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An econometric investigation on the relationship between modal accessibility and the home–work spatial configuration of two-commuter households

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This paper investigates the relationship between modal accessibility and the home–work spatial configuration of two-commuter households in an urban area. The home–work spatial configuration is captured by: (a) total commuting distance of the two commuters (from home to work) and (b) the angle between the two work locations (as measured from the common home location). The household travel survey data of 2011 of the National Capital Region is used for the empirical investigation. The empirical investigation reveals that higher modal accessibility increases the angle and reduces the total commuting distance. This investigation also reveals that certain two-commuter households are not able to optimise their home location in terms of widening the angles and reducing total distances. A correlation between total commuting distance and angle between work locations is observed such that angle decreases as the distance between home location and the Central Business District (CBD) increases. We infer that two-commuter households located far from the CBD live in predominantly residential areas that lack employment centres. As such, land use policies should guide development in areas far from the CBD towards mixed land uses. These findings are useful for urban transportation and land use planning since the proportion of two-commuter households is increasing in many urban areas.

Keywords: two-commuter households; urban form and commuting patterns; accessibility; commuting mode choice; home location choices

1. Introduction

With changing urban landscapes and increasingly costly urban housing, researchers speculate that two-commuter households will make up a greater share of urban residents in the near future (Clark, Huang, and Withers 2003). In many Canadian cities, two-commuter households already make up a significant percentage of total households. For example, two-commuter households comprise 28% of the population in Toronto and 22% in Montreal (Habib 2013). Given that work location choices are apparently not as flexible as home location choices, two-commuter households face dual constraints (two workplaces) in tackling home-commuting tradeoffs (Kim 1995). While some research has shown that residents may move closer to their work as a method of reducing commuting cost (Clark, Huang, and Withers 2003), others have shown that this may only be a ‘North American’ phenomenon which does not necessarily occur in European cities (Schwanen, Dieleman, and Dijst 2003; Van Ommeren and Dargay 2006). The home-commuting tradeoffs of urban residents fundamentally define the urban spatial structure of any city, and

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an increase in two-commuter households may shape the urban economy and spatial structure very differently than expected if urban land use and transportation policies overlook the growing proportion of two-commuter households (Tscharaktschiew and Hirte 2010).

A proper understanding of home–work spatial configuration and the factors that influence it is highly desirable for sustainable urban transportation systems and land use planning. This is why two-commuter households have received attention from researchers in the past two decades. However, many questions related to the relationship between home and work locations for two-commuter households are still not fully explored empirically. This paper uses econometric models to investigate the impact of modal accessibility on the home–work spatial configuration in the National Capital Region (NCR). In this study, the home–work spatial configuration is specified by two variables: (a) total commuting distance of two commuters from home to work and (b) the angle between two fixed work locations measured at the home location (herein referred to as ‘angle’). This research reveals that modal accessibility affects both the two-commuter households’ total commuting distance and the angle. It also reveals that the angle is highly correlated with commuting distance of the two commuters. Moreover, this correlation decreases as distance from the Central Business District (CBD) to the home location increases, a finding that is an indication of urban sprawl.

The paper is organised as follows: A brief literature review on two-commuter households, particularly with regards to the home–work spatial configuration, followed by an explanation of the study area and data available for empirical investigation, the econometric modelling framework for empirical investigation and a discussion of the empirical model. The paper concludes by identifying key findings and recommendations for future studies.

2. Literature review

2.1. Existing research on commuting behaviours and home location choice

There is considerable interest in two-commuter households among urban economists and urban planners. Investigations to date have been motivated by attempts to understand: gender dynamics in the commuting behaviour of two-commuter households, home location choices of two-commuter households compared to single-commuter households (Curran, Carlson, and Ford 1982) and the excess commuting of two-commuter households (White 1988). Some studies investigated two-commuter households to identify how commuters make commuting distance tradeoffs at the household level when determining home location. Researchers found that two-commuter households minimise total commuting distance and the commuting distances of individual commuters are complementary to each other (Kim 1995; Ma and Banister 2006). Most investigations of two-commuter households consider home location choice and commuting tradeoffs in isolation from commuting mode choice considerations. Although some researchers take commuting mode choice into consideration, they either consider it as an exogenous factor in the analytical framework or only consider a very partial representation of commuting mode choice (Freedman and Kern 1997). In a recent study, Surprenant-Legault, Patterson, and El-Geneidy (2013) considered commuting mode choice as an exogenous variable to the commuting distance regression model. Plaut (2005) investigated the commuting distance tradeoff between two commuters in two-commuter households, but considered only car users.

Some researchers do consider the commuting mode choices of two-commuter households but without examining the commuting distance tradeoffs made by the two commuters. Badoe (2002) presents a household-level joint commuting mode choice model for two-commuter households and highlights the importance of considering a joint commuting mode choice model for multi-commuter households. Badoe (2002) argues that household travel survey data used for
commuting mode choices are based on sampling households, not individuals, and hence it is necessary for commuting mode choices to be modelled jointly at the household level for two-commuter households. Matt and Timmermans (2009) also consider commuting mode choice in an investigation of the influence of the built environment on dual-earner households’ commuting patterns, but focus only on car mode choice.

2.2. Considering angles to capture spatial patterns of two-commuter households

Much of the literature on two-commuter households has been dedicated to measures that capture the spatial configuration of the home and work locations. This includes creative measures, such as the use of angles, which have often been employed for understanding residential location (Van Ommeren 2000). The angle that is widely used for two-commuter households (Vandersmissen, Villeneuve, and Thériault 2003) is the home-CBD-workplace angle. The use of this angle is most appropriate for a monocentric city, in which case a narrower angle is ideal as it would lead to faster travel. This is based on the theoretical assumption that it is generally faster to travel in the direction of the CBD since transportation networks are designed to access the CBD. In the context of non-monocentric cities, the angle of workplace1-home-workplace2 has been used to describe the positioning of two-commuter households relative to their associated workplaces (Van Ommeren 2000). In using this approach, acute angles (less than 90 degrees, the extreme being 0 degrees) indicate that commuters travel in similar directions, while obtuse angles (greater than 90 degrees, the extreme being 180 degrees) indicate that commuters travel in dissimilar directions.

2.3. Factors affecting the home–work spatial configuration

As supported by numerous studies, accessibility is an important factor in peoples’ home location decisions. Accessibility is typically used to identify the influence of infrastructure through some measure of access to the transportation network (Iacono, Levinson, and El-Geneidy 2008). There are many factors other than accessibility which contribute to peoples’ home–work spatial configuration. For instance, Frenkel, Bendit, and Kaplan (2013) identify the primary influence of a household’s socio-economic level, housing prices and commute travel time on home location choices while also recognising the secondary influence of lifestyle and cultural amenities. Furthermore, Alonso’s (1960) theory of the urban land market suggests that different socioeconomic groups have different bid rent curves; therefore socioeconomic factors, in particular income, have an important role in home location decisions. Other studies have revealed the influence of life cycle factors, such as the presence of children, on a household’s home location choice (Kim, Horner, and Marans 2005). Varying age groups can have different preferences for home locations since household needs vary depending on the stage of life (Morrow-Jones and Kim 2009).

2.4. Contributions to existing literature

This study builds from the findings of Surprenant-Legault, Patterson, and El-Geneidy (2013) and in particular looks further into the home–work spatial configuration attributes identified as: (a) total commuting distance and (b) the angle (i.e. ‘workplace1-home-workplace2’ angle). This research contributes to literature by examining the influence of modal accessibility on these spatial configuration attributes. Modal accessibility is defined as an accessibility measure that considers the expected maximum utility (EMU) derived from all modes of transportation. In the case of this study, modal accessibility represents the EMU associated with mode choices for two commuters. The use of EMU as explained by Ben-Akiva and Lerman (1985) is a method
of representing accessibility in transportation models concerning choices. According to Silva (2013) EMU is the most theoretically sound and disaggregate accessibility measure.

3. Research design

Any location on a line connecting both work locations, resulting in an angle of 180 degrees, would result in the shortest total commuting distance provided that the two work locations are fixed. The current study identifies this as the ‘Optimum Home Location’ for two-commuter households. Figure 1 depicts examples of possible workplace1-home-workplace2 location patterns. Surprenant-Legault, Patterson, and El-Geneidy’s (2013) research suggests that two-commuter households make tradeoffs, whereby individuals take into account partners’ commuting distances. The intent of our research is to establish a connection between accessibility and the geometrical, spatial distribution of households and jobs. In other words, we aim to explore the existence of important land use factors, in particular modal accessibility, that prevent two-commuter households from achieving their optimal home location. The connection between modal accessibility and total commuting distance and angle will provide greater insight into this issue.

The second intent of this research design is to use the correlation between the total commuting distance and angle of two-commuter households to make inferences about urban sprawl. According to the workplace1-home-workplace2 angle, in land use scenarios where employment opportunities can be found in different locations (i.e. not solely in the CBD), two-commuter households could reduce commuting distances by moving their home location closer to a line connecting the two work locations. It is expected that angle and total commuting distance would have a negative correlation. When considering an urban region, a concentration of households whereby both commuters travel in dissimilar directions (or obtuse angle between work locations) may be an indication that those households are located centrally in close proximity to job centres. Conversely, a concentration of households whereby both commuters generally travel in the same direction (or acute angle between work locations) may indicate that one or more job centres exert significant influence (i.e. the CBD of an urban region) or that there is a lack of employment centres in the home location zone.

Figure 1. Various possible (not an exclusive set) arrangements of home and work locations of two-commuter households.
4. Study area and data for empirical investigation

The empirical investigation of this research examined NCR of Canada, which is composed of the Ottawa-Gatineau metropolitan regions, covering 4715 square km in two provinces, Ontario and Quebec. As the political centre of Canada, the NCR has the highest concentration of government workers in the country and is experiencing rapid growth in terms of jobs and housing (Armstrong and Khan 2004). The 2011 total population of the study area is roughly 1.23 million residing in approximately 500,000 households. The area is crossed by more than five major highways and has a well-developed road network system. The area is also served by a well-developed transit system. The Ontario portion of the NCR is served by an urban transit service, OC Transpo, which consists of a regular bus network and a bus rapid transit system (grade-separated dedicated bus lanes). The Quebec portion of the region is served by a regular bus network system, Société de transport de l’Outaouais. The NCR is divided into 673 traffic zones (TAZ).

An Origin–Destination (O–D) household travel survey was conducted in these TAZs. The latest O–D survey occurred in 2011 and was conducted for 5% of households in the NCR. This sample is considered to be representative of the population and is used in this study. The TRANS Committee (2013) contains a detailed report of the 2011 O–D survey. A total of 25,373 households were surveyed, 5,923 of which are two-commuter households, representing 23% of all households in the study area. The percentage of two-commuter households in the NCR is higher than that of Montreal and lower than in Toronto. However, among all two-commuter households, around 60% (a total of 3553) have both commuters making main commuting trips in the trip diaries. This subset of 3553 households is used for the empirical investigation of this study. After cleaning the data for missing values of key household and personal attributes, a sample consisting of 3225 two-commuter households is retained for empirical investigation.

It is widely recognised that mode choice behaviour is closely related to trip chaining behaviour, which includes activities that travellers take part in before and after work. This close relationship between mode choice selection and trip chaining behaviour has caused research in mode choice behaviour to shift from a trip-based to a tour-based approach in activity-based travel demand modelling (Ben-Akiva et al. 1998). Since the current study focuses on commuting trips, we do not need to consider the rest of the daily trip chain. Furthermore, since we are modelling commuting mode choice, we consider the subset of households that observed commuting trips in the trip diary dataset. Figure 2 presents the map of the study area, the road network of the study area and the distribution of investigated households among 673 TAZs. Figure 2 shows that the density of households increases towards the centre of the urban region.

The dataset retained from the O–D survey contains basic household characteristics, commuters’ personal characteristics and commuting information. To supplement the O–D survey data, we used transportation level-of-service attributes and land use attributes of the study area. Because the spatial unit of analysis is TAZ, all distances and angles are calculated at the zone centroid. Transportation level-of-service attributes are generated by a TRANS model calibrated with the 2011 O–D survey. The TRANS model is developed within EMME traffic assignment software for transportation planning activities in the NCR (TRANS Committee 2013). The relative geographic position of two-commuter households is characterised by two factors:

- the total commuting distance;
- The work1-home-work2 angle (angle between two workplaces).

It is noted that that two-commuter households make tradeoffs based on the total commuting distance of both commuters, rather than adjusting the commuting distance of individual workers separately. Furthermore, in addition to total commuting distance, the angle between two workplaces (measured from the home location) is an important consideration in residential
Figure 2. Study area and distribution of sample households in the study area.

Figure 3. Zonal average household total commuting distances and angle between two workplaces at home location. The direction of commuting of two workers has implications on possible intra-household ride sharing. Figure 3 presents the zonal average household commuting distance and angles between two workplaces at home locations. It is interesting to note that total household
commuting distance and angle are not always paired with comparable (equally high or equally low) values. This leads to the speculation that the total household commuting distance has some form of correlation with the angle that may also be a function of different spatial interaction variables.

5. Econometric modelling framework

This paper proposes a joint econometric modelling structure for household-level commuting mode choices along with total household commuting distance and the angle between two workplaces at the home location. This model captures the influence of endogenous commuting modal accessibility in defining household-level total commuting distance and the angle between two workplaces at the home location, while considering direct correlations between total commuting distance and angle. Also the correlation is explained as a function of different spatial interaction variables. Spatial interaction variables are defined by the interaction of household attributes (dwelling type, household income, etc.) with distance of home location from the CBD. The proposed econometric model has three components:

- (1) Commuting mode choices of both commuters;
- (2) Total commuting distances;
- (3) Angle between two workplaces at the home location.

Regarding household auto ownership level, households are categorised into three major categories:

- (1) No-car households;
- (2) Car-sufficient households (number of cars is more than or equal to the number of commuters with a driver’s license);
- (3) Car-deficient household (one car but two commuters with a driver’s license).

For no-car and car-sufficient households, the household-level commuting mode choices are composed of two mode choice models for two commuters. However, for car-deficient households, an additional car allocation model is necessary for allocating the car to one of the two commuters.

Figure 4 presents the schematic diagram of the modelling structures. Among the three components of the joint model, mode and car allocation models are discrete choice models and should therefore be modelled using an indirect utility-based approach. Conversely, total commuting distance and angle are continuous numbers and we consider a direct utility-based approach to be more appropriate for these components. For the discrete choice components, we use the random utility maximisation (RUM) approach, where:

- (1) The commuting mode choices of two commuters are defined by two random utility functions: $U_{\text{commute1}}$ and $U_{\text{commute2}}$;
- (2) The household-level car allocation choice for car-deficient households is defined by one random utility function: $U_{\text{allocate}}$.

All random utility functions are specified to be composed of systematic utility components ($V_{\text{commute1}}$ and $V_{\text{commute2}}$ for the commuter-specific mode choice; and $V_{\text{allocate}}$ for the car allocation choice at the household level; random utility components $\varepsilon_{\text{commute1}}$ and $\varepsilon_{\text{commute2}}$ for the commuter-specific mode choice; and $\varepsilon_{\text{allocate}}$ for the household-level car allocation choice). Each systematic utility function is considered to have the linear-in-parameter functional forms of variables and corresponding coefficients. To be generic in formulation, we do not differentiate the
two commuters in terms of any sort of hierarchy or role in the household (and we do not have this type of information in the dataset). Rather, we identified the two commuters in each household as commuter 1 and commuter 2. Equations (1)–(3) present these specifications:

\[ U_{\text{allocate}} = V_{\text{allocate}} + \varepsilon_{\text{allocate}} = \sum_{\text{allocate}} \gamma y + \varepsilon_{\text{allocate}}, \]  
\[ U_{\text{commute1}} = V_{\text{commute1}} + \varepsilon_{\text{commute1}} = \sum (\beta x)_{\text{commute1}} + \varepsilon_{\text{commute1}}, \]  
\[ U_{\text{commute2}} = V_{\text{commute2}} + \varepsilon_{\text{commute2}} = \sum (\beta x)_{\text{commute2}} + \varepsilon_{\text{commute2}}. \]  

Here, \( y \) and \( x \) refer to the sets of variables influencing car allocation and commuting mode choice. \( \gamma \) and \( \beta \) refer to the vector of coefficients corresponding to variable sets \( y \) and \( x \). Considering the choice hierarchy, it is logical that each individual commuter’s mode choice influences household-level car allocation for car-deficient households. Household-level car ownership systematically defines the need for car allocation to individual commuters, and car availability to individual commuters systematically defines the choice set for commuting mode choices of the commuters. In the RUM framework, a generalised modelling framework is proposed that can capture three possible household types. For example:

- For car-deficient households of a specific category (one car but two commuters with a driver’s license), the EMU of commuting mode choices of the individual commuters influences the allocation of car between the two commuters as well as the household’s total commuting distance and angle.
• For no-car households, the EMUs of the two commuters influence the household’s total commuting distance and angle.
• For car-sufficient households, the EMUs of the two commuters influence the household’s total commuting distance and angle.

The EMU of mode choices or car allocation choices provides a utility-based accessibility measure for total commuting distance and angle, which is the most theoretically sound and disaggregate accessibility measure (Silva 2013). As the total commuting distance and angle are continuous variables, we considered the Cobb–Douglas formulation of the direct utility function for modeling. Using the Cobb–Douglas formulation, the following formulations are assumed (Varian 1992):

\[
D = e^{\theta (EM_{\text{commute1}} + EM_{\text{commute2}}) + \sum \theta \tau e^\tau} = e^{D_{\text{par}} e^\tau},
\]

(4)

\[
A = e^{\alpha (EM_{\text{commute1}} + EM_{\text{commute2}}) + \sum \alpha \psi e^\psi} = e^{A_{\text{par}} e^\psi}.
\]

(5)

Here, \( D \) refers to the total commuting distance and \( A \) refers to the angle; \( D_{\text{par}} \) and \( A_{\text{par}} \) indicate parameterized functions of \( D \) and \( A \), where \( EM_{\text{commute1}} \) and \( EM_{\text{commute2}} \) refer to expected maximum utility mode choices of two commuters; \( C \) is a set of variables influencing total commuting distance and \( \theta \) refers to their corresponding coefficients; \( \tau \) refers to a set of variables influencing the angle and \( \alpha \) refers to their corresponding coefficients. The random utility components of distance and angle are specified by exponential functions of \( \tau \) and \( \psi \) for distance and angle.

For the econometric formulation of the proposed joint modeling structure, we need to assume the distribution types of the random components of the random utility functions defined by Equations (1)–(5). We assume that:

• The random error component of mode choice utility functions (\( \epsilon_{\text{commute1}} \) and \( \epsilon_{\text{commute2}} \)) follows an independent and identically distributed (IID) type I extreme value distribution with scale parameters \( \mu_{\text{commute1}} \) and \( \mu_{\text{commute2}} \).
• The random error component of household car allocation choice utility function (\( \epsilon_{\text{allocate}} \)) follows a IID type I extreme value distribution with scale parameters \( \mu_{\text{allocate}} \).
• The random error component (\( \tau \) and \( \psi \)) of household distance and angle follows a joint bivariate normal distribution with variances \( \sigma_D^2 \) for distance and \( \sigma_A^2 \) for angle) and the correlation between \( D \) and \( A \) is \( \rho \).

Under the IID random utility assumptions, the choices of commuting mode of the two commuters are (Ben-Akiva and Lerman 1985):

\[
P(\text{commute}_1)|\text{Ch}_1 = \frac{\exp(\mu_{\text{commute1}} V_{\text{commute1}})}{\sum_{\text{M1}\in\text{Ch}_1} \exp(\mu_{\text{commute1}} V_{\text{M1}})},
\]

(6)

\[
P(\text{commute}_2)|\text{Ch}_2 = \frac{\exp(\mu_{\text{commute2}} V_{\text{commute2}})}{\sum_{\text{M2}\in\text{Ch}_2} \exp(\mu_{\text{commute2}} V_{\text{M2}})}.
\]

(7)

Here, \( \text{Ch}_1 \) and \( \text{Ch}_2 \) are the choice sets of commuting modes for the two commuters. Such choice sets are assumed to be systematically identifiable. In the case of car-sufficient and no-car households, both choice sets are assumed to be independent and defined only by feasibilities of modal options depending on home and work destination zones. However, for households with one car but two driving-license-holding commuters, auto drive mode options in choice sets 1 and 2 are mutually exclusive, which is assumed to be defined by the car allocation model. There
are some observations of households with one car but two driving-license-holding commuters where none of the commuters were observed choosing auto driving mode. Unlike the commuting mode choice, the car allocation choice is considered to be the household-level choice and function of different household-level variables along with the EMUs of commuting mode choices of the two commuters. Under the IID type I extreme value assumption of individual commuting mode choice random utility components (Ben-Akiva and Lerman 1985), the expected maximum utilities (EM\textsubscript{commute1} and EM\textsubscript{commute2}) of commuting mode choices are:

\begin{align*}
\text{EM}_{\text{commute1}} &= \ln \left( \sum_{M_1 \in \text{Ch1}} \exp(\mu_{\text{commute1}} V_{M_1}) \right), \quad (8) \\
\text{EM}_{\text{commute2}} &= \ln \left( \sum_{M_2 \in \text{Ch2}} \exp(\mu_{\text{commute2}} V_{M_2}) \right). \quad (9)
\end{align*}

Considering IID type I extreme value distribution assumption of the random utility component, the car allocation choice among households with one car but two driving-license-holding commuters is:

\begin{align*}
\Pr(\text{allocate}_1) &= \frac{\exp(\mu_{\text{allocate}} (V_{\text{allocate1}} + \text{EM}_{\text{commute1}}/\mu_{\text{commute1}}))}{\exp(\mu_{\text{allocate}} (V_{\text{allocate1}} + \text{EM}_{\text{commute1}}/\mu_{\text{commute1}})) + \exp(\mu_{\text{allocate}} (V_{\text{allocate2}} + \text{EM}_{\text{commute2}}/\mu_{\text{commute2}}))}, \quad (10) \\
\Pr(\text{allocate}_2) &= \frac{\exp(\mu_{\text{allocate}} (V_{\text{allocate2}} + \text{EM}_{\text{commute2}}/\mu_{\text{commute2}}))}{\exp(\mu_{\text{allocate}} (V_{\text{allocate1}} + \text{EM}_{\text{commute1}}/\mu_{\text{commute1}})) + \exp(\mu_{\text{allocate}} (V_{\text{allocate2}} + \text{EM}_{\text{commute2}}/\mu_{\text{commute2}}))}. \quad (11)
\end{align*}

Here, \(\Pr(\text{allocate}_1)\) and \(\Pr(\text{allocate}_2)\) refer to the probabilities of allocating the car (making the auto driving option feasible) to commuter 1 and commuter 2.

Under a bivariate normal density assumption for the random direct utilities of total commuting distance and angle (\(\tau\) and \(\psi\) in Equations (4) and (5)), the joint probability of a distance and angle pair (DA), \(P(\text{DA})\), is (Hamedani and Tata 1975):

\begin{equation}
P(\text{DA}) = \frac{1}{2\pi \sigma_D \sigma_A \sqrt{1 - \rho^2}} \exp \left( -\frac{1}{2(1 - \rho^2)} \left[ \frac{(\ln(D) - D_{\text{par}})^2}{\sigma_D^2} + \frac{(\ln(A) - A_{\text{par}})^2}{\sigma_A^2} - \frac{2\rho(\ln(D) - D_{\text{par}})(\ln(A) - A_{\text{par}})}{\sigma_D \sigma_A} \right] \right). \quad (12)
\end{equation}

So, the joint likelihood of two-commuter households’ commuting mode choices for two commuters, the car allocation choice, total commuting distance and angle between two workplaces at home is:

\begin{equation}
L = (P(\text{commute}_1)|\text{Ch1}) \times (P(\text{commute}_2)|\text{Ch2}) \\
\times \Pr(\text{allocate}_1) \times \Pr(\text{allocate}_2) \times P(\text{DA}). \quad (13)
\end{equation}

For no-car or car-sufficient households, car allocation choice is not part of the model and hence the joint likelihood (\(L_2\)) becomes:

\begin{equation}
L = (P(\text{commute}_1)|\text{Ch1}) \times (P(\text{commute}_2)|\text{Ch2}) \times P(\text{DA}). \quad (14)
\end{equation}

This likelihood function is of the joint econometric model and of a closed form. Hence, it can be estimated by using the classical maximum likelihood estimation technique. In this research,
we programmed the joint likelihood functions in GAUSS (Aptech 2013) and the parameters are estimated by using a gradient search algorithm called the Broyden–Fletcher–Goldfarb–Shanno algorithm. This algorithm is an iterative method used in numerical optimisation for solving unconstrained nonlinear optimisation problems.

The IID assumption on the random error component of the mode choice random utility function is restrictive in capturing full substitution patterns of alternative modes. Therefore, we also considered an error component modelling approach for commuting mode choices (Train 2009). The error component modelling approach considered that the random utility components are further divided into an IID random component and a full variance-covariance random component. We rewrite Equations (2) and (3) as:

\[ \varepsilon_{\text{commute}1} = \varepsilon_{\text{commute}1}^{/} + \varepsilon_{\text{commute}1}^{//}, \]
\[ \varepsilon_{\text{commute}2} = \varepsilon_{\text{commute}2}^{/} + \varepsilon_{\text{commute}2}^{//}. \]

Here, \( \varepsilon_{\text{commute}1}^{/} \) and \( \varepsilon_{\text{commute}2}^{/} \) follow the IID type I extreme value distribution, but \( \varepsilon_{\text{commute}1}^{//} \) and \( \varepsilon_{\text{commute}2}^{//} \) have multivariate normal distribution.

A wide variety of substitution patterns can be tested with this specification. Cholesky factorisation (upper triangular matrix of the full variance-covariance matrix) is used to further specify the variance-covariance of multivariate random components inside the choice model formulation as (Train 2009):

\[ P(\text{commute}_1 | \text{Ch}_1) = \int \frac{\exp(\mu_{\text{commute}_1}(V_{\text{commute}_1} + \varepsilon_{\text{commute}_1}^{//})) f(\varepsilon_{\text{commute}_1}^{//}) d\varepsilon_{\text{commute}_1}^{//}}{\sum_{M1 \in \text{Ch}_1} \exp(\mu_{\text{commute}_1}(V_{M1} + \varepsilon_{M1}^{//}))}, \]
\[ P(\text{commute}_2 | \text{Ch}_2) = \int \frac{\exp(\mu_{\text{commute}_2}(V_{\text{commute}_2} + \varepsilon_{\text{commute}_2}^{//})) f(\varepsilon_{\text{commute}_2}^{//}) d\varepsilon_{\text{commute}_2}^{//}}{\sum_{M2 \in \text{Ch}_2} \exp(\mu_{\text{commute}_2}(V_{M2} + \varepsilon_{M2}^{//}))}. \]

The resulting likelihood functions are of a non-closed form and cannot be estimated using the classical maximum likelihood estimation technique. The maximum simulated likelihood (MSL) is widely used for estimation of such models (Train 2009). In this paper, we programmed these likelihood functions in GUASS (Aptech Systems 2013) using the MSL estimation technique. For simulation, we used the scrambled Halton sequence (SHS), which is proven to be the most efficient method that requires a low number of simulation replications (Bhat 2003). We found that with SHS, the parameter estimates stabilise within a very small number (less than 50) of simulation replications. However, we used 100 replications for the final specification.

### 6. Empirical investigation

The summary of empirical models is presented in Table 1. Two types of models are estimated: the first considers IID assumptions for the mode choice random utility component, and the second considers the error component model for mode choices. The former is identified as a non-mixed model, as the mode choice model random utility components are assumed to be non-mixed (same variance for all modes’ random utility function).

The mixed model estimates separate variances for different modes’ random utility functions and accommodates random heteroskedasticity as well as random preference heterogeneity through mixing multivariate normal distribution with IID type I extreme value distribution. The non-mixed model accommodates only the systematic heteroskedasticity through scale parameterisation. The mixed model and non-mixed model are presented for comparison purposes. Both
Table 1. Summary of empirical model estimations.

<table>
<thead>
<tr>
<th></th>
<th>Mixed model</th>
<th>Non-mixed model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>3223</td>
<td>3223</td>
</tr>
<tr>
<td>Log likelihood of the full model</td>
<td>−15,093</td>
<td>−15,238</td>
</tr>
<tr>
<td>Log likelihood of the constant-only model</td>
<td>−25,782</td>
<td>−18,133</td>
</tr>
<tr>
<td>Log likelihood of the null model</td>
<td>−55,086</td>
<td>−46,143</td>
</tr>
<tr>
<td>Rho-Square value against the null model</td>
<td>0.73</td>
<td>0.67</td>
</tr>
<tr>
<td>Rho-Square value against the constant-only model</td>
<td>0.41</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Models have very similar results in terms of expected signs; however, the magnitudes of parameters were moderately different. Since the results are similar, the ensuing discussion generally does not distinguish between the mixed and non-mixed models unless otherwise noted.

6.1. Selection of independent variables

The selection of independent variables is based on theory and a priori hypotheses regarding factors that affect mode choices. The mode choice model consists of individual specific variables and level of service attributes pertaining to travel modes. Gender and Age are alternative specific variables which reflect the difference in preferences for various modes as a function of gender and age. Of all the transportation level of service variables, only In-vehicle travel time and Cost are generic. This represents an assumption that a unit of time and/or cost has the same marginal (dis)utility regardless of the mode (Ben-Akiva and Lerman 1985). In-vehicle travel time, Cost, Age and Gender are all important considerations in mode choice studies, and have been used in models as early as the study by Lisco (1967).

Variables used in the models for Total commuting distance and Angle include Total congestion delays, Household annual income and Age. This is consistent with studies which identify the primary influence of a household’s socio-economic level, housing prices and commute travel time on home location choices (Frenkel, Bendit, and Kaplan 2013). Age is also important to consider as studies have identified that varying age groups – especially the pre-elderly – can have markedly different preferences for residence locations (Morrow-Jones and Kim 2009). The variable income was not specified for the non-mixed model as it was not found to be statistically significant. To capture land use characteristics, the variables Home zonal population density, Total transit distance by auto distance from home to work and Total transit distance by auto distance from home to the CBD are used. The latter two variables are measures of accessibility that are based on the performance of the transit system, which according to Zongag and Pieters (2005) is likely an important factor for car-deficient households. The importance of these variables is illustrated by considering the following example: having greater total transit distance than auto distance (from home to the CBD) is a characteristic of suburban areas in North American cities where population density and transit accessibility are low compared to inner core urban areas. Our intuition is that households in suburban areas commute farther distances to work due to a lack of employment centres in suburban areas. Modal accessibility, which is based on the EMU associated with travel modes, is used as an explanatory variable to draw a relationship with total commuting distance and angle.

6.2. Estimation of empirical models

The presented specifications are the final ones selected by considering expected signs and t-statistics of the parameters. We use a 95% confidence limit for one-tailed tests (critical t-statistics
value of 1.64) while investigating parameters’ statistical significance. One-tailed tests are performed since we had theoretical understanding and in some cases strong intuition regarding the effects of the variables (whether positive or negative) on the models. A small number of parameters with t-statistics lower than 1.64 are retained in the model given their importance in explaining the behaviour and that they have the expected signs. For parsimony, we normalised the variances of total commuting distance and angle to unity, but we parameterised the correlation coefficient ($\rho$) as a function of variables ($q$) and corresponding coefficients ($\eta$). In order to maintain the limits of $-1 \leq \rho \leq +1$, we used the following functional form of parameterisation:

$$
\rho = \frac{1 - \exp(q\eta)}{1 + \exp(q\eta)}.
$$

(19)

Goodness-of-fit (Rho-Square value) of the estimated models is calculated by comparing the final log likelihood values against null and constant-only models. The Rho-Square values are calculated as the difference between 1 and the ratio of the full model log likelihood value to the null or constant-only model log likelihood value. A higher Rho-Square value indicates a better fit of the joint econometric model to the observed data. The mixed model clearly shows a higher goodness-of-fit than the non-mixed model. This clearly demonstrates that there is considerable random heteroskedasticity in the commuting mode choice in the two-commuter household. It follows that the sources of randomness for choosing a different commuting mode are not the same for all modes.

### 6.3. Systematic utility functions of the mode choice model

The Alternative Specific Constant (ASC) values are not very high, which indicates that the final specification has a sufficient number of variables that explain systematic utilities of commuting models. Travel time and cost have the expected negative signs in both models. Travel distance is considered for bike and walk modes. Intuitively, it is clear that commuters who walk are more sensitive to distance than commuters who bike for commuting. Access walk time and waiting time are considered for all transit modes and have the expected negative signs. Among commuter attributes, only age and gender are found to be significant in both models. Compared to male commuters and auto driving mode, female commuters prefer the bike mode the least. Auto passengers and kiss and ride are the two most preferred modes for female commuters. Park and ride is preferable to transit-walk access mode for female commuters, and the walk mode is less than transit modes. Age plays a significant role in influencing mode choice utility. Older commuters prefer auto driving to kiss and ride, auto passenger and transit-walk access modes. However, non-motorised modes are more preferable to older commuters than younger commuters (Table 2).

### 6.4. Scale parameter of the car allocation model and mode choice model

The car allocation model is considered for households with one car and two commuters with a driver’s license. For these households, a two-level nested logit modelling framework is proposed whereby the mode choice model (lower level choice) is nested within the car allocation choice model (upper level choice). To confirm the validity of this nesting structure, the scale parameter of the lower level choice must be greater than that of the upper level choice. The scale parameters of the choice models must be checked to confirm the scale hierarchy of a joint model (Sasic and Habib 2013). The scale parameter of the car allocation choice model is referred to as the ‘root scale parameter’. In order for the proposed nesting structure to hold true, the scale parameter of the mode choice model is assumed to be the summation of the root scale parameter (or the scale
Table 2. Mode choice model-systematic utility functions.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$t$-Stat</th>
<th>Parameter</th>
<th>$t$-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ASC</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: Auto driving</td>
<td>-2.06</td>
<td>-5.85</td>
<td>-0.80</td>
</tr>
<tr>
<td>2: Auto passenger</td>
<td>0.00</td>
<td>-</td>
<td>0.00</td>
</tr>
<tr>
<td>3: Transit-walk access</td>
<td>3.38</td>
<td>12.43</td>
<td>1.30</td>
</tr>
<tr>
<td>4: Park and ride</td>
<td>-4.72</td>
<td>-4.43</td>
<td>-2.76</td>
</tr>
<tr>
<td>5: Kiss and ride</td>
<td>-4.39</td>
<td>-2.12</td>
<td>-3.42</td>
</tr>
<tr>
<td>6: Bike</td>
<td>-5.43</td>
<td>-4.17</td>
<td>-4.49</td>
</tr>
<tr>
<td>7: Walk</td>
<td>2.58</td>
<td>5.26</td>
<td>0.55</td>
</tr>
<tr>
<td><strong>In-vehicle travel time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Generic across all modes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.05</td>
<td>-16.92</td>
<td>-0.04</td>
<td>-13.76</td>
</tr>
<tr>
<td><strong>Cost (2011 Canadian dollars)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Generic across all modes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.02</td>
<td>-2.88</td>
<td>-0.02</td>
<td>-3.23</td>
</tr>
<tr>
<td><strong>Total distance</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6: Bike</td>
<td>-0.43</td>
<td>-10.64</td>
<td>0.27</td>
</tr>
<tr>
<td>7: Walk</td>
<td>-1.75</td>
<td>-20.15</td>
<td>-1.10</td>
</tr>
<tr>
<td><strong>Access walk time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3, 4, 5: Transit walk access, park and ride, kiss and ride</td>
<td>-0.01</td>
<td>-4.16</td>
<td>-0.01</td>
</tr>
<tr>
<td><strong>Waiting time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3, 4, 5: Transit walk access, park and ride, kiss and ride</td>
<td>-0.02</td>
<td>-1.77</td>
<td>-0.02</td>
</tr>
<tr>
<td><strong>Gender: female</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: Auto driving</td>
<td>0.00</td>
<td>-</td>
<td>0.00</td>
</tr>
<tr>
<td>2: Auto passenger</td>
<td>0.83</td>
<td>8.55</td>
<td>0.57</td>
</tr>
<tr>
<td>3: Transit-walk access</td>
<td>0.44</td>
<td>5.63</td>
<td>0.29</td>
</tr>
<tr>
<td>4: Park and ride</td>
<td>0.62</td>
<td>2.73</td>
<td>0.42</td>
</tr>
<tr>
<td>5: Kiss and ride</td>
<td>0.82</td>
<td>2.55</td>
<td>0.82</td>
</tr>
<tr>
<td>6: Bike</td>
<td>-0.77</td>
<td>-4.00</td>
<td>-0.58</td>
</tr>
<tr>
<td>7: Walk</td>
<td>0.18</td>
<td>1.04</td>
<td>0.16</td>
</tr>
<tr>
<td><strong>Logarithm of age</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: Auto driving</td>
<td>0.00</td>
<td>-</td>
<td>0.00</td>
</tr>
<tr>
<td>2: Auto passenger</td>
<td>-1.31</td>
<td>-12.43</td>
<td>-0.92</td>
</tr>
<tr>
<td>3: Transit-walk access</td>
<td>-1.26</td>
<td>-13.43</td>
<td>-0.75</td>
</tr>
<tr>
<td>4: Park and ride</td>
<td>-0.72</td>
<td>-2.60</td>
<td>-0.20</td>
</tr>
<tr>
<td>5: Kiss and ride</td>
<td>-1.53</td>
<td>-2.63</td>
<td>-0.48</td>
</tr>
<tr>
<td>6: Bike</td>
<td>0.71</td>
<td>3.04</td>
<td>0.75</td>
</tr>
<tr>
<td>7: Walk</td>
<td>0.49</td>
<td>3.16</td>
<td>0.45</td>
</tr>
</tbody>
</table>

**Exponential function of the root scale parameter for car allocation in 1 car household**

| Number of car per household members | 0.21 | 4.50 |
| Logarithm of the ratio of total transit distance from home to two work places by auto distance from home to two work places | 0.19 | 2.78 |

**Household annual income:**

- **$0–$29,999**
  - 0.22 | 3.20 |
- **$30,000–$59,999**
  - 0.06 | 1.46 |

**Additional exponential function to the root scale parameter function for the mode choice**

| Household size | -6.00 | -0.40 |
parameter of the car allocation choice model) and an additional exponential function which is parameterised to capture the heteroskedasticity across two-commuter households.

### 6.5. Systematic utility of car allocation choice model

The car allocation choice model has three variables in addition to the EMU of mode choices. Among these variables, job status shows the highest value coefficient. It seems that in car-deficient households, commuters with a full-time job have a higher utility in using the car. Males also have higher priority in using the car for the auto driving mode. Also, it is clear that the commuter who has a longer transit commuting distance than auto distance in the household has a higher preference to use the car. This is reflected in the positive coefficient for the *ratio of transit distance by auto distance* (Table 3).

### 6.6. Workplace1-home-workplace2 angle of two-commuter households

This study does not model home location choice and as such we do not draw definitive conclusions that a causal relationship has been identified. Rather, this study aims to identify any positive or negative correlations between modal accessibility and the home–work spatial configuration attributes. The direct utility function of the angle between two workplaces at the home location is significantly affected by the EMU of the two commuters’ commuting mode choices. The positive coefficient of total EMU indicates that a higher modal accessibility leads to a wider angle. A wider angle signifies that the home location tends to be in between two workplaces (closer to the centre line connecting two workplaces); the widest possible angle is 180 degrees, when the home location is anywhere on the straight line between two workplaces. Household annual income plays a significant role in defining the angle. In this study, annual household incomes between $30,000 and $59,999 have a positive correlation with the angle leading to a home location with wider angles. Also, annual household incomes between $60,000 and $89,999 have a negative correlation with the angle leading to home locations with narrower angles. Transit accessibility from home to the CBD plays a significant role in influencing the degree of angle. We found that the logarithm of the ratio of travel distance by transit to the total distance by car transit accessibility measure is significant in the model. It is clear that longer distances of the transit route from home to the CBD lead to a narrower angle.

Similarly, we found that the logarithm of the ratio of total travel distance by transit to total distance by car for home to two workplaces significantly influences the angle between two workplaces at the home location. It is clear that a longer distance of transit route from the home to two workplaces is positively correlated with the angle leading to home locations with wider angles. In other words, longer transit distances than driving distances encourages two-commuter households to choose a home location with a wider angle between two workplaces. Similarly, the

Table 3. Car allocation model-systematic utility function.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter</th>
<th>t-Stat</th>
<th>Parameter</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of transit distance by auto distance</td>
<td>0.89</td>
<td>17.56</td>
<td>0.74</td>
<td>7.80</td>
</tr>
<tr>
<td>Job status: full time</td>
<td>2.52</td>
<td>14.98</td>
<td>1.79</td>
<td>9.64</td>
</tr>
<tr>
<td>Gender: male</td>
<td>0.51</td>
<td>3.46</td>
<td>0.34</td>
<td>3.21</td>
</tr>
<tr>
<td>EMU of mode choice model</td>
<td>1.00</td>
<td>–</td>
<td>Inverse of scale parameter of mode choice model</td>
<td></td>
</tr>
</tbody>
</table>
location of two workplaces relative to the CBD, measured by the angle between the two workplaces at the CBD, plays a significant role in influencing the angle between two workplaces at the home location. It appears that a wider angle between two workplaces at the CBD is associated with a wider angle between two workplaces at the home location. We also considered congestion delays, measured as the difference between actual auto travel times and free-flow auto travel time, as a variable in the model. The result shows that higher congestion delays are associated with a wider angle.

Home zone population density is a significant variable and it is clear that a denser home zone is associated with a wider angle between workplaces at the home location. A higher average age of the two commuters also leads to a wider angle. This indicates that older pairs of workers tend to locate their home in between two workplaces, which results in a wider angle (Table 4).

### 6.7. Total commuting distance

As expected, it is clear that the higher EMUs of the commuting mode choice reduce the total commuting distances of two-commuter households. A higher EMU indicates higher modal accessibility. If modal accessibility is high, the two-commuter households do not need to be located far away from the workplaces. Unlike the direct utility function of the angle, we did not find household income categories as significant variables in the model. Transit accessibility from home to the CBD plays a significant role in influencing total commuting distance. The results show that the logarithm of the ratio of travel distance by transit to the total distance by car from home to the CBD transit accessibility measure is significant in the model. It is clear that a longer transit distance of the transit route from home to the CBD leads to a shorter total commuting distance. Similarly, relative transit accessibility from home to two workplaces plays a significant role in influencing total commuting distances. We found that the logarithm of the ratio of total travel distance by transit to total distance by car for the home to two workplaces significantly influences total commuting distances. It is clear that a longer distance of transit route from home to two workplaces influences a longer total commuting distance.

The relative location of two workplaces from the CBD measured by the angle between two workplaces at the CBD plays a significant role in influencing total commuting distances. It

<table>
<thead>
<tr>
<th></th>
<th>Mixed model Parameter</th>
<th>Mixed model t-Stat</th>
<th>Non-mixed model Parameter</th>
<th>Non-mixed model t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.38</td>
<td>-2.21</td>
<td>-0.39</td>
<td>-1.46</td>
</tr>
<tr>
<td>Logarithm of total congestion delays (minutes)</td>
<td>0.08</td>
<td>7.46</td>
<td>0.04</td>
<td>2.39</td>
</tr>
<tr>
<td>Angle of two workplace with the CBD divided by 180</td>
<td>2.10</td>
<td>32.20</td>
<td>2.17</td>
<td>23.88</td>
</tr>
<tr>
<td>Logarithm of the ratio of total transit distance from home to two workplaces by auto distance from home to two workplaces</td>
<td>2.52</td>
<td>24.17</td>
<td>2.42</td>
<td>12.87</td>
</tr>
<tr>
<td>Logarithm of average age of two workers</td>
<td>0.42</td>
<td>11.79</td>
<td>0.38</td>
<td>7.39</td>
</tr>
<tr>
<td>Logarithm of home zone population density in 10,000</td>
<td>0.01</td>
<td>1.50</td>
<td>0.03</td>
<td>1.95</td>
</tr>
<tr>
<td>Logarithm of the ratio of total transit distance from home to the CBD by auto distance from home to the CBD</td>
<td>-0.54</td>
<td>-3.93</td>
<td>-0.53</td>
<td>-2.19</td>
</tr>
<tr>
<td>Household annual income: $60,000–$89,999</td>
<td>-0.15</td>
<td>-3.27</td>
<td>0.00</td>
<td>–</td>
</tr>
<tr>
<td>Household annual income: $30,000–$59,999</td>
<td>0.04</td>
<td>1.23</td>
<td>0.00</td>
<td>–</td>
</tr>
<tr>
<td>Sum of expected maximum utilities of mode choices</td>
<td>0.18</td>
<td>19.76</td>
<td>0.18</td>
<td>9.28</td>
</tr>
</tbody>
</table>
Table 5. Total commuting distances.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mixed model Parameter</th>
<th>t-Stat</th>
<th>Non-mixed model Parameter</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2.04</td>
<td>9.90</td>
<td>1.66</td>
<td>5.23</td>
</tr>
<tr>
<td>Logarithm of total congestion delays (minutes)</td>
<td>0.26</td>
<td>10.15</td>
<td>0.16</td>
<td>8.55</td>
</tr>
<tr>
<td>Angle of two work places with the CBD divided by 180</td>
<td>–</td>
<td>0.13</td>
<td>–</td>
<td>1.19</td>
</tr>
<tr>
<td>Logarithm of the ratio of total transit distance from home to two work places by auto distance from home to two work places</td>
<td>–</td>
<td>0.18</td>
<td>–</td>
<td>0.84</td>
</tr>
<tr>
<td>Logarithm of average age of two workers</td>
<td>–</td>
<td>0.08</td>
<td>1.16</td>
<td></td>
</tr>
<tr>
<td>Logarithm of home zone population density in 10,000</td>
<td>-0.10</td>
<td>-2.65</td>
<td>-0.07</td>
<td>-4.50</td>
</tr>
<tr>
<td>Logarithm of the ratio of total transit distance from home to the CBD</td>
<td>-0.44</td>
<td>-1.61</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household annual income: $60,000-$89,999</td>
<td>-0.16</td>
<td>-0.75</td>
<td>0.00</td>
<td>–</td>
</tr>
<tr>
<td>Sum of expected maximum utilities of mode choices</td>
<td>-0.16</td>
<td>-5.27</td>
<td>-0.37</td>
<td>-13.65</td>
</tr>
</tbody>
</table>

Table 6. Correlation between angle and distance.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mixed model Parameter</th>
<th>t-Stat</th>
<th>Non-mixed model Parameter</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.26</td>
<td>-2.17</td>
<td>-0.18</td>
<td>-3.59</td>
</tr>
<tr>
<td>‘Driving distance from home to CBD’ × ‘dwelling type: apartment/condos’</td>
<td>-0.01</td>
<td>-0.96</td>
<td>-0.01</td>
<td>-1.01</td>
</tr>
<tr>
<td>Household annual income greater than $119,999</td>
<td>0.05</td>
<td>0.31</td>
<td>0.07</td>
<td>1.17</td>
</tr>
<tr>
<td>Angle between two work places at the CBD normalised by 180</td>
<td>-0.20</td>
<td>-0.54</td>
<td>-0.20</td>
<td>-1.28</td>
</tr>
</tbody>
</table>

appears that a wider angle between two workplaces at the CBD is associated with longer commuting distances. We also considered congestion delay measured as the difference between actual auto travel times to free-flow auto travel time as a variable in the model. It is clear that higher congestion delay is associated with longer total commuting distances. Home zone population density is a significant variable and it is evident that a denser home zone is associated with shorter total commuting distances. A higher average age of two commuters leads to longer total commuting distances (Table 5).

6.8. Correlation between angle and total commuting distance

We used spatial variables to parameterise the correlation coefficient between unobserved factors affecting utilities of commuting distance and the angle. It becomes evident that larger angles between two workplaces at the CBD increase the negative correlations between angle and total commuting distance. However, a higher annual income reduces the correlation between total commuting distance and the angle. The driving distance from home to the CBD is interacted with apartment/condo dwelling type. It is found that with increasing distances from the CBD, the negative correlation between total commuting distance and angle reduces (refer to Table 6).
7. Conclusions and recommendations for future research

It is speculated that two-commuter households may not always be able to optimise the home location. This is reflected in the NCR’s 2011 household travel survey, which demonstrates that two-commuter households are highly auto-dependent (the auto driving mode makes up 47% of commuting trips and more than 60% of households are car sufficient). Moreover, shared commuting modes (e.g. auto passenger and transit kiss and ride) have a lower modal share than one would expect for two-commuter households. These statistics lead to the speculation that perhaps the NCR’s existing urban form and transportation system may not favour two-commuter households’ ability to optimise home location relative to the two commuters’ workplaces. When the home location is in an auto-centric area outside the CBD and the work locations are in the CBD and the angle between them is small, thus indicating poor home location optimisation opportunities. Ideally speaking, the optimum home location of two-commuter households should be along the line connecting the two work locations. This pattern would result in a shorter total commuting distance coupled with a wider angle. A favourable urban form and transportation system would at least induce a high and negative correlation between total commuting distance and angle.

The results of this study show that the closer the home location is to the work location, a high and negative correlation between the two attributes is observed. A mixed use urban form would be favourable as it creates more opportunities for home and work to be located in close proximity. A larger transportation system that brings service to more areas would be favourable as it can increase the modal accessibility of a greater number of households.

In order to test this theory, we used the NCR’s 2011 household travel survey dataset and an econometric modelling framework of jointly modelled commuting mode choices for two commuters, including total commuting distance and the angle between their two workplaces at the home location. The empirical model shows a very high goodness-of-fit to the observed dataset, which indicates the appropriateness of the proposed econometric modelling framework for the intended investigation.

As expected, the empirical model reveals that increasing commuting mode choice accessibility allows a wider angle and shorter total commuting distance. Although total distance and the angle should be negatively correlated, it appears that modal accessibility has a moderately higher impact on angle than total commuting distance. The results of this study reveal that modal accessibility has a parameter of 0.18 and −0.16 for the angle and total commuting distance, respectively. Empirical models also reveal that greater modal accessibility is associated with two-commuter households located in between two workplaces, creating a wider angle between two workplaces at the home location. In reality, a wide variety of combinations of angle and distance is possible. The widest angle (180°) may be paired with the shortest total commuting distance if the home is located in between two work locations. However, the angle can be 180°, but the total commuting distance may increase if the home is located on the straight line connecting two work places, but not in between two work places.

In fact, land use (which dictates availability of homes and workplaces) and the transportation system play role in defining these combinations. So, in reality the angle and total commuting distance may not always be in perfect correlation with each other. We identified that many variables, such as transit accessibility to jobs, transit accessibility to the CBD, transit accessibility to workplaces, household income, age of the commuters and congestion delays, among other factors, reduced the correlation between total commuting distance and angle. The understanding is that focusing only on commuting distance and/or considering the angle as an exogenous variable will not sufficiently capture the home location choice tradeoffs of two-commuter households.

In the NCR, it seems that two-commuter households are not able to optimise their home location. We find that two-commuter households are highly auto-dependent and shared modes are not preferred travelling options. These are all indicators of two commuters within the household.
7.1. Policy implications

Policies suggested as a result of this study are aimed at improving the ability of two-commuter households to optimise their home location. The basis of these suggestions is the assumption that optimal home locations result in shorter daily trips to work which consequently alleviate strains on the transportation infrastructure by reducing automobile use and road congestion.

In this study, high modal accessibility implies that there are multiple transportation options or mode choices for work trips. Home locations without direct access to public transportation or where the only viable transportation option is the automobile could be considered to have a lower level of modal accessibility than a home location that is within a short distance to a bus route or subway stop. Results of this study indicate that if modal accessibility is high, there is generally a shorter total commuting distance to the two work locations. For the most part, access to automobile travel is largely a function of household income or the financial ability to own and operate an automobile. Therefore the policy implications referred to herein do not deal with increasing modal accessibility through improving transportation via the automobile. Instead, the results of this study are used to suggest improving access to public transit, which can be influenced by transportation and land use policies. Transportation policies should be aimed at providing public transit service where it currently does not exist. Expanding public transit coverage may be more beneficial to the optimisation of home locations than improving frequency of service on existing transit lines as it would increase the modal accessibility of a greater number of households. Ultimately, transportation policies should reduce household reliance on the automobile for daily work trips.

Results of this study show that total commuting distances become less responsive to changes in the position of the home location relative to the two work locations as the home location moves away from the CBD. This finding is consistent with the geometry of a triangle. Suppose two fixed points on a triangle represent the work locations (consider Figure 1(b)). Moving the third point, representing the home location, away from the line connecting the two fixed points would result in a reduced correlation between angle and distance. In other words, reduced correlation between angle and distance is a property of the third point’s distance. If the third point (home location) was located in an area closer to the two fixed points (work locations), correlation would be higher. Since the correlation holds for this study, it is an indication that households located far from the CBD also work primarily in the CBD or in job centres situated away from the residential zones, and therefore have longer commuting distances.

This ultimately inhibits them from optimally locating. Land use policies which direct activity centres to areas located far from the CBD that may be dominated by residential land uses can create opportunities to optimise home location. A land use policy framework that promotes a mix of uses (including office, commercial and retail) can help to establish workplaces outside of the CBD, allowing two-commuter households to live and work in closer proximity, thus reducing the need to travel into the CBD for work. For instance, when both workers in a household travel from their suburban dwelling to the CBD for work, the angle created between the home location and workplaces is very small, which is an indicator of poor home location optimisation. Land use policies (i.e. zoning by-law designations) that require new development outside the CBD...
to include office space or other forms of employment uses can help to create a more complete environment where all types of destinations are accounted for.

7.2. Future research

This research focused on the existing conditions in the NCR and investigated the relationship between commuting modal accessibility and the total commuting distances and the angle between two workplaces at the home location. In the proposed econometric modelling framework, home and work locations are given as exogenous inputs to the model. However, for future research, a more comprehensive modelling framework could include jointly modelled home and work location choices. Also, work locations and opportunities are not as flexible as leisure activities. We surmise that modal accessibility to work locations is a more important determinant of home location choices than modal accessibility to leisure activities. Nevertheless, it would be interesting to estimate a similar model as described in this paper, however considering non-commuting trips to assess whether the findings of this paper also hold non-commuting trips.

The empirical investigation of this research reveals facts that raised further questions on the reason for the findings. Though it is beyond the scope of this study, it would be interesting to combine this investigation with job location choice as well as directions of commuting. Further data on employment distribution and more detailed land use information would be necessary to do so, and these are considered for future investigations.

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References


