in this effort. For transit distance, however, the shortest distance along the transit network, instead of the road network, was employed.

3.7.2.3. Daily Per-Capita Vehicle GHG Emissions by Activity Type

Daily GHG emissions related to vehicle use (VEHCL GHG) by activity-tour type were measured at a per-capita scale. Detailed information on trip distance and vehicle occupancy for each vehicle trip taken in the 1999 GVRD Trip Diary Survey was used to estimate vehicle GHG emissions. GHG emission estimates were also calculated for transit modes for descriptive analysis purposes (see Section 4.5). These were ultimately not included in the analysis as the focus of this research is on vehicle use and vehicle emissions. The methods described here are comparable to previous approaches developed to explore and assess criteria air pollution in elsewhere (Frank et al., 2000, Frank et al., 2009). Emission modeling followed three main steps: 1) determine travel path and distance for a given trip; 2) calculate GHG estimates based on the above for all motorized modes; and 3) aggregate emission estimates to activity tour type, each of which is discussed in detail below.

1) Determine travel path and distance: Respondents in the 1999 GVRD Trip Diary Survey specified origin and destination points as well as mode used for each recorded trip. The actual route followed for each trip in the travel survey was not recorded and required calculation. For vehicle trips, the self-recorded location of trip ends (postal code or intersection) was spatially matched to the nearest postal code centroid in the Walkability Index. The 'Network Analyst' tool in ArcGIS 9.3 was utilized to estimate the path and approximate distance (in kilometers) for each origin and destination pair along the regional road network. For trips and tours involving transit use, self-reported route number information allowed for trip distances to be estimated based on detailed bus, SkyTrain, SeaBus, and West Coast Express route networks. The exact transit stops used to board and disembark a specified transit route was not accounted for in the survey. The postal code centroid of the nearest transit stops where the specified route stopped was used. Again, the 'Network Analyst' tool in ArcGIS 9.3 was employed to estimate the path and approximate distance (in kilometers) by reported transit mode for each origin and destination pair along the regional transit network.

2) Calculate distance-based GHG estimates per mode: GHG emission estimates were calculated for trips made using vehicles, public transit, taxis, and school buses. Non-motorized modes like walking and bicycling were assigned zero emissions. Mode-specific GHG per kilometer estimates provided by TransLink (measured as gCO_2e/km and converted to $kgCO_2e/km$) were applied to the calculated distance traveled for each reported trip in the sample (see Table 3.4).

TABLE 3.4. GHG emission estimates by transport mode per vehicle kilometer.

Transport Mode	kgCO2e/km
Private Mode	0.3127
Car (gasoline engine)	0.2596
Light Truck/SUV (gasoline engine)	0.3776
TransLink Diesel Bus	1.7647
TransLink Electric Trolley Bus	0.0679
TransLink Diesel Community Shuttle Bus	0.6832
SkyTrain Electric Rail Car	0.0868
SeaBus Vessel	21.7831
West Coast Express Passenger Car	2.8640

Source: TransLink, 2009a. Reproduced with permission.

The formula in Equation 3.7 was employed to calculate emissions per travel mode per trip:

$$GHG = (D_x \times EF_x) / O \qquad \text{(EQUATION 3.7)}$$

Where GHG is the greenhouse gas emissions (CO_2e) per mode per trip, D is distance traveled in kilometers in mode X, EF is that mode X's associated emission factor measured in $kgCO_2e/km$, and O is vehicle occupancy. Of note, TransLink supplied separate GHG estimates for both automobile and light-duty trucks. This level of detail regarding mode choice was not reported in the travel survey and so a single GHG emission factor was developed to estimate emission levels from vehicle travel. Local data on Metro Vancouver's fleet distribution share was unavailable for this effort and so a regional fleet distribution of 55% autos and 45% light duty trucks was assumed. This distribution reflects a common range in regional fleet distribution in North American cities (Frank et al., 2009). Self-reported and estimated vehicle occupancy rates were then applied to generate emission levels per trip on a per-capita scale. For vehicle (auto) modes, corresponding GHG per passenger kilometers was divided by the occupancy reported by survey respondents. Transit route-specific weekday average ridership estimates supplied by TransLink were employed for calculating per-capita transit trip emissions. Average vehicle occupancy for school buses was assumed to be 35 individuals. Vehicle occupancy in taxi modes was assumed to be 1. Although taxis will have at least two persons in them, occupancy of one is justified based on the reason that the sole reason of the trip occurring is due to a single person (like a personal auto trip). Therefore, all emissions generated are assigned to that individual. Transit route specific boardings (average weekday occupancy over 24-hour period) and vehicle types used to calculate transit GHG emission estimates are summarized in Appendix A.

3) Aggregate emission estimates to activity tour: Per capita GHG emission estimates were scaled up from the individual trip to the activity tour level in order to facilitate an analysis of the linkages between the built environment, daily activity patterns and emissions. Total emissions from all tours within each tour type (i.e. home-based work and home-based other) were then calculated. This value was used as the final dependent variable tested for sensitivity to urban form characteristics in the structural equation models.

The limitations of the emission estimation methods employed in this research are acknowledged. The current modeling process is not sensitive to variations in travel speed and engine temperature. Lower operating speeds and cold engine starts have been shown to yield additional emission levels from personal vehicles due to inefficient operating conditions (Stead, 1999). Crane (1996) suggests that compact development policies may actually have secondary emission effects by reducing average travel speeds and producing greater trip frequencies that may yield additional cold start trips. However, emission penalties associated with cold engine starts and low speeds are likely to be small for several reasons. Ewing et al (2008) cite evidence that CO_2 emissions from all vehicle starts account for only 3.3% of total passenger travel emissions. Vehicle trip rates in more compact areas are also lower due to trip shifting from the automobile to alternative, less carbon intensive modes (Cerver and Radisch, 1996). Finally, any efficiency gained by designing roads for more free-flow traffic may be largely offset by associated increases in VMT as explained by the phenomenon of induced travel demand (Cervero, 2002; Barr, 2000). Regardless of these minute effects, emission modeling based on detailed congestion-based travel speeds, actual trip path, and duration of out-of-home activities would provide additional leverage through a more accurate representation of daily GHG emissions. Also absent is the ability to employ vehicle specific GHG emission factors (i.e. light-duty truck SUV versus small car) (see Table 3.3). Limited modeling capabilities, especially those of the Metro Vancouver regional travel demand model, and trip diary data prohibited the estimation of speed and engine temperature variables, and the inclusion of specific vehicle mode (i.e. light truck or car) in the current research.

4. SAMPLE PROFILE

4.1. Study Area

This study focuses on Metro Vancouver (formerly, the Greater Vancouver Regional District), a regional district in the southwestern corner of British Columbia, Canada. Metro Vancouver consists of 21 local municipalities and one unincorporated area (see Figure 4.1.). The region has a current population of just over 2.1 million persons and is expected to grow by 800,000 residents to approach 3 million over the next 25 years (Metro Vancouver, 2009a). This significant population increase presents a challenge to local policymakers who will need to properly anticipate and co-ordinate future growth and development. Adding to this are the geographic constraints limiting the region's future outward growth potential, notably water and ocean, mountains, the Agriculture Land Reserve, and United States border. Historically, these characteristics have culminated as a natural urban containment boundary resulting in a relatively smaller land base and compact urban form compared to other urban regions in North America

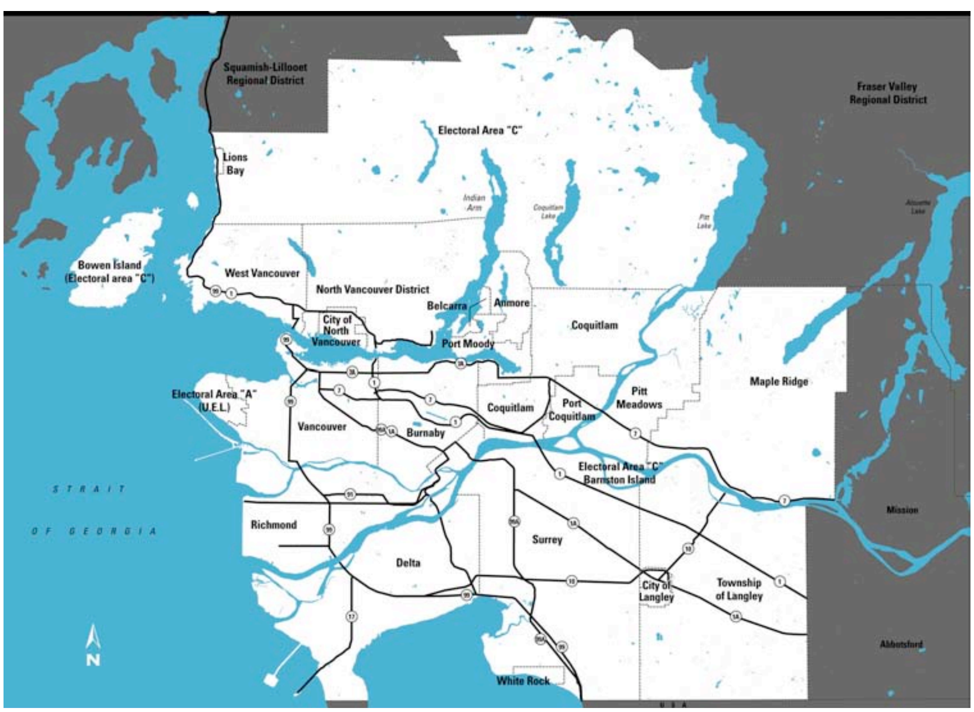


FIGURE 4.1. Metro Vancouver and member municipalities.
Source: Greater Vancouver Regional District, 1996. Reproduced with permission.

4.2. Data Sample

The 1999 TransLink Travel Diary Survey provided the detailed travel, person and household level socio-economic and demographic data used in this research. A sample of 2,690 individuals reporting 5,464 trips within 3,746 tours was separated for analysis. The sample used in this research is generally representative of the regional population (see Table 4.1). Representativeness was assessed against median age, gender and median household income. Other characteristics like education attainment, marital status, language and ethnicity collected in the 2001 Census were absent from the regional trip diary survey.

TABLE 4.1. Regional representativeness of sample population.

Attribute	Sample Population (a)	Regional Population (b)
Median Age	42.0	37.4
Gender (Female)	1,437 (53.4%)	1,014,235 (51.0%)
Median Household Income	\$30,000 - \$59,000	49,940

(a) n = 2,690 persons, 1,888 households (Source: 1999 TransLink Trip Diary Survey).
(b) 1,986,965 persons (Source: Statistics Canada, 2001 Community Profile, Vancouver CMA).

The following tables and paragraphs provide a general descriptive analysis of the sample data attributes and characteristics. Attributes related to the sample are reviewed at the individual, household, trip and tour level of measurement. Representativeness

4.3. Individual Characteristics

Individual-level attributes are described in Table 4.2. The distribution across age cohorts is as expected. The core adult age groups are well represented with close to 80% of all respondents between 25 and 65 years of age. Comparatively, seniors and young adults are underrepresented. Holding a driver's license does not imply immediate access to a vehicle in the sample: close to 90% of all individuals hold a valid driver's license, although it is estimated that persons in the sample have access to a vehicle only 73% of the time. Approximately three-quarters of the sample are employed in some capacity while 15% reported being a student. This highly skewed distribution is reflective of the relatively older age characteristics of the sample.

Individuals reporting employment were measured to reside, on average, 12.6 kilometers from their self-reported place of employment. A standard deviation of 9.8 kilometers suggests a rather large degree of variation in this distance and this is confirmed by large positive skew value and the breakdown of distance to work by category. Just over half of the sample reporting employment resides within 10 kilometers of their place of work. Similar distances to school are also estimated and expected as adults frequenting school are attending universities or colleges that are more dispersed over the region, unlike elementary and secondary school that are situated in most neighbourhoods.

4.4. Household Characteristics

Household-level attributes are summarized in Table 4.3. Nearly half of the sample households have two or more vehicles, as compared to only 13% with none. Households with over 3 persons make up the largest share of households in the sample. However, single person households account for one-quarter of households. One-third of households report one or more persons under the age of 18 living at home. Middle income-earning households characterize three-quarters of the sample population. Comparatively, low and high earning households are underrepresented.

Metro Vancouver has 15 designated metro, regional and town centres within its borders (see Figure 3.4). It is estimated that, on average, most households are situated around 3 kilometers from these locations and well-over three-quarters are located less than 5 kilometers away, suggesting relatively good regional access sample-wide. Geographically, half of households in the sample are located in the suburban areas of the region. Only a third are located in Vancouver proper. This uneven geographic allocation is expected and illustrates the current population distribution of the region. Table 4.3 also summarizes the distribution of households by neighbourhood walkability. All walkability quartiles are generally well represented in the sample. The higher share of households in the most walkable neighbourhood quartile likely reflects the compact, pedestrian-friendly nature of several of the region's major population areas, including Vancouver, New Westminster, West Vancouver and parts of Burnaby.

TABLE 4.2. Individual-level sample characteristics.

Attribute	Mean (SD)	Skew / Kurtosis	Count	Share
Age	42.9 (15.4)	0.47 / -0.44		
15-19			97	3.6%
20-24			204	7.6%
25-34			625	23.2%
35-44			597	22.2%
45-54			567	21.1%
55-64			322	12.0%
65-74			180	6.7%
75 or older			98	3.6%
Total			2,690	100.0%
Gender				
Male			1,253	46.6%
Female			1,437	53.4%
Total			2,690	100.0%
Hold a Valid Driver's License				
Yes			2,404	89.4%
No			286	10.6%
Total			2,690	100.0%
Vehicle Access (%)	73.9 (0.34)	-1.01 / -0.24		
Employment Status				
Employed Full Time			1,274	47.4%
Employed Part Time			405	15.1%
Self Employed			201	7.5%
Employed (Basis Not Specified)			10	0.4%
Not Employed			800	29.7%
Total			2,690	100.0%
Student Status				
Student Full Time			236	8.8%
Student Part Time			171	6.4%
Student (Basis Not Specified)			7	0.3%
Not a Student			2,276	84.6%
Total			2,690	100.0%
Distance to Work (km)	12.6 (9.8)	1.33 / 2.20		
Less than 5 km			351	24.1%
5 km - 10 km			442	30.3%
11 km - 15 km			226	15.5%
16 km - 20 km			147	10.1%
Greater than 20 km			293	20.1%
Total			1,459	100.0%
Distance to School (km)	11.8 (9.6)	1.38 / 1.86		
Less than 5 km			75	26.6%
5 km - 10 km			86	30.5%
11 km - 15 km			49	17.4%
16 km - 20 km			25	8.9%
Greater than 20 km			47	16.7%
Total			282	100.0%
Number of Tours	1.4 (0.67)	1.91 / 4.40		
1 tour			1,857	69.0%
2 tours			636	23.6%
3 or more tours			197	7.3%
Total			2,690	100.0%
Total Daily Distance Traveled (km)	29.2 (25.3)	2.16 / 9.32		
Total Daily Distance Traveled by Mode (km)				
Vehicle (km)	29.8 (25.6)	2.20 / 9.76		
Public Transit (km)	23.1 (21.1)	3.69 / 15.79		
Walk (km)	2.7 (2.6)	5.32 / 37.39		
Bicycle (km)	14.4 (10.6)	9.95 / 119.06		
Total Daily Vehicle GHG Emissions (kgCO_2e)	5.7 (6.6)	1.93 / 6.08		

Source: 1999 TransLink Trip Diary Survey. Author's own analysis.
n = 2,690 persons

TABLE 4.3. Household-level sample characteristics.

Attribute	Mean (SD)	Skew / Kurtosis	Count	Share
Persons per household	2.52 (1.3)	0.85 / 0.35		
1			440	23.3%
2			687	36.4%
3			316	16.7%
4 or more			445	23.6%
Total			1,888	100.0%
Household Income	2.44 (0.99)	0.14 / -1.02		
Less than $30,000 (1)			357	18.9%
$30,000 - $59,000 (2)			675	35.8%
$60,000 - $89,000 (3)			501	26.5%
$90,000 or more (4)			355	18.8%
Total			1,888	100.0%
Vehicles per household	1.51 (0.99)	0.73 / 1.52		
0			243	12.9%
1			744	39.4%
2			677	35.9%
3 or more			224	11.9%
Total			1,888	100.0%
Individuals under 18 years old	0.51 (0.89)	1.72 / 2.17		
0			1,330	70.4%
1			254	13.5%
2 or more			304	16.1%
Total			1,888	100.0%
Distance to nearest Town/Regional Centre (km)	3.12 (3.5)	2.73 / 10.39		
Less than 5 km			1,523	80.7%
5 km - 10 km			299	15.8%
11 km - 15 km			27	1.4%
16 km - 20 km			16	0.8%
Greater than 20 km			23	1.2%
Total			1,888	100.0%
Regional location				
Urban(a)			668	35.4%
Suburban(b)			987	52.3%
Exurban(c)			233	12.3%
Total			1,888	100.0%
Walkability quartile				
Lowest quartile			384	20.3%
2nd quartile			435	23.0%
3rd quartile			417	22.1%
Highest quartile			652	34.5%
Totals			1,888	100.0%

Source: 1999 TransLink Trip Diary Survey. Author's own analysis.
(a) Vancouver
(b) Burnaby, Richmond, Surrey, New Westminster, City of North Vancouver, District of North Vancouver, West Vancouver, White Rock, Port Moody, Coquitlam, Port Coquitlam
(c) Bown Island, Lion's Bay, Langley City, Distruct Municipality of Langley, Maple Ridge, Pitt Meadows, Belcarra, Anmore, Delta, Electoral District A
n = 1,888 households

4.5. Trip and Activity Characteristics

Key dependent variables in this research are related to activity patterns, vehicle travel and related GHG emissions. Detailed activity tour attributes are summarized in Table 4.4. The most common purpose for making tours is for work although, when combined, non-work or school tours make up over half of all tours in the sample. Shopping, recreational, social, and personal business trip were the most prevalent purposes for non-work tours. Overall, diversity in tour complexity is fairly limited across the sample with close to three-quarters of all tours containing only a single stop (i.e. home-shopping-home). A private vehicle is the most common primary mode of travel for all tours. However, variations in primary mode choice exist between main tour purpose and tour complexity (see Tables 4.5 and 4.6, respectively). HBWS tours are accomplished primarily by drive alone nearly half the time. This is more than double the use of shared auto rides and transit use. The drive alone mode share decrease substantially for non-work tours with shared auto rides being the most common primary mode. Walking is third commonly reported as the primary mode for non-work travel, behind shared auto rides and drive alone. Cycling is a more prevalent primary mode for work tours compared to non-work tours. Similar patterns are observed for primary mode choice by tour complexity. Auto drive alone accounts for over a third of all simple, one-stop tours while shared ride is the most common mode for complex tours. Walking is more popular for simple tours compared to complex tours. Walk tours, on average, have the fewest number of stops, followed by drive alone (Table 4.7). Auto shared ride and walk to transit have the highest mean number of stops, likely attributable to the nature of these modes to include a mode related stop (i.e. transfer) or to pick up or drop off individuals. These patterns are expected. Vehicle use, transit and even cycling are more appealing for regional trips to work or school where distances are greater. Walking, cycling and transit is less favourable for tours with multiple errands, given the potential distance between stops or the need to carry several items.

TABLE 4.4. Activity tour-level sample characteristics.

Attribute	Mean (SD)	Skew / Kurtosis	Count	Share
Main Tour Purpose				
Work/Work-related			1,457	38.9%
School			282	7.5%
Recreation/Social			480	12.8%
Dinning/Restaurant			91	2.4%
Shopping			558	14.9%
Personal Business			461	12.3%
To Pick-up/Drop-off Passenger			394	10.5%
Other			23	0.6%
Total			3,746	100.0%
Number of Tours	1.40 (0.68)	1.91 / 4.40		
1 tour			2,756	73.6%
2 or more tours			990	26.4%
Total			3,746	100.0%
Number of Work/School Tours	1.01 (0.11)	-0.16 / -0.88		
1 tour			1,720	98.9%
2 or more tours			19	1.1%
Total			1,739	100.0%
Number of Other Tours	1.46 (0.76)	1.35 / 2.00		
1 tour			1,449	72.2%
2 or more tours			558	27.8%
Total			2,007	100.0%
Tour Complexity (# of stops)	1.49 (0.87)	2.94 / 13.34		
1 stop			2,756	73.6%
2 stops			575	15.3%
3 or more stops			415	11.1%
Total			3,746	100.0%
Tour Complexity for Work/School Tour (# of stops)	1.40 (0.78)	2.11 / 4.19		
Simple (1 stop)			1,303	74.9%
Multi-stop (2 or more stops)			436	25.1%
Total			1,739	100.0%
Tour Complexity for Other Tours (# of stops)	1.55 (0.99)	3.02 / 13.42		
Simple (1 stop)			1,453	72.4%
Multi-stop (2 or more stops)			554	27.6%
Total			2,007	100.0%
Primary Mode of Travel				
Transit			651	17.4%
Vehicle			2,721	72.6%
Bicycle			78	2.1%
Walk			296	7.9%
Total			3,746	
Distance Traveled per Tour by Tour Type (km)				
Home-based Work/School (km)	26.9 (21.0)	1.34 / 2.37		
Home-based Other (km)	15.2 (18.4)	3.66 / 26.49		
All tours (km)	20.7 (20.5)	2.19 / 9.75		
Daily Per-Capita Vehicle GHG by Tour Type (kgCO_2e)				
Home-based Work/School	5.9 (6.1)	1.54 / 3.26		
Home-based Other	2.8 (3.8)	3.86 / 27.15		
All Tours	4.2 (5.3)	2.31 / 7.99		
Daily Per-Capita Vehicle GHG by Tour Complexity (kgCO_2e)				
Simple (1 stop)	3.5 (4.9)	2.29 / 6.65		
Multi-stop (2 or more stops)	5.4 (6.0)	2.28 / 8.97		

Source: 1999 TransLink Trip Diary Survey. Author's own analysis.
n = 3,746 activity tours

TABLE 4.5. Primary mode of travel by main tour purpose.

Primary Mode of Travel	HBW Tours		HBO Tours		All Tours	
	Count	Share	Count	Share	Count	Share
Auto Drive Alone	811	46.6%	481	24.0%	1,292	34.5%
Auto Shared Ride	359	20.6%	1,070	53.3%	1,429	38.1%
Vehicle to Transit	16	0.9%	5	0.2%	21	0.6%
Walk to Transit	418	24.0%	212	10.6%	630	16.8%
Walk	83	4.8%	213	10.6%	296	7.9%
Bicycle	52	3.0%	26	1.3%	78	2.1%
Total	1,739	100.0%	2,007	100.0%	3,746	100.0%

Source: 1999 TransLink Trip Diary Survey. Author's own analysis.
n = 3,746 activity tours

TABLE 4.6. Primary mode of travel by tour complexity.

Primary Mode of Travel	Simple Tours		Multi-Stop Tours		All Tours	
	Count	Share	Count	Share	Count	Share
Auto Drive Alone	1,026	37.2%	266	26.9%	1,292	34.5%
Auto Shared Ride	921	33.4%	508	51.3%	1,429	38.1%
Vehicle to Transit	16	0.6%	5	0.5%	21	0.6%
Walk to Transit	480	17.4%	150	15.2%	630	16.8%
Walk	256	9.3%	40	4.0%	296	7.9%
Bicycle	57	2.1%	21	2.1%	78	2.1%
Total	2,756	100.0%	990	100.0%	3,746	100.0%

Source: 1999 TransLink Trip Diary Survey. Author's own analysis.
n = 3,746 activity tours

The mean distance traveled per capita in the sample population was a total of 30 kilometers during the 24-hour period (Table 4.2). On average, individuals traveled approximately 20 kilometers per activity tour (Table 4.4). A standard deviation of over 20 kilometers, however, suggests significant variation in this estimated distance. Indeed, comparing mean distance traveled between work and non-work tours, it is observed that non-work tours are more than 10 kilometers shorter than work tours at 15 kilometers round-trip. Average daily distance traveled was estimated to be highest (29 km) for vehicle travel. Mean daily cycling distance of those reporting the use of a bicycle was approximately 14 km. Those who walked did so an average of 2.7 kilometers during the 24-hour period. The small standard deviation suggests that most individuals will only walk for those activities and purposes that are relatively close by. The relatively large and positive skew and kurtosis values associated with distance traveled by public transit, walking and bicycle suggest that these distributions are highly non-normal and slanted to the left (shorter distances). This is expected as these modes are more influenced by time and spatial constraints thereby making them more ideal for shorter trips and tours (i.e.

walking not feasible for long haul trips, long trips by transit may require additional transfers and waiting).

TABLE 4.7. Mean number of stops per tour by primary mode of travel.

Primary Mode of Travel	Mean # of Stops (SD)	Number of Tours
Auto Drive Alone	1.21 (0.66)	1,292
Auto Shared Ride	1.65 (1.11)	1,429
Vehicle to Transit	1.33 (0.65)	21
Walk to Transit	1.37 (0.81)	630
Walk	1.19 (0.62)	296
Bicycle	1.38 (0.76)	78
Total	1.49 (0.87)	3,746

Source: 1999 TransLink Trip Diary Survey. Author's own analysis.
n = 3,746 activity tours

Finally, turning to vehicle GHG emissions, individuals in the sample emitted, on average, 5.7 kgCO_2e during the 24-hour sample period (see Table 4.2). The mean amount of GHG emissions per tour was estimated at 4.2 kgCO_2e, although measurable differences were observed between tour purpose and complexity. On average, vehicle emissions associated with simple tours are 20% less than multi-stops tours. Average emissions for work-tours are 5.9 kgCO_2e compared to only 2.8 kgCO_2e for non-work tours. All emission characteristics are highly skewed and kurtotic suggesting significant non-normal distributions.

4.6. Spatial Characteristics of Key Variables

Data in Table 4.8 illustrates that regional variations exist in average neighbourhood walkability, regional accessibility, transit levels-of-service, vehicle use, activity patterns and travel GHG emissions across the sample. The most apparent differences occur between central and outlying municipalities. Generally, individuals residing in Vancouver, the region’s central core, drive the fewest kilometers and emit the least amount of carbon dioxide. As distance from the regional core increases, so too does average daily vehicle kilometers traveled and vehicle emissions. Individuals in the outlying areas of White Rock, Maple Ridge, Delta, Langley and Port Moody, drive the most kilometers daily and emit some of the higher daily averages of GHGs. These observations are expected. Compared to those in the core areas, individuals in the most outlying suburban and exurban areas of the region have greater distances to work, school, and local and regional town centres, and are under-serviced by public transit (low number of accessible bus routes close by). Such circumstances make vehicle use both attractive and required for most daily travel.

A similar dichotomy in regional vehicle use and GHG emissions exists between more and less walkable municipalities. Vancouver and the City of North Vancouver, two of the region's most walkable municipalities, yield relatively low levels of vehicle kilometers traveled and GHG emissions region wide. The compact, mixed-use nature of these places helps to support higher levels of transit service and reduces distances between destinations. However, data in Table 4.8 suggests that regional location may have a greater effect on these variables than local neighbourhood urban form. White Rock proves a good case in point for this observation. Although measured as the third most walkable municipality in the region, attributable largely to its geographically small size and traditional downtown, White Rock is situated well to the south of many regional population, employment and shopping centres. Residents in this area, on average, drive the greatest distance daily (37.5km) and emit some of the most GHG emissions region-wide. The analytical models and results described in the following chapter will help to yield empirical insight into the relative effects of regional location and local neighbourhood urban form and walkability on vehicle use and related GHG emissions. Of note, no apparent spatial pattern between either regional location or neighbourhood walkability and average daily activity pattern characteristics (fraction of stops near home and fraction of tours simple) is discernable at this scale.

TABLE 4.8. Mean spatial characteristics of key variables.

Municipality	Regional Location	Daily Vehicle Kilometers Traveled	Daily Vehicle GHG (kgCO2e)	Distance to Work / School	Distance to Nearest Town/ Regional Centre	Transit Route Density	Neigbour-hood Walkability	Proportion of Daily Tours Simple	Proportion of Daily Stops Near Home
Vancouver	Urban	12.78	3.10	7.50	2.83	16	4.48	71.2%	10.1%
Burnaby	Suburban	17.15	4.36	10.82	0.81	7	-0.32	71.8%	4.8%
Richmond	Suburban	27.69	6.93	13.96	2.81	7	-1.33	70.5%	5.8%
Surrey	Suburban	31.62	7.86	16.95	2.24	4	-2.24	72.5%	5.8%
New Westminster	Suburban	27.81	6.33	14.08	1.03	9	4.32	61.8%	7.2%
North Vancouver (City)	Suburban	15.33	4.01	8.55	0.98	8	1.62	68.2%	12.1%
North Vancouver (District)	Suburban	26.13	6.33	12.58	4.86	5	-1.57	68.3%	5.1%
West Vancouver	Suburban	31.03	7.50	16.58	3.00	6	-1.41	67.8%	2.4%
White Rock	Suburban	38.54	9.51	22.84	0.01	7	2.15	65.8%	9.8%
Port Moody	Suburban	37.65	9.65	15.99	1.46	5	-0.77	73.5%	3.5%
Coquitlam	Suburban	27.62	7.25	15.72	1.46	5	-1.53	69.2%	6.7%
Port Coquitlam	Suburban	36.74	7.35	14.67	1.35	5	-0.53	68.1%	2.6%
Langley (City)	Exurban	25.01	5.69	13.93	1.20	4	-1.59	84.4%	20.0%
Langley (District)	Exurban	36.90	8.55	18.11	6.00	3	-2.90	64.7%	1.1%
Maple Ridge	Exurban	35.84	9.43	24.41	6.74	5	-2.35	76.7%	8.7%
Pitt Meadows	Exurban	21.84	5.49	23.92	0.01	6	-1.98	78.5%	9.5%
Delta	Exurban	37.54	9.52	19.35	11.59	5	-1.26	68.5%	5.7%

Source: 1999 TransLink Trip Diary Survey. Author's own analysis.
n = 2,690 persons

5. RESULTS & DISCUSSION

5.1. Overview

Detailed results concerning the nature and strength of effects between built environment measures, daily activity patterns, vehicle use, and vehicle GHG emissions as estimated using structural equation modeling are presented in this chapter. Findings for each activity-tour type model are summarized and interpreted separately. A detailed discussion of all model results in the context of the research questions and objectives is included in the final section.

5.2. Note on Model Interpretation

Both un-standardized and standardized parameter coefficients between variables are estimated for all structural equation models in this research. Un-standardized coefficients are similar to B-values in traditional linear regression and interpreted as the direction and strength of effect between variables: that is, the numbers of units change in the dependent variable per one unit increase in the independent variable. Standardized estimates are transformations of the un-standardized coefficients and interpreted as the number of standard deviations change in the dependent variable per standard deviation change in the independent variable. These values are similar to Beta coefficients in linear regression frameworks. Standardized coefficients lack true scaling information but illustrate the relative magnitude and importance of a given parameter effect throughout a model. Both values yield important insight into the nature of effects in a given model. Having said this, however, interpreting meaningful marginal effects using the un-standardized coefficients proved to be extremely arduous for all models given the need to transform a number of variables from their original scale in order to achieve multivariate normality (discussed below). The results described herein generally speak to the magnitude of effect between variables as indicated by the standardized coefficients. Unstandardized coefficient results are reported in Appendix B.

5.3. Home-Based Other Tours Model Results

5.3.1. Model Exploration and Specification

Model specification was consistent with the conceptual framework in Figure 3.1, which followed anticipated relationships and linkages between variable types drawn from the literature (see discussions in Chapter 2 and Section 3.4). Several iterations were required to obtain a final, multivariate normal and well-fitted model to be estimated. The "Initial" and "Final" HBO tour statistical models are illustrated in Figure 5.1 with the full specification process described below.

The "Initial" structural equation model (n = 1,371) consisted of 15 total observed variables, of which 11 were specified as exogenous (e.g. NRD, INTDEN, RFA, MIX, DIST TO CENTRE, TRANSIT AVLBLTY, AGE, FEMALE, PERS<18, VEHICLE ACCESS, and HH INC) and the remaining as endogenous (e.g. % TOURS SIMPLE, % STOPS NEAR HOME, VKT, VEHICLE GHG). A trial estimation of the model was performed to screen the nature (e.g. direction and strength) of the parameter coefficients and test for multivariate non-normality. Some individual urban form variables yielded opposite, non-significant effects on the endogenous variables they were specified to interact with. The multicolinear character of these variables was identified as a likely reason for this occurrence (as discussed in Section 3.7.2.2). These variables were removed from the model and replaced with the composite neighbourhood walkability index value (NEIGHBRHD WALK). Although the inclusion of this variable addresses the issue of multicolinearity, its use precludes the ability to segment out the relative impact of each individual urban form component on the endogenous variables in the model. The re-estimated "Initial" model was identifiable (df = 10), however, issues of multivariate non-normality were observed (Mardia's coefficient = 66.19, c.r. = 66.85). Variables exhibiting the highest skew and kurtosis values were transformed using the square root method (REG ACCESS, TRANSIT AVLBLTY, % TOURS SIMPLE, % STOPS NEAR HOME, VKT, VEHICLE GHG). Because these variables all had the probability of being zero, logarithm transformation is problematic since the natural log function is undefined for zero and negative numbers. The resulting Mardia's coefficient

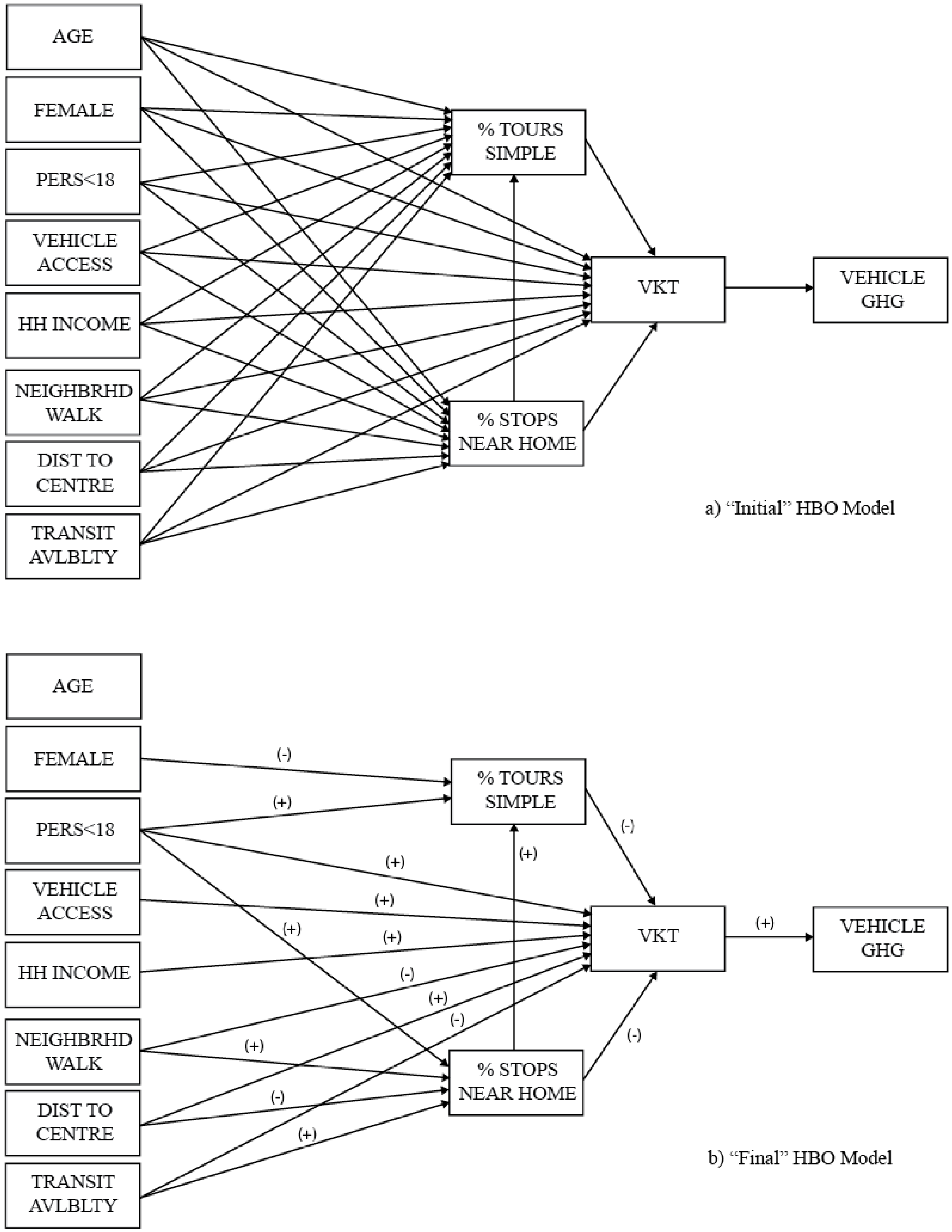


FIGURE 5.1. HBO statistical model specification process. The (-) and (+) symbols above or to the right of the paths in b) denote the direction of association between variables estimated in the "Final" model. Refer to Table 5.2 for specific parameter coefficients.

for this “Transformed” model was improved but still suggested non-normality in the model data (2.58, c.r = 2.61). Cases flagged as significant outliers were identified using the Mahalanobis distance statistic. The removal of a single case (~0.01% of the total original sample) led to the “Reduced” model with a reasonably multivariate normal sample (n = 1,370) (Mardia’s coefficient = 0.73, c.r. = 0.74).

A “Final” empirical model was achieved by retaining only those direct linkages yielding statistically significant parameter estimates (p-value < 0.05). The regression weights of non-significant parameters were fixed to zero to control for any spurious effect on model fit. Failing to suppress non-significant pathways has been demonstrated to potentially result in Type I error, whereby a model is rejected based on poor model fit when it appropriately reproduces the correlations in a given dataset (Hoyle, 1995).

5.3.2. Model Fit

Model fit indices are summarized in Table 5.1. Overall, the “Final” HBO model was deemed to effectively reproduce the covariances in the sample data, with most indices falling within acceptable ranges. Only the relatively large and statistically significant chi-square value suggested poor model fit. The literature indicates this is not abnormal, as the chi-square is very sensitive to sample size and model complexity (Hooper et al., 2008).

TABLE 5.1. Model fit results for HBO models.

Model	X^2	df	p -value	X^2/df	RMSEA	SRMR	CFI	TLI
Initial (*)	52.04	10	0.000	5.21	0.055	0.009	0.990	0.933
Transformed (*)	71.78	10	0.000	7.18	0.067	0.008	0.989	0.926
Reduced ((**)	70.21	10	0.000	7.02	0.066	0.008	0.989	0.929
Final (**)	79.71	22	0.000	3.62	0.044	0.014	0.990	0.969
Reference Standards			> 0.005	< 5.00	< 0.080	< 0.05	> 0.90	> 0.90

*   n = 1,371 persons
** n = 1,370 persons

Table 5.2 also compared fit indices between the four model iterations. It is interesting to note that all models preceding the “Final” estimated model were measured by many of the goodness of fit indices to adequately reproduce the correlations in the dataset despite moderate to extreme violations in multivariate normality. This confirms the possibility of a certain degree of robustness with model specification and estimation using the maximum likelihood in the face of non-normal datasets (Golob, 2003). In this context, one may be tempted to ignore the normality of a given dataset, as is often done in practice (Kaplan, 2000). Nevertheless, it was felt that achieving multivariate normality in the dataset would maintain a high degree of reliability and integrity in the final model results.

5.3.3. Estimation Results

Table 5.2 reports on the standardized direct, indirect and total significant effects measured between explanatory and endogenous variables in the "Final" HBO model. Un-standardized effects can be found in Table B.1 in Appendix B. Blank cells in the table represent those parameter coefficients allowed to enter the model but constrained to zero due to non-significant effects. Sample covariance and correlation matrices are reported in Tables C.1 and C.2 in Appendix C to facilitate replication of this research.

5.3.3.1. Effects on Activity Patterns

A dichotomy in the nature of effects between key endogenous variables on activity pattern characteristics in Table 5.2 is apparent. Socio-demographic variables yield a stronger role in shaping the complexity of HBO tours (square root of fraction of tours simple). Conversely, physical environment characteristics are stronger predictors of the location of stops (square root of fraction of stops near home) on these tours. The effect of local neighbourhood walkability on the fraction of stops near home is nearly double that of distance to the nearest regional or town centre. The indirect effects between all physical environment variables on the fraction of simple HBO tours undertaken in the sample are notable and suggest a supporting role in shaping tour complexity as mediated through the location of stops.

TABLE 5.2. Estimated standardized effects (structural coefficient estimates) for "Final" HBO model.

Explanatory Variable	DIRECT EFFECTS Endogenous Variable				INDIRECT EFFECTS Endogenous Variable				TOTAL EFFECTS Endogenous Variable			
	% TOURS SIMPLE*	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*	% TOURS SIMPLE*	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*	% TOURS SIMPLE*	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*
AGE												
FEMALE	-0.092						0.014	0.013	-0.092		0.014	0.013
PERSONS<18	0.114	0.077	0.058		0.002		-0.017	0.057	0.116	0.077	0.041	0.057
VEHICLE ACCESS			0.254					0.243			0.254	0.243
HH INCOME			0.048					0.046			0.048	0.046
NEIGHBRHD WALK		0.122	-0.116		0.004		-0.025	-0.126	0.004	0.122	-0.141	-0.126
DIST TO CENTRE *		-0.067	0.062		-0.002		0.012	0.072	-0.002	-0.067	0.074	0.072
TRANSIT AVLBLTY *		0.083	-0.085		0.003		0.016	-0.097	0.003	0.083	-0.069	-0.097
% TOURS SIMPLE *			-0.151					-0.144			-0.151	-0.144
% STOPS NEAR HOME *	0.036		-0.196				0.005	-0.192	0.036		-0.191	-0.192
VKT *				0.955								0.955

NOTES: * = Square root transformation.
All parameter estimates significant at or above 95% confidence interval.
Standardized coefficients illustrate the relative magnitude of effect of a variable on the whole model (i.e. the total effect of VHCL ACCESS on VKT is 92% greater than that of NEIGHBRHD WALK).
n = 1,370 persons

5.3.3.2. Effects on Vehicle Use

Vehicle availability enters the model as the most influential of all explanatory variables affecting vehicle use (square root of vehicle kilometers traveled) associated with HBO tours. All else being equal, individuals who have greater vehicle access on a daily basis are more likely to utilize a vehicle for travel and drive a further distance. Pursuing simpler HBO tours with more stops within one's immediate neighbourhood yields strong negative effects on VKT. Reflected in these findings may be that individuals will substitute vehicle use for less carbon-intensive modes like walking, cycling and transit that are easier and more appealing for simple, shorter tours (Frank et al., 2007b). Local neighbourhood walkability generates the strongest total effect on VKT relative to the other physical environment characteristics, although its magnitude is less than that of vehicle availability. The negative relationship between these variables substantiates relationships found in previous studies: the more compact and diverse one's neighbourhood is in terms of possible destinations the fewer VKT generated (Cervero and Kockelman, 1997; Frank and Pivo, 1994). A unique contribution of this research, however, is the explicit modeling that the effect of the built environment on VKT is mediated by an individuals HBO activity patterns, namely tour complexity and location of stops.

5.3.3.3. Effects on Vehicle GHG Emissions

All structural relationships in the model influence how much vehicle GHG emissions related to HBO tours one generates daily. Not surprisingly, VKT is the strongest explanatory variable predicting vehicle emissions, with a magnitude of effect nearly four times greater than the next strongest predictor (vehicle availability). This suggests that regardless of one's socio-demographic dispositions, local built environment, regional accessibility, and activity pattern, the more you drive, the more emissions are generated. Although intuitive, this observation neglects the structural relationships that help to shape an individual's daily VKT and, subsequently, emission levels. Vehicle availability (standardized coefficient = 0.243) and neighbourhood walkability (standardized coefficient = -0.126) yield the largest total effect on vehicle emissions relative to the all purely independent variables in the model. However, the total effect of vehicle availability on GHG emissions is over 90% greater than that of local neighbourhood walkability. These results are anticipated given their influences on daily HBO vehicle use. Both effects are entirely indirect. Increased vehicle access is positively associated with a rise in VKT and vehicle emissions relative to those with less access to a vehicle that are likely using alternative modes of travel. The negative effect of neighbourhood walkability on vehicle emissions operates through its associations with daily activity patterns and VKT. Being female, having children or youth in the household and larger household incomes are all found to have a significant positive effect on vehicle GHG emissions, although the magnitude of these effects is small relative to the other explanatory variables in the model.

5.4. Home-Based Work/School Tours Model Results

5.4.1. Model Exploration and Specification

Model specification for HBWS activity tours was, again, consistent with the conceptual framework in Figure 3.1. An "Initial" model was specified and tested for issues of multivariate non-normality and the nature of parameter estimates (see Figure 5.2.a). Exogenous variables included AGE, FEMALE, PERS<18, VEHICLE ACCESS, and HH INCOME, NEIGHBRHD WALKABILITY, DIST TO WRK/SCHL, and TRANSIT AVLBLTY. The variables TOUR CMPLXTY, % STOPS NEAR HOME, VKT, and VEHICLE GHG were specified as endogenous. The NEIGHBRHD WALK variable was used in place of the individual urban form measures to overcome any potential issues with multicolinearity as was observed in the HBO model in Section 5.3. The DIST TO WRK/SCHL variable replaced distance to nearest town or regional centre as the measure of regional accessibility. The TOUR CMPLXTY (average number of stops per tour) measure was used in place of the % TOURS SIMPLE. This substitution is justified as close to 99% of those taking work or school tours in the sample data completed only one tour. In this context, the "% TOURS SIMPLE" measure would essentially be rendered an endogenous dummy variable, thereby violating the assumption that all endogenous variables are continuous. This limited diversity is reflective of both the one-day collection of the travel survey and the nature of work and school tours (i.e. usually only one such tour per day).

This "Initial" model (n = 1,739) was subject to extreme violations of multivariate normality (Mardia's coefficient = 127.43, c.r. = 140.06). Significant non-normal variables were transformed using the square root (DIST TO WRK/SCHL, TRANSIT AVLBLTY, % STOPS NEAR HOME, VKT, and VEHCL GHG) or natural logarithm method (TOUR CMPLXTY). The "Transformed" model was re-estimated but maintained extremely high levels of non-normality (Mardia's coefficient = 36.48, c.r. = 41.06). The % STOPS NEAR HOME variable contributed the most to violations of normal skew and kurtosis in the model. Additional data exploration found that over 90% of individuals in the HBWS sample were reporting all stops occurring beyond their immediate neighbourhood (i.e. 1-km postal code network buffer). Reaching multivariate normality with the % STOPS NEAR HOME variable in the model would have required the additional removal of over 200 outlying cases, or close to 12.5% percent of the entire dataset. Given that so many cases were removed from the original sample due to issues with incomplete data (see Section 3.6.1), it was assumed that removing such a large number of cases would lend to limiting the already trimmed natural variations in the dataset. A model was not specified or estimated to assess the effects such a decision would have on model fit or regression coefficients. The % STOPS NEAR HOME variable was ultimately removed from the model to overcome this limitation. A "Reduced" model achieved multivariate normality through the removal of 26 cases identified as outliers using the Mahalanobis distance statistic (Mardia's coefficient = 1.58, c.r. = 1.92). The "Final" model (n = 1,713) retained only those direct linkages yielding statistically significant parameter estimates (p value < 0.05) (see Figure 5.2.b).

The % STOPS NEAR HOME variable was anticipated to be both a key endogenous and explanatory measure in all SEM's developed for this research. As such, its exclusion from the model described above (HBWS Model A), although required to achieve multivariate normality, was considered to possibly neglect any nuanced effects of the physical environment on how activity patterns are shaped. This is particularly true for the

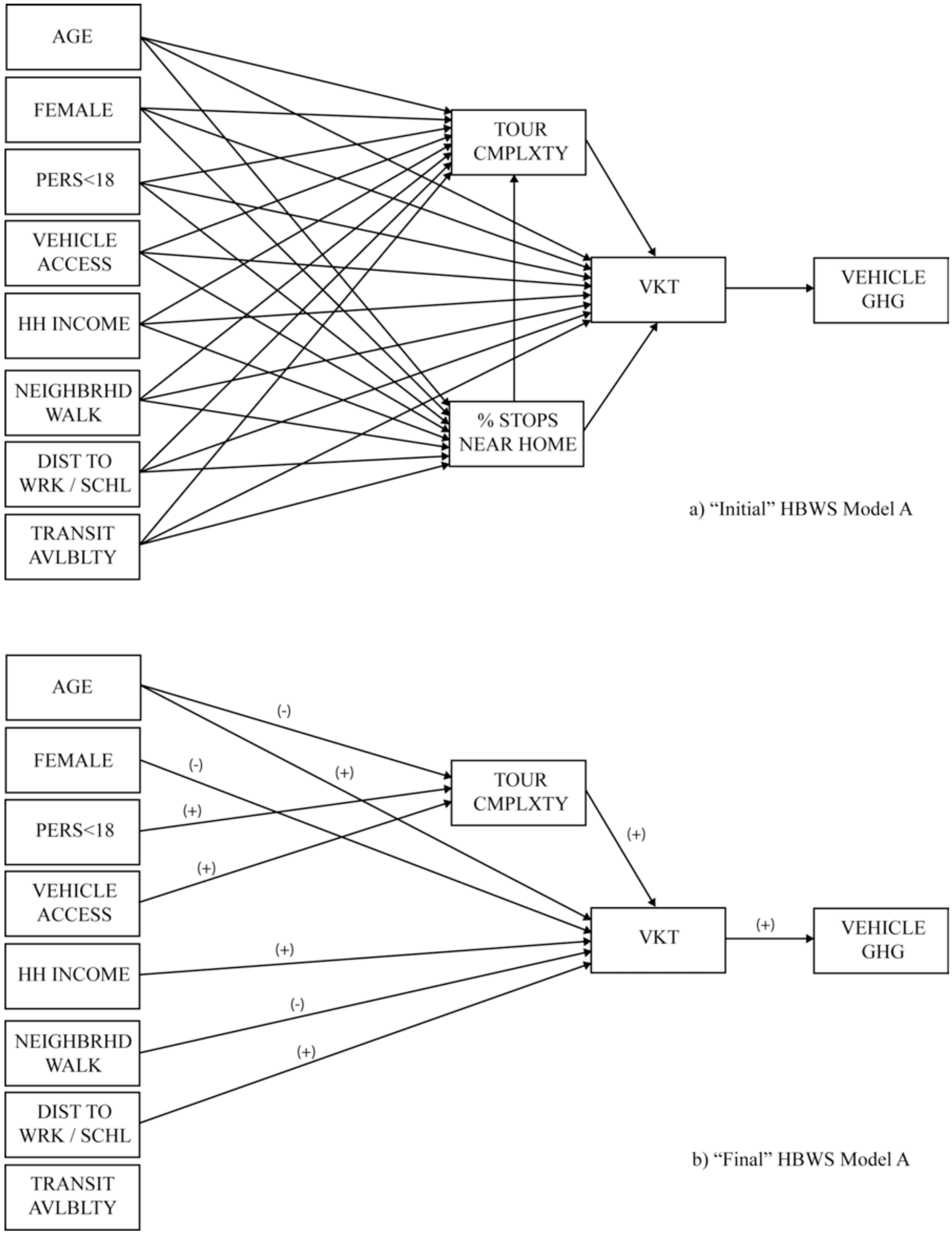
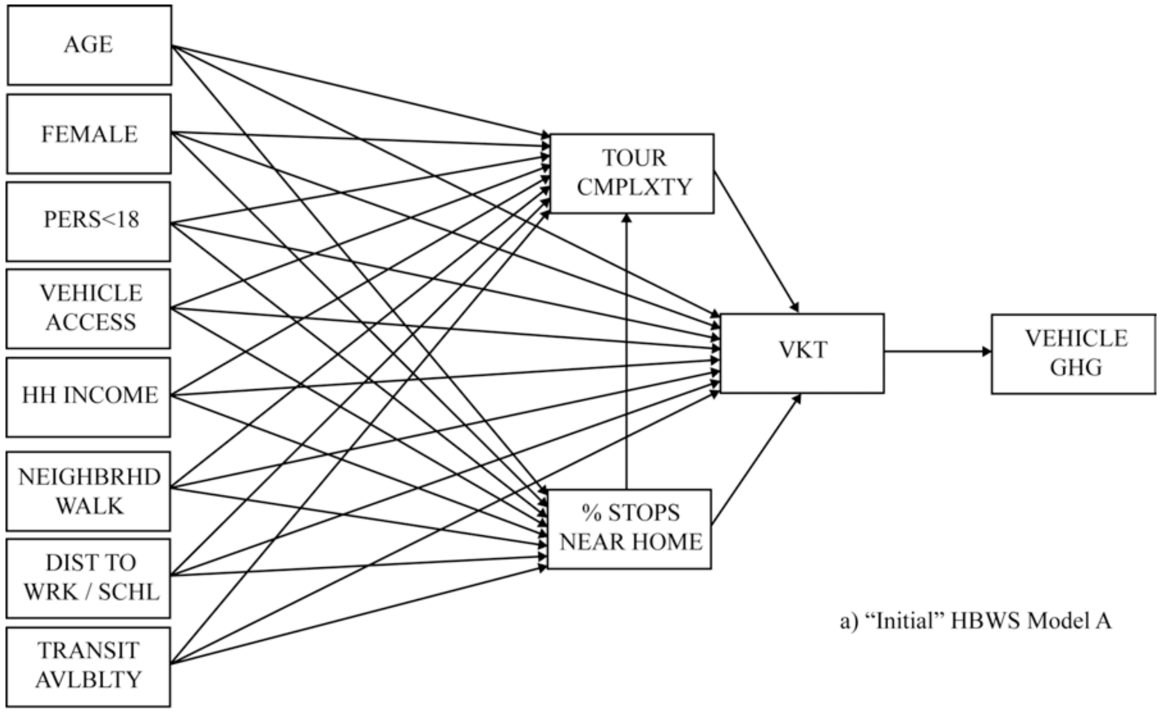


FIGURE 5.2. HBWS Model A statistical model specification process. The (-) and (+) symbols above or to the right of the paths in b) denote the direction of association between variables estimated in the “Final” model. Refer to Table 5.4 for specific parameter coefficients.

10% reporting to make some fraction of their daily HBWS tour stops within their immediate neighbourhood. In order to meaningfully assess the structural effects between all pertinent variables, a second HBWS model (HBWS Model B) was specified for a reduced sample of only those individuals completing complex work/school tours (i.e. two or more stops) (n = 496). This sub-sample captured over three quarters of all individuals reporting at least one stop close to home (n=78), be this for work/school or maintenance/discretionary stops made as part of the trip chain. The remaining 22% (n=22) who made a simple HBWS completely within their neighbourhood could not be included based on their simple tour complexity. A model was tested that included only those individuals reporting some fraction of daily HBWS stops within their immediate neighbourhood, regardless of tour complexity. However, the sub-sample was considered too small to produce significant results in an SEM analytical framework (n=100).

HBWS Model B included all endogenous and exogenous variables as specified in the HBWS Model A (Figure 5.3.a). Variables known to exhibit extremes in skew and/or kurtosis were transformed using either square root or natural logarithm methods. The "Initial" model exhibited multivariate normality (Mardia's coefficient = 3.07, c.r. = 1.84). The "Final" model retained only those direct linkages yielding statistically significant parameter estimates (p value < 0.05) (see Figure 5.3.b).

The multi-model approach to analyzing the structural effects between the built environment, activity patterns and vehicle GHG emissions in the HBWS tour sample is not ideal, but was required given the nature of the travel diary dataset. The study produced the best possible models given data limitations encountered to study the relationships between the built environment, activity travel and associated GHG emissions. The same is to be said for the HBO tour model discussed earlier. Indeed, the complex nature of interactions between countless variables influencing travel emissions, many of which are not, and could not be, included in the current analysis make a truly perfect model or series of models unattainable. The models in this research are specified so as to yield meaningful and instructive results in a framework that is consistent with typical SEM practice.



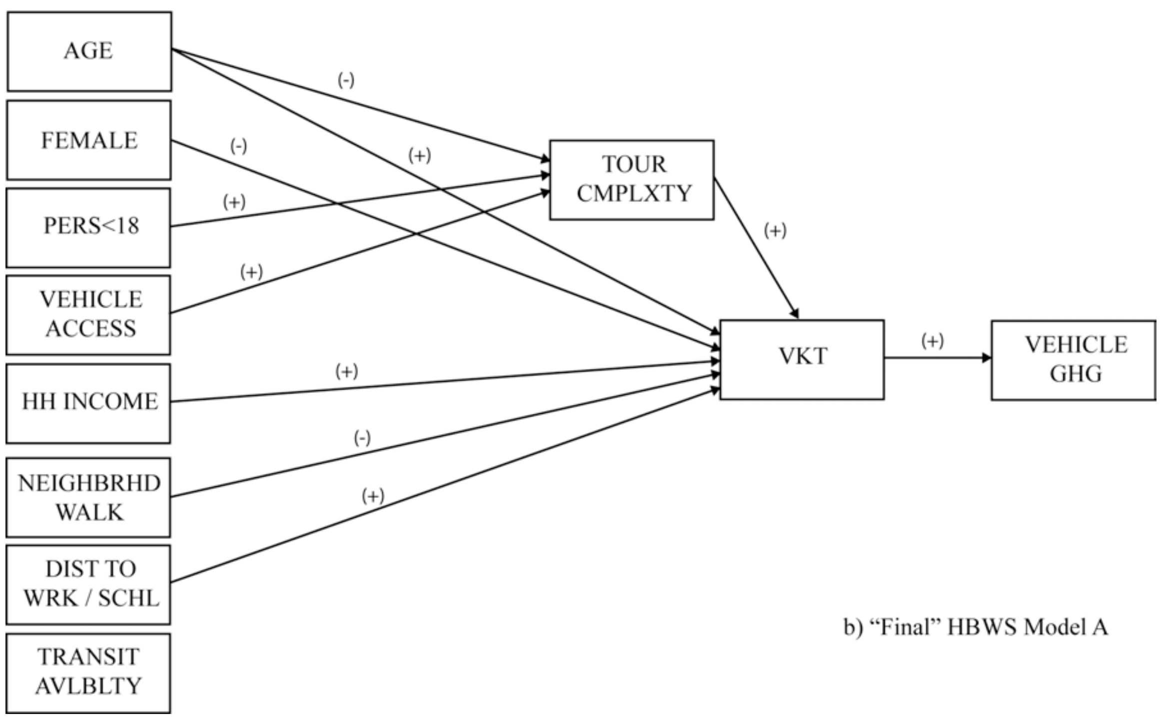


FIGURE 5.3. HBWS Model B statistical model specification process. The (-) and (+) symbols above or to the right of the paths in b) denote the direction of association between variables estimated in the "Final" model. Refer to Table 5.6 for specific parameter coefficients.

5.4.2. HBWS Model A Model Fit

Model fit indices are summarized in Table 5.3. Overall, the “Final” model was deemed to effectively reproduce the covariances in the sample data, with most indices falling below good to acceptable cut-off values.

TABLE 5.3. Model fit results for HBWS Model A models.

Model	X^2	df	p -value	X^2/df	RMSEA	SRMR	CFI	TLI
Initial (*)	124.60	10	0.000	12.46	0.082	0.006	0.987	0.914
Transformed (*)	123.24	9	0.000	13.690	0.086	0.007	0.987	0.919
Reduced ((**)	133.13	9	0.000	14.79	0.091	0.006	0.986	0.916
Final (**)	141.46	17	0.000	8.321	0.066	0.009	0.986	0.955
Reference Standards			> 0.005	< 5.00	< 0.080	< 0.05	> 0.90	> 0.90

*   n = 1,739 persons
** n = 1,713 persons

5.4.3. HBWS Model A Estimation Results

Un-standardized coefficient parameters are reported in Tables 5.4. Standardized coefficient results are located in Table B.2 in Appendix B. Blank cells in the table represent those parameter coefficients allowed to enter the model but constrained to be zero due to non-significant effects. Sample covariance and correlation matrices are reported in Tables C.3 and C.4 in Appendix C to facilitate replication of this research.

5.4.3.1. Effects on Activity Patterns

Vehicle availability yields the strongest effect on tour complexity (standardized coefficient = 0.067), however its magnitude is not as considerable as other relationships found in this research. This suggests other variables or measures may be more pertinent in shaping tour complexity for HBWS tours across the full sample. Nevertheless, the positive parameter coefficient suggests that as vehicle availability increases, so does the average umber of stops per HBWS tour. The age of an individual is found to generate the only other significant effect on tour complexity, although its magnitude is also quite small. Physical environment variables entered the initial model but were found be yield insignificant effects on HBWS tour complexity in the full sample and, so, were constrained to zero in the final model.

TABLE 5.4. Estimated standardized effects (structural coefficient estimates) for "Final" HBWS Model A.

Explanatory Variable	DIRECT EFFECTS Endogenous Variable			INDIRECT EFFECTS Endogenous Variable			TOTAL EFFECTS Endogenous Variable		
	TOUR CMPLXTY**	VKT*	VEHICLE GHG*	TOUR CMPLXTY**	VKT*	VEHICLE GHG*	TOUR CMPLXTY**	VKT*	VEHICLE GHG*
AGE	-0.059	0.054			0.011	0.042	-0.059	0.065	0.042
FEMALE		-0.072				-0.022		-0.072	-0.022
PERSONS<18									
VEHICLE ACCESS	0.067	0.290			0.013	0.298	0.067	0.303	0.298
HH INCOME		0.064				0.063		0.064	0.063
NEIGHBRHD WALK		-0.099				-0.097		-0.099	-0.097
DIST TO WRK/SCHL *		0.509				0.500		0.509	0.500
TRANSIT AVLBLTY *									
TOUR CMPLXTY **		0.193				0.190		0.193	0.190
VKT *			0.983						0.983

NOTES: * = Square root transformation.
** = Natural logarithm transformation.
All parameter estimates significant at or above 95% confidence interval.
Standardized coefficients illustrate the relative magnitude of effect of a variable on the whole model (i.e. the total effect of VHCL ACCESS on VKT is 68% greater than that of NEIGHBRHD WALK).
n = 1,713 persons

5.4.3.2. Effects on Vehicle Use

The total magnitude of effect of distance to work on vehicle kilometers traveled for HBWS tours across the full sample is over 67% greater than that of vehicle availability (standardized coefficient = 0.509 vs. 0.303). This is to be expected, as long commute distances would be anticipated to decrease the ability to travel to work via transit or even cycling, thereby making vehicle use more appealing. That this measure was stronger than vehicle availability also suggests vehicle use may be prevalent even for those individuals who do not own or have access to a vehicle, possibly accrued through car-pooling or ridesharing for longer HBWS tours. The total effect produced by local neighbourhood walkability was significantly negative (-0.099) but is eclipsed by that of distance to work/school. This result suggests that, to a certain degree, individuals residing in more walkable areas will generate fewer VKT associated with HBWS tours, possibly due in part to trading off vehicle use for transit that may be more readily available in these areas. Transit availability was not a significant predictor of either activity patterns or VKT in the final model. The average number of stops per HBWS tour in the full sample is positively associated with VKT and is the third strongest predictor of vehicle use. Other variables exhibiting significant influence on VKT, but to a lesser extend include: being female, household income, and age.

5.4.3.3. Effects on Vehicle GHG Emissions

Aside from VKT, Table 5.4 demonstrates that the strongest explanatory predictor of vehicle GHG related to daily HBWS in the model was distance to work/school (standardized coefficient = 0.500), followed by vehicle availability (0.298) and tour complexity (0.190). The total structural effect of distance to work/school on emissions was over 400% greater than that of the local neighbourhood walkability. This finding suggests that significant emission reduction for HBWS tours may more likely be achieved through increasing connectivity between population and employment centres in the region. An individual's age, gender, and household income were significant, but among the least strongest predictors of vehicle emissions in the full HBWS sample.

These results are anticipated and explained by their previous influences on daily HBWS activity patterns and/or vehicle use.

5.4.4. HBWS Model B Model Fit

Model fit indices are summarized in Table 5.5. Overall, the "Final" model was deemed to effectively reproduce the covariances in the sample data, with most indices falling below good to acceptable cut-off values.

TABLE 5.5. Model fit results for HBWS Model B models.

Model	χ^2	df	p -value	χ^2/df	RMSEA	SRMR	CFI	TLI
Initial (*)	71.89	10	0.000	7.18	0.113	0.009	0.976	0.843
Final (*)	86.92	21	0.000	4.14	0.078	0.022	0.975	0.921
Reference Standards			> 0.005	< 5.00	< 0.080	< 0.05	> 0.90	> 0.90

* n = 496 persons

5.4.5. HBWS Model B Estimation Results

The second HBWS model is a departure from the first in that its sample includes only those that recorded a complex (i.e. multiple stop) tour (n = 496). Compared to the full HBWS sample, a larger share of individuals in this sub-sample reported making a stop, be it for work/school or otherwise, within their immediate neighbourhood (15.7% compared to 5.8%). As discussed in section 5.3.1, this sub-sample is considered diverse enough to allow for the inclusion of the % STOPS NEAR HOME measure within the SEM. The results described below, then, offer additional insight into the relationship between the physical environment and vehicle GHG emissions. Standardized coefficient parameters are reported in Table 5.6. Blank cells in the table represent those parameter coefficients allowed to enter the model but constrained to be zero due to non-significant effects. Un-standardized results are reported in Table B.3 located in Appendix B. Sample covariance and correlation matrices are reported in Table C.5 and C.6 in Appendix C to facilitate replication of this research.

TABLE 5.6. Estimated standardized effects (structural coefficient estimates) for "Final" HBWS Model B.

Explanatory Variable	DIRECT EFFECTS Endogenous Variable				INDIRECT EFFECTS Endogenous Variable				TOTAL EFFECTS Endogenous Variable			
	TOUR CMPLXTY**	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*	TOUR CMPLXTY**	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*	TOUR CMPLXTY**	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*
AGE			0.077					0.075			0.077	0.075
FEMALE	0.092		-0.071				0.010	-0.060	0.092		-0.061	-0.060
PERSONS<18	0.114						0.129	0.126	0.114		0.129	0.126
VEHICLE ACCESS		-0.117	0.298		0.000		-0.013	0.278		-0.117	0.285	0.278
HH INCOME			0.066					0.064			0.066	0.064
NEIGHBRHD WALK		0.036	-0.082		0.000		0.004	-0.076		0.036	-0.078	-0.076
DIST TO WRK/SCHL *	0.141	-0.140	0.557		0.000		-0.002	0.574	0.141	-0.140	0.555	0.574
TRANSIT AVLBLTY *		0.205			0.000		-0.024	-0.023		0.205	-0.024	-0.023
TOUR CMPLXTY**			0.105					-0.112			0.105	-0.112
% STOPS NEAR HOME *	-0.002		-0.115				0.000	0.102	-0.002		-0.115	0.102
VKT *				0.976								0.976

NOTES: * = Square root transformation.
** = Natural logarithm transformation.
All parameter estimates significant at or above 95% confidence interval.
Standardized coefficients illustrate the relative magnitude of effect of a variable on the whole model (i.e. the total effect of VHCL ACCESS on VKT is 265% greater than that of VEHCL ACCESS).
n = 496 persons

5.4.5.1. Effects on Activity Patterns

Results in Table 5.6 indicate the all built environment measures yield significant effects on the average number of stops per tour and/or location of these stops for those individuals taking complex HBWS tours. Distance to work/school yields nearly equally strong, but opposite direction of, effect on both tour complexity and the location of stops (standardized coefficients of 0.141 and –0.140, respectively). Two phenomenon are likely being reflected in these findings: 1) that individuals with longer commutes pursue additional errands either on the way to or from work/school so as to reduce the need to go back out again in the evening (McGuckin et al., 2005) and, 2) that longer commutes expose individuals to a higher number of activities and destinations likely found in their local neighbourhood and so possibly encouraging a greater number of additional stops, especially if a vehicle is utilized (Krizek, 2003b). That the effect between commute distance and tour complexity is entirely direct is interesting and suggests that regional accessibility plays a more dominant role in shaping activity tour patterns in complex HBWS tours compared to an indirect role as seen in the in HBO tours model (see Table 5.3). Transit availability generates the largest effect on the fraction of stops on these complex tours located near home (standardized coefficient = 0.205). This is an interesting result and may be illustrating that individuals taking complex HBWS tours who reside in areas that are well serviced by transit (and also, by definition, likely quite compact and walkable) are also completing more errands near home, perhaps by foot either on the way to or from home using transit. Increased vehicle availability reduces the share of stops made near home, potentially indicating that the degree of flexibility afforded by the automobile makes it easier to run errands in a number of different locations on the way to or from work/school. Being female and the presence of youth/children in the household also necessitated an increase in the number of stops on these complex HBWS tours, most likely to pick up/drop off children at school or daycare.

5.4.5.2. Effects on Vehicle Use

Comparing the results in Table 5.6 to the results of the previous HBWS model, similar magnitudes of effect are observed between several explanatory variables and VKT.

Distance to work/school is, again, the largest, most significant predictor of VKT in the model. Vehicle availability is also a strong, positive predictor of VKT for those taking complex HBWS tours. Of note, the presence of children or youth enters into the second HBWS model as yielding the third strongest positive effect on VKT, likely demonstrating the need to pickup/drop off youth at school adds extra mileage onto ones HBWS tour. Transit availability is a significant predictor of vehicle use in this model, however the magnitude of its negative effect on VKT is the weakest among all explanatory variables. This effect may be suggesting that vehicle use may remain high, even in well-serviced transit neighbourhoods, if an individual needs to pursue a number of errands as part of the HBWS tour.

5.4.5.3. Effects on Vehicle GHG Emissions

VKT is shown to generate the largest total effect on vehicle GHG emissions in the HBWS complex tour sample. The second strongest total effect is that of distance to work/school (standardized coefficient = 0.574), which is over 100% greater than the influence of vehicle availability and 650% larger than local neighbourhood walkability. The nature of the results in Table 5.6 suggest that, for those individuals pursuing multi-stop HBWS tours, bringing people and potential employment opportunities closer together will have the strongest effect of reducing VKT and associated GHG emissions by shortening commute distances. This may result in 1) public transit or cycling becoming a more appealing commute option, and 2) additional non-work stops being made near home, perhaps made by foot, after disembarking from transit.

5.5. Discussion

This research was centered on providing clarification and additional insight into four key questions concerning the interactions between the physical environments where people live, their daily activity patterns, vehicle use, and associated emissions (see Section 1.3). The following section provides a more comprehensive discussion of the model estimation results in the context of these questions.

5.5.1. GHG Emissions Vary by Built Environments

Are variations in self-reported vehicle use and vehicle GHG emission estimates statistically associated with different built environment and regional accessibility characteristics in Metro Vancouver? The models in this research generally confirm hypotheses that vehicle use and associated GHG emissions systematically vary by the type of physical environment within which one resides (Ewing et al., 2008). Unique to this study, however, is the explicit modeling of the structural linkages between key variables that combine to influence per-capita daily travel emissions. Therefore, it is possible to state with some degree of certainty not just what, but how, key explanatory variables are associated with travel emissions.

Beginning with the local built environment, results suggest that residing in a highly walkable neighbourhood, characterized by a compact urban form, a functional mix of various destinations needed on a daily basis, and a well-connected street network that allows for more direct routes between stops, reduces vehicle use and vehicle emissions. This is especially true for HBO tours. The structural effects in Table 5.2 explicitly demonstrate that walkable neighbourhoods help to increase the number of stops within one's immediate neighbourhood, thereby facilitating more simple tours. These findings substantiate those in previous studies (Maat and Timmermans, 2006; Lee et al., 2009; Krizek, 2003b; Frank et al., 2007b). The model indicate that this behaviour lends to a reduction in VKT and associated emissions, as these simple and short tours can be easily accomplished by foot or transit. Those reporting multi-stop HBWS tours were found to report more stops near home, but fewer total stops per tour if residing in a compact and walkable neighbourhood. The reduced VKT and emissions associated with this behaviour indicate that in many cases these stops are being accessed on foot, likely on the way to/from work/school using transit. Results show that these individuals make fewer stops on their way to or from work/school – which suggests they can more easily go back out again in the evening to accomplish additional errands, also on foot or transit – when destinations are within a walkable distance.

Regional accessibility, as measured by commuting distance and proximity to a town or regional centre, yields significant effects on vehicle emissions. Regional accessibility's strongest effects are found in the HBWS tour models. All else being equal, longer commutes are likely to decrease the ability to travel to work via transit, thereby increasing the relative utility of vehicle use for HBWS tours. This is reflected in the significant increases in VKT and GHG emissions associated with larger distance to work/school. At the same time, longer commutes may also expose individuals to a greater number of possible activities and destinations along their preferred route of travel, encouraging more complex tours with more stops located beyond one's immediate neighbourhood, especially if a vehicle is utilized (Krizek, 2003b). The farther removed an individual is from their work/school or a concentration of possible activities and destinations, the more likely they will chain their trips in order to save time and reduce the need to travel again after returning home. These longer, more complex trip chains are difficult to make by transit, cycling and especially on foot and so the more vehicle use and emissions are accrued.

A larger number of transit routes accessible within one's immediate neighbourhood helps to facilitate reductions in both VKT and emissions. These effects, however, are generally not as strong as those from local walkability and regional accessibility across all models. More transit options connecting an individual to a greater number of possible destinations across a city or region help to increase the relative utility of transit compared to a private vehicle, particularly in terms of travel time and (especially parking) costs. This is especially true for HBO and multi-stop HBWS tours. Where individuals are possibly substituting vehicle use for transit, the effect is a reduction in VKT and associated emissions. The estimation results in the HBO and multi-stop HBWS models indicate that greater transit availability has the effect of increasing the fraction of stops near home but reducing the complexity of tours. The fixed routes and schedules of transit service help to explain this behaviour because complex tours accomplished by transit may require additional transfers, thereby introducing additional burdens on the traveler. This finding is important in light of the growing trend toward increasingly complex daily activity and travel patterns (McGuckin et al., 2005). Public transit does not readily allow for complex trip-chains to be made in a timely and cost-effective manner. This poses significant policy challenges if trips are to be shifted away from single-occupant vehicles in order to help reduce emissions.

These observations, however informative, are generalizations. The model estimation results demonstrate that socio-demographic variables also yield significant degrees of influence on vehicle use and related emissions. An assessment of the relative differences in effect between these variable types is provided next.

5.5.2. Socio-Demographics vs. Built Environment Effects

What are the relative structural effects of built environment and regional accessibility as opposed to individual and household socio-economic variables on per-capita vehicle GHG emissions and other endogenous variables? As the standardized coefficients of the predictive models represent magnitudes of effect, it is possible to compare the relative influence between key sets of variables. Most built environment and regional accessibility measures yield a significant effect on vehicle use and emissions in all models in this research. Just as powerful, and in some cases more so, however, is that of vehicle availability. The large magnitude of its total effects across all models highlights two important points. For one, it confirms the idea of sunk costs associated with vehicle ownership and access. Resources "sunk" into ownership, rental, insurance, and gas cannot be recovered, and so individuals may feel obliged to use their vehicle for a given activity tour even though they may not want or need to for some of their travel (Litman, 2009). This is particularly illustrated in the HBO tours model where vehicle access yields the strongest magnitude of influence on VKT and associated emissions in the sample, almost double that of local neighbourhood walkability. The second, and related, point is that increased vehicle availability appears to facilitate access to a greater number of destinations scattered throughout a city or region. This situation allows for more complex tours to be pursued with a greater number of stops located beyond one's immediate neighbourhood, possibly even if one's neighbourhood is well serviced by a number of destinations and activities, thereby having the effect of increasing both VKT and emissions. This behaviour is generally exhibited in both HBWS tour models. These findings are important from a policy perspective and suggest that actions to get individuals onto less carbon-intensive modes of travel, for both work and non-work tours, may need to go beyond improving neighbourhood walkability or increasing regional connectivity.

The structural approach to this research helped to clarify that activity patterns generate significant influence in shaping vehicle use and associated GHG emissions. How these patterns themselves are affected is likely to generate important policy implications for reducing travel emissions. Generalizing across models, it appears that socio-demographic variables like age, gender, the presence of youth in the household, and vehicle availability yield consistently significant direct effects on tour complexity. Most notably, females are less likely to complete simple HBO tours, but more likely to undertaken complex HBWS tours over the course of a day, suggesting that these individuals often taken on a greater number of household responsibilities (McGukin and Murakami, 1999). Individuals with children in their household are more likely to pursue simple HBO tours and more complex HBWS tours. This behaviour makes sense as the limited mobility of youth coupled with the divergent scheduling of their activities may lead to them being picked up and dropped off at any number of activities throughout the day (Vovsha et al., 2004, Krizek, 2003b). Some of these, like school, may be best accomplished on the way to/from work. Other activities, like recreation, may necessitate additional simple tours at other times during the day. Older adults are less likely to make complex HBWS tours, likely attributable to fewer responsibilities for others, especially children or youth who are more likely to have grown up and moved out of the house (Maat and Timmermans, 2006). On the other hand, it is local built environment variables and regional accessibility measures that generate stronger, if not the only, direct effects on the location of stops across tours. The nature of these findings are interesting and suggest that, on the whole, the demand to participate in various activities is driven predominantly by intra- and inter-household responsibilities and scheduling, and not, necessarily, the distribution of these activities in space.

However, model results indicate a role of the built environment in helping shape tour complexity. For example, the results in the HBO tour model demonstrate an indirect effect between built environment measures and tour complexity as mediated by the location of stops on these tours. This relationship explicitly illustrates the idea of a time-based trade-off between tour complexity and the location of stops (Frank et al., 2007b). It is clearly shown that simple HBO tours are more readily made in walkable areas, that is neighbourhoods with a greater likelihood of having a variety of services and destinations close by. Those residing in less walkable locations, where destinations are more likely to be scattered away from the home, will tend to chain trips so as to save time. A second example is noted in the complex HBWS model (HBWS Model B). Although influenced by an individual's gender and the presence of youth in the household, the number of stops on these tours is also directly affected by commute distance. This is interesting and indicates that individuals with longer commutes pursue additional errands either on the way to or from work/school, regardless of other socio-demographic dispositions, likely so as to reduce the need to go back out again in the evening.

5.5.3. Estimated Built Environment Effects Vary by Activity Tour Type

Do the structural effects of local built environment characteristics and regional accessibility measures on vehicle related GHG emissions differ depending on activity travel type? Findings in this research suggest they do. Beginning with HBO tours, the total effect of local neighbourhood walkability on VKT and vehicle emissions is 90% and 75% greater than that of regional accessibility (as measured by distance to nearest town/regional centre), respectively. The nature of this finding suggests that people may trade-off traveling beyond their neighbourhood for non-work/school tours if the activity (or set of activities) they need to fulfill can be accomplished locally. The discretionary (i.e. flexible) nature of these tours and the potential ubiquity of non-work or school destinations (i.e. grocery stores, hardware stores, post offices, restaurants) across neighbourhoods in a region and not just solely in town or regional centres may help to facilitate this trade-off. These individuals are also likely able to substitute vehicle use for less carbon-intensive modes like walking, cycling and transit that are easier and more appealing for simple, shorter tours, thereby reducing their overall VKT and emissions.

These results are intriguing as they conflict with those in a seminal study that suggests otherwise (Handy, 1993). A review of this earlier research yielded a possible explanation for this discrepancy; namely, the geographic scale used to measure local neighbourhood characteristics. In her study, Handy assessed the relative effects of average regional accessibility and neighbourhood design (i.e. traditional, neo-traditional, and suburban-style) for a series of "super districts" in the San Francisco Bay Area. The main concern with employing such large, seemingly arbitrary, definitions of a local neighbourhood is that they have the effect of diluting finer differences in the local built environment within an individuals more immediate neighbourhood. This can result in an ecological fallacy, whereby average urban form characteristics within a large area are assumed to apply to any given neighbourhood resident when, in reality, they may not and should not (Krizek, 2003c). The research in this study addresses these issues by estimating a household's neighbourhood to be that within a smaller, 1-km network buffer of its location. Neighbourhood built environment characteristics like density, land use mix, and walkability are then measured within that buffer. As explained in Section 3.6.2, a 1-kilometer buffer is the distance that can generally be covered in a 10-minute walk along the road network and a measurement that is more able to assess true effects of the local built environment on travel (Moudon et al., 2006; Lee and Moudon, 2006). So, even though the nature of the effects between the local built environment, travel behaviour and emissions is inconsistent with previous findings, this is considered a non-issue. Instead, the findings in the current research suggest that the use of a more appropriately scaled definition of neighbourhood helps yield enhanced insights into how the local built environment influences non-work/school travel behaviour and GHG emissions.

Turning to the HBWS tour models, Tables 5.4 and 5.6 illustrate that the effect of distance to work/school on VKT is approximately 415% and 600% greater than that of local neighbourhood walkability, respectively. Similar significant differences in the magnitude of effect between distance to work/school and emissions are also apparent in both models. The nature of these findings are consistent with previous studies that suggest work or school activities may be more constrained by time of day, route, location, and mandatory participation and, as such, be less influenced by local built environment characteristics (Ewing et al., 1994). However, that the local built environment does yield a certain degree of influence suggests local built environment does have somewhat of a supportive role in encouraging less carbon-intensive HBWS travel behaviour.

Collectively, the varying magnitudes of effect between variables and activity tour types suggest unique repercussions for future policy development aimed at curbing vehicle use and associated emissions in Metro Vancouver. This discussion now turns to articulating key policy implications emerging from this work.

5.5.4. Policy Implications

Which land use and transportation strategies may be most effective at supporting a reduction in vehicle GHG emissions in Metro Vancouver? Average vehicle-related greenhouse gas emissions levels associated with daily work and school related tours are nearly twice as large as those generated from non-work and school tours in Metro Vancouver (see Section 4.5). This suggests that the most significant reductions in daily GHG emission levels may be best accomplished by minimizing the carbon-intensity of the daily commute - admittedly, an aspect of household travel that may not be the most modifiable given scheduling realities or work requirements. Regardless, the results in this research highlight a number of policy options related to land use and transportation planning that may be employed in this regard.

A key finding in both HBWS tour models was that distance between home and work/school yielded the strongest effect on vehicle use and emissions in the sample. Reducing this distance may help to make modes like transit and cycling a more viable commuting option. Policies centred on increasing the balance between jobs and housing in both new and existing areas of the region may help to decrease commuting distance by allowing a greater diversity of employment opportunities to locate closer to where individuals reside (Levine, 1998; Cervero and Duncan, 2006). Evidence suggests, however, that a high jobs-housing ratio where people live does not necessarily translate into working closer to home. Miller and Ibrahim (1998) found the ratio of jobs to residents and the number of jobs within 5-kilometers of where people live in Toronto had little influence on VKT for work travel. Guiliano and Small (1993) found a statistically significant but extremely small relationship between jobs-housing balance and commuting data in Los Angeles, concluding that other factors are likely to explain job and residential choice. These findings suggest that individuals may seek specific employment opportunities that match their training, expertise, and compensation expectations. There is no guarantee that a job close to where one resides will satisfy these and other preferences. In this light, a more appropriate policy to reduce emissions may be to increase the level of transit service to both established and emerging employment centres within the region. Doing so may help to improve the utility of transit relative to the private vehicle. Metro Vancouver already has a well-established bus and SkyTrain system servicing many of the designated town and regional centres where much of the employment in this region is located. As such, level-of-service improvements may need to go beyond introducing new routes and instead focus on reducing travel costs and travel time through decreased fares, promoting employer-subsidized transit passes, increasing frequency of buses and SkyTrains, or constructing dedicated bus lanes, especially on the regions network of suburban highways.

Fixed transit routes, regardless of their cost or time savings, however, will likely do little to encourage those individuals who are inclined to take on complex HBWS tours, perhaps because they reside far from work or because their neighbourhood offers no additional services, to switch to public transit for these tours (Ye et al., 2007; Hensher and Reyes, 2000). Results from the complex HBWS tour sample suggest that where both transit availability and neighbourhood walkability is high, individuals will make fewer stops to/from work or school and generate less VKT and GHG emissions in the process. This suggests that efforts to increase transit service levels need to be coupled with policies that allow for a functional mixing of land uses in and around transit hubs close to where individuals reside (i.e. Transit-Oriented Development). Uses like daycares, grocery stores, post offices, dry cleaners and other uses people may need on a daily basis located in these areas may help to facilitate transit use if additional errands can be made by walking to/from transit.

Results suggest that regionally-scaled policies focused on increasing regional connectivity, improving transit level of service, and investing in more compact, transit-oriented urban form are also likely to yield significant potential for reducing emissions from HBO activity tours as well. The analytical models demonstrate that vehicle use and emissions related to HBO tours share similar effects to differences in regional connectivity and transit availability. Unique to this research however, is the finding that local neighbourhood urban form yields a stronger effect on HBO vehicle use and emissions than regional characteristics. This points to increasing neighbourhood walkability as being a key strategy for reducing emissions related to HBO tours. Walkable areas, characterized by compact, well-connected and mixed-use urban form, are demonstrated in this research to encourage more simple, shorter HBO tours with more stops located within one's immediate neighbourhood. Findings also suggest these kinds of tours help to reduce VKT and associated emissions, likely as these are easily made on foot, by bicycle or public transit. Region-wide, initiatives to increase local neighbourhood walkability need to be focused toward existing nodes and corridors. Policies that encourage higher development densities in these areas will help to support both a greater mix of functional land uses and more efficient transit service within reasonable walking distance of a large number of individuals.

The complex nature of activity scheduling and demands will likely require a suite of initiatives including, but not limited to, those described above in order to encourage less carbon-intensive modes of travel and activity patterns in Metro Vancouver. Indeed, the consistently strong positive effect of vehicle accessibility on vehicle emissions across all models in this research suggests that additional and more direct approaches targeted at vehicle ownership and use may be warranted. Such targeted initiatives may include insurance restructuring to allow for "pay-as-you-drive" policies, increased vehicle registration fees, road tolls, and parking levies: all strategies that, in effect, penalize individuals for driving. Coupling these "stick" strategies with stronger regional growth, local development, and transportation policies that make alternative modes of travel more appealing (the "carrots") is likely to add significant leverage to reducing emissions region-wide.

6. CONCLUSIONS

6.1. Summary of Findings

This research represents a comprehensive empirical assessment of the nature and strength of effects yielded by both local and regional-scale built environment characteristics on vehicle use and related GHG emissions in Canada's Metro Vancouver region. The study is part of a growing body of research focused on understanding and appraising the role of land use and transportation planning in reducing the carbon-intensity of daily travel (see Ewing et al., 2008). The research offers two unique contributions to the existing body of knowledge in this area. First, the use of structural equation modeling techniques permitted the explicit modeling of the indirect relationship between the built environment and travel emissions as mediated by other variables, such as activity patterns and vehicle use. By doing so, results generated explain not only what characteristics are most likely to reduce emission levels, but how such effects occur. Second, effects of the built environment on emissions are estimated for different activity tour types (e.g. work/school tours and non-work/school tours). This approach allowed for possible variations in effects between different built environment characteristics to be modeled.

Consistent with the literature, model results show the built environment to be a significantly strong predictor of vehicle-related GHG emissions in Metro Vancouver. However, the strength and magnitude of these effects is demonstrated to vary by activity tour type. The local built environment is a stronger predictor of vehicle use and related emissions for non-work/school tours, while regional accessibility measures yielded larger effects on the carbon-intensity of work and school tours. These findings indicate that the largest emission reductions may be achieved as part of a balanced effort to concentrate urban population and employment growth, increase existing transit levels-of-service region-wide, and invest in measures to create more, and expand existing, walkable neighbourhoods. Confounding these effects, however, is the consistently strong influence of key socio-demographic characteristics on vehicle use and emissions across all models. Most notable is that of vehicle availability: the greater one's access to a vehicle, the more vehicle use and associated emissions increase, sometimes regardless of the built environment within which one resides. Taken collectively, results suggest that policy directives are required beyond merely promoting more compact, walkable development to curb emissions. These strategies may include those that address vehicle use in a more direct manner, including higher taxation or user fees. As these mechanisms are outside the traditional purview of land use planning, coordination and education across a number of agencies, organizations of levels of government will be needed to facilitate their implementation.

Although conducted in Metro Vancouver, the findings from this research are likely to have applicability for urban areas across Canada. Many regions and municipalities are struggling with the need to prepare for continued population and employment growth while achieving less haphazard development patterns shown to contribute to sedentary lifestyles, increased energy use, and environment degradation. This research offers general guidance regarding where policy and regulations need to be focused to reduce the carbon-intensity of urban travel in the longer term.

6.2. Perspectives on Methodological Approach

Structural equation modeling (SEM) has emerged as yet another analytical approach towards measuring the complex interactions between the built environment, travel behaviour, and the implications that result from these linkages (see Golob, 2003). To the author's knowledge, this research is the first of its kind to employ SEM in modeling the travel-related GHG emission consequences associated with different built environments. Future work considering the use of SEM for similar research is likely to benefit from a brief assessment of the approach developed for the current study.

The most notable benefit of using SEM in the context of this research is its ability to model effects between variables in a manner that more closely matches reality. All models explicitly estimated total effects between built environment measures and vehicle emissions to occur indirectly; that is, through mediating variables related to daily activity patterns (i.e. tour complexity and location of stops) and vehicle use. As detailed in Chapter 2, traditional OLS regression techniques specify all independent measures in a model to yield direct effects on the dependent variable even though linkages may not actually occur as such. Beyond offering a more unique modeling approach, however, there is no way of assessing whether the estimated results in this research are different than those produced by an OLS regression model of the same sample and variables.

Structural equation models estimated using the maximum likelihood approach are extremely sensitive to violations of multivariate normality. Although variable transformation can be used to reduce the skew and kurtosis within models, doing so removes true scaling information, thereby rendering the interpretation of meaningful marginal effects of between variables difficult (i.e. if residential density increases by X unit/acre, vehicle GHG emissions decrease by Y). Findings that are able to quantify these effects are useful from a policy development perspective. The non-linear, non-normal nature of many variables used in travel behaviour research may constrain the applicability of SEM in some studies. Many key exogenous and endogenous variables in this research required transformation across all models. This makes it difficult to use the estimated results to craft detailed land use regulations (i.e. minimum densities, amount of mixed use, etc). Nevertheless, standardized effects do provide direction as to which policy efforts are more likely to yield greater impacts in emissions reductions.

Structural equation models are extremely data intensive. Large datasets with significant natural variation are required to yield meaningful results, especially for complex models. Limited variation may result in multivariate non-normal models. Attaining travel survey and built environment data sets that satisfy these requirements is difficult. One-day travel surveys, as used in this research, may not be sufficient to yield sufficient variation in travel, particularly for work or school related trip tours that are normally made only once a day. This situation was evident in specifying the first HBWS tour model. Where possible, future research employing SEM methods should seek out adequate sample sizes that yield greater variation across travel types.

6.3. Limitations and Caveats

The research presented here, although contributing to the body of knowledge concerning the relationships between the built environment and travel emissions, is not without its weaknesses. Several limitations are worth noting.

The current study was conducted cross-sectionally. This means that travel and activity patterns were compared between individuals in different built environments at a single point in time. A more rigorous study design would experimentally isolate built environment effects from pre-disposition and attitudinal factors and also provide an ordered stimulus (change in neighborhood exposure) and follow on response (travel patterns). There are two ways to do this, either through examining changes in travel behaviour among individuals moving from one type of built environment to another or for individuals that live in places that change dramatically; like around a transit station before and after it opens.

The travel survey data used in this data was recorded over the course of a one-day period only. Longer periods of data collection (usually two or three day surveys, including both weekday and weekend travel) are common in the travel behaviour literature. Two or three-day travel surveys are necessary to establish a more reliable estimate of representative travel behaviour. In addition, objectively measured travel patterns, whereby GPS is used to document the actual travel speed and route individuals take on their daily tours, would be ideal in estimating both distance traveled and vehicle emissions more accurately. These advancements would provide a better link to the GHG emission impacts associated with the built environment.

Travel survey data used in this research was collected nearly one decade ago. Metro Vancouver has been subject to significant changes in population, employment, development and transportation growth and development patterns during that time. Most notably, two new SkyTrain rapid transit lines, several major roadways, and new neighbourhood-style developments have been completed region-wide. It is likely that travel behaviour and patterns have changed somewhat since 1999. The findings in this research, although estimated using unique empirical methods, should by no means be interpreted as representative of the current situation in Metro Vancouver.

The use of the neighbourhood walkability index precluded the ability to segment out the relative impact of each individual urban form component on the endogenous variables in all models in this research. This is an important limitation as it makes the results, although informative, somewhat vague as to the specific land use regulations that may be important in shaping less carbon-intensive activity patterns. At best, the findings in this research allow for only a general idea as to where policy and regulatory strategies need to be guided in this effort.

Regional accessibility was measured as the distance from the household to the nearest of one of three centres defined in the Metro Vancouver Livable Region Strategic Plan: the metropolitan core, regional centres and municipal town centres. The scale of amenities and services varies by type of centre which may have implications on relative measures of regional accessibility. If a household is located close to a municipal but far from a regional centre, their access may be measured as high despite the municipal centre possibly having fewer services and amenities needed on a daily basis than the regional centre. Regional accessibility findings should be interpreted with this in mind.

Data limitations precluded the inclusion of work place and school urban form and regional accessibility measures and mid-day work-based tours. As such, findings need to be interpreted as summarizing an incomplete picture of total daily travel emissions and built environment variables.

6.4. Directions for Future Research

A number of opportunities exist to advance the findings of this research. Future work should endeavor to update these results with a more recent travel survey in order to capture more current travel behaviour trends in Metro Vancouver.

Findings can be strengthened through additional built environment and level of service variables in the statistical models. The inclusion of work place built environment characteristics into would help assess the relative impact of these elements on mode choices for work tours as well as mid day work tours. The Walkability Index could be supplemented with additional variables such as the presence of sidewalks and more subjective characteristics like topography which may significantly influence an individuals propensity to engage in active, less carbon intensive modes like walking and cycling (Leslie et al., 2008). Travel time and costs associated with different modes (especially vehicle parking fees, transit fares, transit wait times, and travel times) have been shown to yield significant influence on mode choice in previous studies (see Frank et al., 2007a; Guo and Wilson, 2004; Bhat and Sardesai, 2006). These measures were excluded here due to data limitations. Where possible, future work on this topic should explore a relative travel time and cost approach in model development and estimation to increase model fit and explanatory power.

Data in this research should be supplemented with emission modeling based on detailed congestion-based travel speeds, actual trip path, and duration of out-of-home activities in order to provide additional leverage through a more accurate representation of daily emissions. GPS travel data would provide for the necessary accurate speed inputs for such an emission modeling process. So to would capturing the specific vehicle (i.e. light duty truck or car) and fuel types of those reporting vehicle travel.

The inclusion of attitudinal data regarding residential and travel preferences in future studies would explicitly control for possible self-selection and help to better establish causality between variables. A longitudinal study design using time-series (i.e. before and after) travel data that assessed how activity and travel patterns and emissions change after moving between neighbourhoods or after a new transportation service has been developed would also yield greater insight into causality.

Different study designs may produce additional insight into the mechanisms affecting travel emissions. A multiple-group analysis between two or more independent groups (i.e. socio-economic status, household income, regional location and neighbourhood walkability) would allow for a more direct and statistically robust comparative assessment of associations between key variables. Such a design could clarify with additional statistical certainty why certain groups have relatively lower or higher travel emissions (i.e. do lower income individuals drive more because they cannot afford to reside in more walkable and connected communities?). Future work employing the SEM analysis framework would benefit by including traditional OLS regression models specified using the same variables. Such a design would allow for a direct comparison between the nature of the parameter estimates, model fit and explanatory power. This would add leverage into the utility of using SEM in travel behaviour research. These extensions of the current study would help address several key limitations described in section 6.3.

This study addresses only one component of urban greenhouse gas emissions. Future research should conduct a comprehensive assessment of the broader emission impacts associated with alternative built environment characteristics in urban areas. Such research would measure the effects of urban development characteristics such as density, building size and overall neighbourhood and regional structure on emissions and energy use related to both transportation choices and building use and operations (i.e. electricity, heating and cooling). Results from this work would provide a more holistic understanding of the broader carbon footprint impacts of land development practices and may yield where specific measures to reduce urban emissions and energy use should be targeted.

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APPENDIX A: AVERAGE WEEKDAY TRANSIT BOARDINGS BY ROUTE

TABLE A.1. Average weekday transit passenger boardings by route and vehicle type.

Route / Line	Average # Passengers on Board over Full Weekday Operating Period	Vehicle Type
002 MACDONALD-16TH AVE/BURRARD STN	14.1	Diesel Bus
003 MAIN/DOWNTOWN	13.8	Electric Trolley Bus
004 PHIBBS EXCH/POWELL/DOWNTOWN/UBC	13.8	Electric Trolley Bus
005 ROBSON/DOWNTOWN	11.7	Electric Trolley Bus
006 DAVIE/DOWNTOWN	11.2	Electric Trolley Bus
007 NANAIMO STN/DUNBAR	13.6	Electric Trolley Bus
008 FRASER/DOWNTOWN	14.8	Electric Trolley Bus
009 BDRY/BWAY STN/GRAN/ALMA/UBC	12.9	Electric Trolley Bus
010 HASTINGS/DOWNTOWN/GRAN	11.4	Electric Trolley Bus
015 CAMBIE/DOWNTOWN	6.9	Diesel Bus
016 29TH AVENUE STN/ARBUTUS	11.8	Electric Trolley Bus
017 OAK/DOWNTOWN/UBC	13.0	Electric Trolley Bus
019 METROTOWN STN/STANLEY PARK	13.7	Electric Trolley Bus
020 VICTORIA/DOWNTOWN	13.8	Electric Trolley Bus
022 KNIGHT/MACDONALD	19.1	Diesel Bus
025 BRENTWOOD STN/UBC	18.1	Diesel Bus
026 JOYCE STN/29TH AVENUE STN	11.7	Diesel Bus
027 KOOTENAY LOOP/JOYCE STN	10.7	Diesel Bus
028 CAP COLLEGE/PHIBBS EXCH/JOYCE STN	14.7	Diesel Bus
029 ELLIOTT/29TH AVENUE STN	9.7	Diesel Bus
032 DUNBAR/DOWNTOWN	25.5	Diesel Bus
041 JOYCE STN/CROWN/UBC	21.8	Diesel Bus
043 JOYCE STN/UBC	25.3	Diesel Bus
044 UBC/DOWNTOWN	32.5	Diesel Bus
049 METROTOWN STN/DUNBAR LOOP/UBC	14.6	Diesel Bus
050 WATERFRONT STN/FALSE CREEK SOUTH	9.0	Diesel Bus
084 UBC/VCC STATION	17.5	Diesel Bus
097 COQUITLAM STN/LOUGHEED STN (B-LINE)	18.3	Diesel Bus
098 BURRARD STN/RICHMOND CTR (B-LINE)	36.2	Diesel Bus
099 BROADWAY STN/UBC (B-LINE)	35.5	Diesel Bus
100 22ND ST STN/AIRPORT STN	16.6	Diesel Bus
101 LOUGHEED STN/22ND ST STN	10.7	Diesel Bus
104 22ND ST STN/ANNACIS ISLAND	10.2	Diesel Bus
106 NEW WESTMINSTER STN/METROTOWN STN	15.2	Diesel Bus
110 LOUGHEED STN/METROTOWN STN	6.9	Diesel Bus
112 EDMONDS STN/LOUGHEED STN	6.0	Diesel Bus
116 EDMONDS STN/METROTOWN STN	9.6	Diesel Bus
123 NEW WEST ST/BRENTWOOD STN/KOOTENAY	11.3	Diesel Bus
129 METROTOWN STN/EDMONDS STN	10.1	Diesel Bus
130 METROTOWN/HASTINGS/KOOTENAY LOOP	16.0	Diesel Bus
134 LAKE CITY STN/BRENTWOOD STN	5.1	Diesel Bus
135 SFU/BURRARD STN	23.4	Diesel Bus
136 LOUGHEED STN/BRENTWOOD STN	6.5	Diesel Bus
143 COQUITLAM STN/SFU	21.6	Diesel Bus
144 SFU/METROTOWN STN	13.7	Diesel Bus
145 SFU/PRODUCTION STN	33.0	Diesel Bus

TABLE A.1. Continued.

Route / Line	Average # Passengers on Board over Full Weekday Operating Period	Vehicle Type
151 COQUITLAM STN/LOUGHEED STN	8.9	Diesel Bus
152 COQUITLAM STN/LOUGHEED STN	10.3	Diesel Bus
153 COQUITLAM REC CTR/BRAID STN	5.1	Diesel Bus
154 BRAID STN/22ND STREET STN	9.8	Diesel Bus
155 BRAID STN/22ND STREET STN	11.2	Diesel Bus
156 BRAID STN/LOUGHEED STN	9.8	Diesel Bus
157 COQUITLAM REC CENTRE/LOUGHEED STN	7.7	Diesel Bus
159 PORT COQUITLAM STN/BRAID STN	17.2	Diesel Bus
160 PORT COQUITLAM STN/VANCOUVER	19.2	Diesel Bus
169 COQUITLAM STN/BRAID STN	18.0	Diesel Bus
177 COQUITLAM STN/BRAID STN	9.3	Diesel Bus
179 COQUITLAM STN/JOHNSON	1.7	Diesel Bus
189 COQUITLAM STN/COAST MERIDIAN	6.5	Diesel Bus
190 COQUITLAM STN/VANCOUVER	18.1	Diesel Bus
210 UPPER LYNN VALLEY/VANCOUVER	20.7	Diesel Bus
211 SEYMOUR/PHIBBS EXCH/VANCOUVER	14.9	Diesel Bus
212 DEEP COVE/PHIBBS EXCH	8.3	Diesel Bus
214 BLUERIDGE/PHIBBS EXCH/VANCOUVER	12.9	Diesel Bus
228 LYNN VALLEY/LONSDALE QUAY	10.9	Diesel Bus
229 WESTLYNN/PHIBBS EXCH/LONSDALE QUAY	9.9	Diesel Bus
230 UPPER LONSDALE/LONSDALE QUAY	11.9	Diesel Bus
232 GROUSE MOUNTAIN/PHIBBS EXCH	13.5	Diesel Bus
236 GROUSE MOUNTAIN/LONSDALE QUAY	14.2	Diesel Bus
239 CAPILANO COLLEGE/PARK ROYAL	18.7	Diesel Bus
240 15TH STREET/VANCOUVER	22.9	Diesel Bus
241 UPPER LONSDALE/VANCOUVER	27.0	Diesel Bus
242 UPPER LONSDALE/VANCOUVER	7.6	Diesel Bus
246 LONSDALE QUAY/HIGHLAND/VANCOUVER	7.4	Diesel Bus
247 UPPER CAPILANO/GROUSE/VANCOUVER	22.1	Diesel Bus
250 HORSESHOE BAY/DUNDARAVE/VANCOUVER	17.8	Diesel Bus
251 QUEENS/VANCOUVER/PARK ROYAL	21.2	Diesel Bus
252 INGLEWOOD/VANCOUVER/PARK ROYAL	17.8	Diesel Bus
253 CAULFEILD/VANCOUVER/PARK ROYAL	15.1	Diesel Bus
254 BRITISH PROPERTIES/PARK ROYAL/VAN	14.0	Diesel Bus
255 DUNDARAVE/LYNN VALLEY CENTRE	15.2	Diesel Bus
257 HORSESHOE BAY/VANCOUVER EXPRESS	36.6	Diesel Bus
258 UBC/WEST VANCOUVER	11.9	Diesel Bus
259 LIONS BAY/HORSESHOE BAY	-0.2	Diesel Bus
290 DEEP COVE	17.8	Diesel Bus
292 UPPER LYNN VALLEY	23.9	Diesel Bus
301 NEWTON EXCHANGE/RICHMOND CENTRE	12.3	Diesel Bus
311 SCOTTSDALE/VANCOUVER	29.9	Diesel Bus
312 SCOTTSDALE/SCOTT ROAD STN	10.7	Diesel Bus
314 SURREY CENTRAL/SUNBURY/SCOTT RD STN	7.3	Diesel Bus
316 SURREY CENTRAL STN/SCOTTSDALE	10.6	Diesel Bus
319 SCOTT ROAD STN/SCOTTSDALE	18.4	Diesel Bus

TABLE A.1. Continued.

Route / Line	Average # Passengers on Board over Full Weekday Operating Period	Vehicle Type
320 LANGLEY/GUILDFORD/SURREY CTRL STN	17.0	Diesel Bus
321 WHITE ROCK/NEWTON/SURREY CTRL STN	18.2	Diesel Bus
323 NEWTON EXCH/SURREY CENTRAL STN	14.5	Diesel Bus
324 NEWTON EXCH/SURREY CENTRAL STN	13.1	Diesel Bus
325 NEWTON EXCH/SURREY CENTRAL STN	13.8	Diesel Bus
326 GUILDFORD/SURREY CENTRAL STN	10.8	Diesel Bus
329 SURREY CENTRAL STN/SCOTTSDALE	8.9	Diesel Bus
332 GUILDFORD/SURREY CENTRAL STN	13.4	Diesel Bus
335 FLEETWOOD/SURREY CENTRAL STN	12.6	Diesel Bus
340 NEWTON/22ND ST	17.2	Diesel Bus
341 GUILDFORD/LANGLEY CENTRE	8.5	Diesel Bus
341 GULDFORD/CLOVERDALE	0.2	Diesel Bus
345 KING GEORGE STN/WHITE ROCK CENTRE	16.9	Diesel Bus
351 CRESCENT BEACH/VANCOUVER	12.0	Diesel Bus
352 OCEAN PARK /VANCOUVER	26.9	Diesel Bus
354 WHITE ROCK SOUTH/VANCOUVER	25.5	Diesel Bus
375 WHITE ROCK/WHITE ROCK STH/GUILDFORD	8.3	Diesel Bus
391 SCOTTSDALE/SCOTT ROAD STN	13.6	Diesel Bus
393 NEWTON EXCH/SURREY CENTRAL STN	17.9	Diesel Bus
394 WHITE ROCK/KING GEORGE STN EXPRESS	13.8	Diesel Bus
395 WILLOWBROOK/KING GEORGE STN	19.8	Diesel Bus
401 ONE ROAD/GARDEN CITY	8.2	Diesel Bus
402 TWO ROAD/RICHMOND CENTRE	6.6	Diesel Bus
403 THREE ROAD/RICHMOND CENTRE	6.9	Diesel Bus
404 LADNER EXCH/RICHMOND CTR	7.3	Diesel Bus
405 FIVE ROAD/CAMBIE	4.5	Diesel Bus
407 GILBERT/BRIDGEPORT	5.1	Diesel Bus
410 22ND ST STN/QUEENSBOROUGH/RAILWAY	18.0	Diesel Bus
424 AIRPORT/AIRPORT STN	11.5	Diesel Bus
430 METROTOWN/RICHMOND CENTRE	20.1	Diesel Bus
480 UBC/RICHMOND CENTRE	29.5	Diesel Bus
488 GARDEN CITY/BURRARD STN	25.3	Diesel Bus
490 STEVESTON/BURRARD STN	33.2	Diesel Bus
491 ONE ROAD/BURRARD STN	12.7	Diesel Bus
492 TWO ROAD/BURRARD STN	25.3	Diesel Bus
496 RAILWAY/BURRARD STN	26.0	Diesel Bus
501 LANGLEY CENTRE/SURREY CENTRAL STN	16.0	Diesel Bus
502 ALDGR/BRKSWD/LANGLEY/SURREY STN	18.8	Diesel Bus
509 WALNUT GROVE/SURREY CENTRAL STN	17.6	Diesel Bus
590 LANGLEY SOUTH/SURREY CENTRAL STN	13.3	Diesel Bus
601 SOUTH DELTA/BOUNDARY BAY/VANCOUVER	17.9	Diesel Bus
602 TSAWWASSEN HEIGHTS/VANCOUVER	30.7	Diesel Bus
603 BEACH GROVE/VANCOUVER	31.8	Diesel Bus
604 ENGLISH BLUFF/VANCOUVER	21.7	Diesel Bus
606 LADNER RING	-2.9	Diesel Bus
608 LADNER RING	3.9	Diesel Bus

TABLE A.1. Continued.

Route / Line	Average # Passengers on Board over Full Weekday Operating Period	Vehicle Type
640 LADNER EXCH/SCOTT ROAD STN	14.7	Diesel Bus
701 HANEY/MAPLE RIDGE EAST/COQ STN	4.8	Diesel Bus
791 HANEY PLACE/BRAID STN	8.8	Diesel Bus
804 HOLY CROSS SCHOOL	12.4	Diesel Bus
807 SCHOOL SPECIAL	9.1	Diesel Bus
828 KWANTLEN PARK SCHOOL	6.8	Diesel Bus
848 PORT MOODY SS	11.5	Diesel Bus
855 ELGIN PARK SCHOOL SPECIAL	8.0	Diesel Bus
863 TERRY FOX/ARCH CARNEY	14.4	Diesel Bus
865 ROBERTSON	11.9	Diesel Bus
867 HERITAGE WOODS SCHOOL	30.2	Diesel Bus
881 CARSON GRAHAM SCHOOL SPECIALS	23.6	Diesel Bus
N10 DOWNTOWN/RICHMOND NIGHTBUS	2.6	Diesel Bus
N15 DOWNTOWN/CAMBIE NIGHTBUS	0.0	Diesel Bus
N16 NANAIMO/RENFREW NIGHTBUS	0.9	Diesel Bus
N17 DOWNTOWN/UBC NIGHTBUS	11.2	Diesel Bus
N19 DOWNTOWN/SURREY CNTRL STN NIGHTBUS	8.1	Diesel Bus
N20 DOWNTOWN/VICTORIA NIGHTBUS	4.8	Diesel Bus
N22 DOWNTOWN/DUNBAR NIGHTBUS	3.0	Diesel Bus
N24 DOWNTOWN/UPPER LONSDALE NIGHTBUS	5.5	Diesel Bus
N35 DOWNTOWN/SFU NIGHTBUS	15.2	Diesel Bus
N6 DOWNTOWN/WEST END NIGHTBUS	0.5	Diesel Bus
N8 DOWNTOWN/FRASER NIGHTBUS	5.7	Diesel Bus
N9 DOWNTOWN/COQUITLAM STN NIGHTBUS	4.8	Diesel Bus
SKYTRAIN MILLENIUM LINE	20 / CAR	SkyTrain Electric Vehicle
SKYTRAIN EXPO LINE	20 / CAR	SkyTrain Electric Vehicle
SEABUS	126	Diesel Boat
WEST COAST EXPRESS	58 / CAR	Diesel Train

Source: Translink, 2009b. Reproduced with permission.

APPENDIX B: UNSTANDARDIZED PARAMETER COEFFICIENTS

TABLE B.1. Estimated unstandardized effects (structural coefficient estimates) for "Final" HBO model.

Explanatory Variable	DIRECT EFFECTS Endogenous Variable				INDIRECT EFFECTS Endogenous Variable				TOTAL EFFECTS Endogenous Variable			
	% TOURS SIMPLE*	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*	% TOURS SIMPLE*	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*	% TOURS SIMPLE*	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*
AGE												
FEMALE	-0.077 (-3.40)						0.072	0.032	-0.077		0.072	0.032
PERSONS<18	0.100 (4.23)	0.052 (2.87)	0.317 (2.42)		0.005		-0.171	0.060	0.105	0.052	0.146	0.060
VEHICLE ACCESS			1.844 (9.90)					0.822			1.844	0.822
HH INCOME			0.123 (1.99)					0.055			0.123	0.055
NEIGHBRHD WALK		0.011 (3.34)	-0.084 (-3.52)		0.001		0.018	-0.045	0.001	0.011	-0.102	-0.045
DIST TO CENTRE *		-0.022 (-2.36)	0.167 (2.45)		-0.002		0.037	0.092	-0.002	-0.022	0.204	0.092
TRANSIT AVLBLTY *		0.019 (2.20)	-0.159 (-2.51)		0.002		-0.032	-0.085	0.002	0.019	-0.191	-0.085
% TOURS SIMPLE *			-0.936 (-6.42)					-0.417			-0.936	-0.417
% STOPS NEAR HOME *	0.097 (2.04)		-1.577 (-8.16)				0.091	-0.703	0.097		-1.486	-0.703
VKT *				0.446 (119.11)								0.446

NOTES: * = Square root transformation.

Beta coefficients are listed without parentheses. *T* -statistic listed in parentheses (value greater or equal to +/-1.96 indicates significance at or above 95% confidence interval) and calculated only for direct effects.

Interpretation of effects is similar to OLS regression: *B* coefficient of 1.0 suggests the endogenous variable increases by 1.0 unit for each unit increase in the explanatory variable.

TABLE B.2. Estimated unstandardized effects (structural coefficient estimates) for "Final" HBWS Model A.

Explanatory Variable	DIRECT EFFECTS Endogenous Variable			INDIRECT EFFECTS Endogenous Variable			TOTAL EFFECTS Endogenous Variable		
	TOUR CMPLXTY**	VKT*	VEHICLE GHG*	TOUR CMPLXTY**	VKT*	VEHICLE GHG*	TOUR CMPLXTY**	VKT*	VEHICLE GHG*
AGE	-0.002 (-2.41)	0.012 (3.25)			-0.003	0.005	-0.002	0.009	0.005
FEMALE		-0.400 (-4.47)				-0.213		-0.400	-0.213
PERSONS<18									
VEHICLE ACCESS	0.085 (2.73)	2.422 (16.54)			0.109	1.347	0.085	2.531	1.347
HH INCOME		0.183 (3.72)				0.097		0.183	0.097
NEIGHBRHD WALK		-0.080 (-5.45)				0.043		-0.080	0.043
DIST TO WRK/SCHL *		1.066 (28.92)				0.567		1.066	0.567
TRANSIT AVLBLTY *									
TOUR CMPLXTY **		1.283 (11.99)				0.683		1.283	0.683
VKT *			0.532 (217.54)						0.532

NOTES: * = Square root transformation

** = Natural logarithm transformation

Unstandardized coefficients (*B*) are listed without parentheses. Critical ratio values are listed in parentheses (c.r. >= +/-1.96 suggest significance to 95% interval) and calculated only for direct effects.

Interpretation of effects is similar to OLS regression: *B* coefficient of 1.0 suggests the endogenous variable increases by 1.0 unit for each unit increase in the explanatory variable.

n = 1,713 persons

TABLE B.3. Estimated unstandardized effects (structural coefficient estimates) for "Final" HBWS Model B.

Explanatory Variable	**DIRECT EFFECTS** Endogenous Variable				**INDIRECT EFFECTS** Endogenous Variable				**TOTAL EFFECTS** Endogenous Variable			
	TOUR CMPLXTY**	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*	TOUR CMPLXTY**	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*	TOUR CMPLXTY**	% STOPS NEAR HOME*	VKT*	VEHICLE GHG*
AGE			0.018 (2.66)					0.009			0.018	0.009
FEMALE	0.055 (2.04)		-0.376 (-2.54)				0.051	0.170	0.055		-0.325	0.170
PERSONS<18	0.073 (2.53)						0.068	0.036	0.073		0.068	0.036
VEHICLE ACCESS		0.093 (2.54)	2.569 (10.17)		0.000		-0.116	1.288		0.093	2.453	1.288
HH INCOME			0.178 (2.29)					0.093			0.178	0.093
NEIGHBRHD WALK		0.002 (1.97)	-0.062 (-2.58)		0.000		0.002	-0.033		0.002	-0.060	-0.032
DIST TO WRK/SCHL *	0.034 (3.10)	-0.027 (-2.84)	1.172 (17.78)		0.000		0.034	0.650	0.034	-0.027	1.206	0.650
TRANSIT AVLBLTY *		0.039 (3.54)			0.000		-0.048	-0.025		0.039	-0.048	-0.025
TOUR CMPLXTY**			0.928 (3.77)					0.487			0.928	0.487
% STOPS NEAR HOME *	-0.003 (-1.98)		-1.242 (-4.09)				-0.003	-0.653	-0.003		-1.244	-0.653
VKT *				0.525 (98.24)								0.525

NOTES: * = Square root transformation
** = Natural logarithm transformation
Unstandardized coefficient of 0.000 equals near negligible effect.
Unstandardized coefficients (B) are listed without parentheses. Critical ratio values are listed in parentheses (c.r. >= +/-1.96 suggest significance to 95% interval) and calculated only for direct effects.
Interpretation of effects is similar to OLS regression: B coefficient of 1.0 suggests the endogenous variable increases by 1.0 unit for each unit increase in the explanatory variable.
n = 496 persons

APPENDIX C: COVARIANCE / CORRELATION MATRICES

TABLE C.1. "Final" HBO tour model sample covariance matrix.

Variable	DIST TO CENTRE *	TRANSIT AVLBLTY *	NEIGHBRHD WALK	HH INCOME	VEHCLE ACCESS	PERSONS < 18	FEMALE	AGE	% STOPS NEAR HOME *	% TOURS SIMPLE *	VKT *	VEHCLE GHG *
DIST TO CENTRE *	0.906											
TRANSIT AVLBLTY *	-0.477	1.876										
NEIGHBRHD WALK	-0.855	3.345	12.517									
HH INCOME	0.161	-0.260	-0.580	1.012								
VEHCLE ACCESS	0.036	-0.129	-0.389	0.111	0.124							
PERSONS < 18	0.044	-0.103	-0.242	0.055	0.013	0.221						
FEMALE	-0.029	0.020	0.096	0.019	-0.002	-0.027	0.244					
AGE	0.795	-2.169	-8.555	-2.136	0.459	-2.399	0.578	278.359				
% STOPS NEAR HOME *	-0.037	0.078	0.208	-0.023	-0.008	0.006	-0.004	-0.420	0.101			
% TOURS SIMPLE *	-0.001	0.010	0.015	0.000	0.001	0.020	0.016	-0.518	0.005	0.171		
VKT *	0.459	-1.095	-2.934	0.500	0.318	0.116	-0.011	2.520	-0.215	-0.162	6.576	
VEHICLE GHG *	0.211	-0.499	-1.337	0.217	0.153	0.023	0.012	1.618	-0.096	-0.071	2.931	1.432

* = Square root transformation
n = 1,370 persons

TABLE C.2. "Final" HBO tour model sample correlation matrix.

Variable	DIST TO CENTRE *	TRANSIT AVLBLTY *	NEIGHBRHD WALK	HH INCOME	VEHCLE ACCESS	PERSONS < 18	FEMALE	AGE	% STOPS NEAR HOME *	% TOURS SIMPLE *	VKT *	VEHCLE GHG *
DIST TO CENTRE *	1.000											
TRANSIT AVLBLTY *	-0.366	1.000										
NEIGHBRHD WALK	-0.254	0.690	1.000									
HH INCOME	0.168	-0.189	-0.163	1.000								
VEHCLE ACCESS	0.108	-0.268	-0.312	0.314	1.000							
PERSONS < 18	0.099	-0.159	-0.146	0.116	0.077	1.000						
FEMALE	-0.061	0.029	0.055	0.038	-0.013	-0.116	1.000					
AGE	0.050	-0.095	-0.145	-0.127	0.078	-0.306	0.070	1.000				
% STOPS NEAR HOME *	-0.121	0.180	0.185	-0.070	-0.070	0.039	-0.026	-0.079	1.000			
% TOURS SIMPLE *	-0.003	0.017	0.010	0.001	0.006	0.105	0.077	-0.075	0.071	1.000		
VKT *	0.188	-0.312	-0.323	0.194	0.352	0.096	-0.008	0.059	-0.264	-0.153	1.000	
VEHICLE GHG *	0.185	-0.304	-0.316	0.180	0.361	0.040	0.020	0.081	-0.252	-0.143	0.955	1.000

* = Square root transformation
n = 1,370 persons

TABLE C.3. "Final" HBWS tour Model A sample covariance matrix.

Variable	DIST TO WRK / SCHL *	TRANSIT AVLBLTY *	NEIGHBRHD WALK	HH INCOME	VEHCLE ACCESS	PERSONS < 18	FEMALE	AGE	TOUR CMPLXTY **	VKT *	VEHICLE GHG *
DIST TO WRK/SCHL *	1.748										
TRANSIT AVLBLTY *	-0.552	1.625									
NEIGHBRHD WALK	-1.793	2.841	11.783								
HH INCOME	0.162	-0.259	-0.685	0.941							
VEHCLE ACCESS	0.085	-0.115	-0.338	0.097	0.110						
PERSONS < 18	0.062	-0.139	-0.374	0.016	0.007	0.212					
FEMALE	0.076	-0.009	-0.045	0.039	0.008	0.018	0.250				
AGE	0.952	-1.857	-5.039	2.398	0.654	-0.012	0.134	144.396			
TOUR CMPLXTY **	0.003	-0.004	0.006	0.007	0.008	0.006	-0.007	-0.242	0.173		
VKT *	2.287	-1.247	-3.866	0.690	0.422	0.134	0.204	4.966	0.239	7.636	
VEHICLE GHG *	1.236	-0.657	-2.030	0.360	0.237	0.062	0.123	2.954	0.111	4.065	2.240

* = Square root transformation
** = Natural logarithm transformation
n = 1,713 persons

TABLE C.4. "Final" HBWS tour Model A sample correlation matrix.

Variable	DIST TO WRK / SCHL *	TRANSIT AVLBLTY *	NEIGHBRHD WALK	HH INCOME	VEHCLE ACCESS	PERSONS < 18	FEMALE	AGE	TOUR CMPLXTY **	VKT *	VEHICLE GHG *
DIST TO WRK/SCHL *	1.000										
TRANSIT AVLBLTY *	-0.327	1.000									
NEIGHBRHD WALK	-0.395	0.649	1.000								
HH INCOME	0.127	-0.209	-0.206	1.000							
VEHCLE ACCESS	0.194	-0.272	-0.297	0.303	1.000						
PERSONS < 18	0.102	-0.236	-0.237	0.035	0.044	1.000					
FEMALE	0.115	-0.014	-0.026	0.080	0.046	0.080	1.000				
AGE	0.060	-0.121	-0.122	0.206	0.164	-0.002	0.022	1.000			
TOUR CMPLXTY **	0.005	-0.007	0.004	0.019	0.058	0.030	-0.033	-0.048	1.000		
VKT *	0.626	-0.354	-0.408	0.257	0.461	0.105	0.147	0.150	0.208	1.000	
VEHICLE GHG *	0.625	-0.344	-0.395	0.248	0.478	0.091	0.165	0.164	0.179	0.983	1.000

* = Square root transformation
** = Natural logarithm transformation
n = 1,713 persons

TABLE C.5. "Final" HBWS tour Model B sample covariance matrix.

Variable	DIST TO WRK / SCHL *	TRANSIT AVLBLTY *	NEIGHBRHD WALK	HH INCOME	VEHCLE ACCESS	PERSONS < 18	FEMALE	AGE	% STOPS NEAR HOME *	TOUR CMPLXTY **	VKT *	VEHICLE GHG *
DIST TO CENTRE *	1.587											
TRANSIT AVLBLTY *	-0.571	1.673										
NEIGHBRHD WALK	-1.962	2.887	12.230									
HH INCOME	0.125	-0.228	-0.605	0.958								
VEHCLE ACCESS	0.067	-0.102	-0.287	0.054	0.094							
PERSONS < 18	0.033	-0.201	-0.479	0.063	0.018	0.214						
FEMALE	-0.053	0.047	0.034	-0.050	0.007	-0.018	0.250					
AGE	0.813	-1.303	-7.296	2.520	0.729	0.412	-0.470	120.947				
% STOPS NEAR HOME *	-0.054	0.063	0.108	-0.005	0.004	0.001	0.012	0.091	0.060			
TOUR CMPLXTY **	0.053	-0.020	-0.033	-0.015	-0.004	0.016	0.011	0.020	-0.001	0.089		
VKT *	2.326	-1.338	-4.216	0.550	0.350	0.192	-0.161	6.043	-0.139	0.132	6.963	
VEHICLE GHG *	1.227	-0.697	-2.197	0.267	0.201	0.075	-0.096	3.539	-0.067	0.052	3.653	2.012

* = Square root transformation
** = Natural logarithm transformation
n = 496 persons

TABLE C.6. "Final" HBWS tour Model B sample correlation matrix.

Variable	DIST TO WRK / SCHL *	TRANSIT AVLBLTY *	NEIGHBRHD WALK	HH INCOME	VEHCLE ACCESS	PERSONS < 18	FEMALE	AGE	% STOPS NEAR HOME *	TOUR CMPLXTY **	VKT *	VEHICLE GHG *
DIST TO CENTRE *	1.000											
TRANSIT AVLBLTY *	-0.351	1.000										
NEIGHBRHD WALK	-0.445	0.638	1.000									
HH INCOME	0.101	-0.180	-0.177	1.000								
VEHCLE ACCESS	0.173	-0.258	-0.268	0.180	1.000							
PERSONS < 18	0.056	-0.336	-0.296	0.140	0.125	1.000						
FEMALE	-0.084	0.072	0.020	-0.103	0.048	-0.078	1.000					
AGE	0.059	-0.092	-0.190	0.234	0.216	0.081	-0.086	1.000				
% STOPS NEAR HOME *	-0.176	0.201	0.126	-0.021	0.050	0.006	0.096	0.034	1.000			
TOUR CMPLXTY **	0.140	-0.052	-0.032	-0.052	-0.044	0.114	0.071	0.006	-0.055	1.000		
VKT *	0.700	-0.392	-0.457	0.213	0.432	0.158	-0.122	0.208	-0.216	0.167	1.000	
VEHICLE GHG *	0.687	-0.380	-0.443	0.193	0.463	0.115	-0.136	0.227	-0.194	0.124	0.976	1.000

* = Square root transformation
** = Natural logarithm transformation
n = 496 persons