Life History-oriented Residential Location Choice Model: A Stress-based Two-tier Panel Modeling Approach

Abstract

This paper presents a life history-oriented modeling framework to investigate residential location decisions as a two-tier process of location search and location choice. In the first tier, a stress-based location search model is developed by assuming that households search for a new location due to the continual generation of stress at different life-domains. The search model adopts a fuzzy logic-based modeling method that mimics the inter-dependencies between push and pull factors. In the second tier, a location choice model is developed that accommodates how location decisions interact with life-cycle events at different life-domains. The model utilizes a latent segmentation-based logit modeling technique to address the panel effect of the households' housing career. The model results suggest that households in general show preference for larger lots, and locations closer to work place, transit stop, and health service. Location choice is found to be significantly influenced by life-cycle events as well as lead and lagged effects. For example, birth of a child magnifies the need of larger lots. The life-history effects however vary across two segments. Suburbanite households in segment two prefer larger lots following job change; whereas, urbanite households in segment one show a negative relationship. The adjustment period for job change is found longer than that of addition of a new job. A longer adjustment time is also found for first time vehicle purchase compared to vehicle acquisition. Presence of children influences suburbanite households to reside closer to work place; in contrast, urbanite households with children prefer to live closer to school. The proposed model offers behavioral insights for policy making and adds capacity in a life-oriented large-scale simulation modeling of urban system.

Keywords: Life history-oriented Approach; Residential Stress; Location Search; Location Choice; Fuzzy Logic Model; Latent Segmentation-based Logit Model

1. Introduction

Choice of residential location evolves over the life-time of the households, as they move from one location to another along the life-course. Households relocate due to the continual generation of residential stress along their life-time (Rossi 1955). Residential stress is induced by the life-cycle events and decisions in different life-domains, which causes discrepancies between the desired and current situation, and results in the aspiration to reside in certain locations. Hence, location choice interacts with multi-domain decisions and changes occurring at different life-stages of the households (Zhang 2015). The interactions have a temporal dimension as lead and lagged effects, since households require an adjustment period to adapt prior or after a change in life-stage (Oakil et al. 2014). Moreover, location decision has an inherent process orientation in relation to location search and location choice. While households decide to move, they first undertake a search process to identify potential location alternatives and finally move to a location. Although a vast amount of literature exists on modeling residential location decisions (Pinjari et al. 2011, Eluru et al. 2010, Gehrke et al. 2014, Lee and Waddell 2010), limited studies have focused on the multi-domain interactions and behavioral dynamics of the process. Life-course perspective offers the opportunity to map such process orientation and interactions among different life-domains. Life-course perspective addresses the whole life-time or segment of a life-time, and focuses on how interactions among the multi-domain decisions and life-cycle events along the life-time shape people's behavior (Zhang 2015, Chatterjee and Scheiner 2015). Therefore, the research question for this study is: how to develop a modeling framework which is consistent with the theoretical underpinning of the life-course perspective that captures the behavioral process of search and location choice, and improves the empirical estimation?

This study proposes a life history-oriented modeling framework that addresses the complex temporal dynamics of the location choice process and captures how location choice interacts with multi-domain changes and decisions evolving over the life-course of the households. Residential location choice is modeled as a two-tier process of location search and location choice. In the first tier, a stress-based location search model is developed. The search model assumes that households search for locations on the basis of the residential stress generated by the life-cycle events and decisions occurring at different life-domains. The residential stress acts as a push factor and the characteristics of the location that holds the potential to minimize the stress acts as a pull factor. The search model assumes that households' search process is constrained by their affordability. Hence, constraints regarding household income and property value are imposed in the search model. The proposed search model follows a fuzzy logic-based modeling method, which offers a mechanism to recognize the release of stress by minimizing discrepancies between the current and aspiration level. The modeling process of fuzzy logic accommodates the stress-driven theoretical framework by addressing the inter-dependencies between push and pull factors. The push and pull factors continuously evolve with the changing stress of the households over the life-course.

In the second tier, location choice is modeled, where households choose a location from the pool of alternatives generated in the first tier. The model disentangles the effects of decisions and changes at different life-domains; for example, how purchase of a car, job change, addition of a job, and birth of a child, among others, interact with location choice. The model also addresses the influence of timing of such multi-domain decisions by examining the lead and lagged effects. The location choice model is developed utilizing a latent segmentation-based logit (LSL) modeling technique. The LSL model assumes that correlated sequence of choices exists due to the repeated choices made by the same households during their housing career. The model captures unobserved heterogeneity among the sample households by allocating them into discrete latent segments using a flexible segment allocation model within the LSL framework. Hence, the model offers the opportunity to test the variation in location preferences by life-history attributes among the households in different latent segments. The models developed in this study uses data from a retrospective Household Mobility and Travel Survey (HMTS) 2012-2013 conducted in Halifax, Canada. The models are developed at the most fine-grained spatial choice unit of parcel.

The remainder of the paper is organized as follows: the second section provides a brief discussion on the theoretical framework used in this study and the context of the study. The third section describes the data used for the empirical application. The fourth section discusses the modeling approach, followed by a discussion of the independent variables used in the model in the fifth section. Model fit comparisons along with discussion of results are presented in the sixth section. Finally, the paper concludes with a summary of contributions and future works in the seventh section.

2. Theoretical Framework and Context

Life history-oriented approach, also known as life-course perspective, focuses on the inter-dependencies among the decisions and changes occurring at different domains along the life-time of the people (Zhang 2015). Zhang et al. (2011) identified eight major life-domains, such as residence, job, education and learning, health, family life, family budgets, neighborhood, and leisure and recreation; and revealed that interactions exist among the decisions taken in different life-domains. To develop better empirical models of household-level decision processes, it is imperative to examine changes in multiple life-domains, since choices at any domain are part of the extended inter-connected choices made hierarchically across different domains (Salomono and Ben-Akiva 1983, Lanzendorf 2003).

Life-course perspective emphasizes on how changes along the life-course shape individuals' or households' behavior (Chatterjee and Scheiner 2015). The changes during life-course include life-events and decisions taken at different stages along the life-time (Oakil et al. 2014). Such life-events and decisions include birth of a child, getting a job, job change, and household formation, among others (Habib and Miller 2009). Unlike conventional cross-sectional modeling approaches, which focus on a snapshot of an individual's life-time; the life-oriented approach considers the whole life-time or a segment of the life-time (Chatterjee and Scheiner 2015). Among the decisions taken at different life-domains, residential location choice is one of the most critical decisions; since decisions of where to live significantly interacts with decisions of the same domain (i.e. where to work) and decisions in other domains (i.e. whether or not to own a vehicle, and when to make a trip). Therefore, the residential location choice models need to disentangle the relationship among multi-domain choices and decision outcomes.

The theory of residential stress is a mechanism to address the interactions among the changes at different life-domains (Rossi 1955). The theory suggests that household's decision to move from a residential location is triggered by residential stress, which is generated by the experienced or desired changes in life-stages (Miller 2005), dwelling characteristics (Van Ham and Feijten 2008), and neighborhood attributes (Van Ham and Clark 2009), among others. Such stress arises from discrepancies between the desired and current situation of a household. As a result, households search for locations that hold the potential to minimize their stress. Empirically, residential stress can be disentangled by push and pull factors that generate continuous frictions between why a household would like to move and what they would like to achieve. In other words, the changes occurring at different life-stages are push factors, whereas the characteristics of the location that act as attractors to minimize stress are pull factors. For example, increase in commute distance due to job change acts as a push factor to relocate, if households desire to maintain shorter commute distance. Households with such stress search for locations that are close to their work place, which acts as a pull factor. Finally, the stress is released by relocating to one of the searched locations.

Majority of the previous studies on residential location choice are static in nature as they ignore the interactions of multi-domain life-stage changes and the process orientation of search and location choice. Some studies have attempted to investigate the search process. For example, Rashidi et al. (2012) developed a housing search model on the basis of commute distance and average land value, Fatmi et al. (2015) developed a search model based on distance to the CBD, and Bhat (2015) developed a probabilistic search model using multidimensional housing attributes. However, such attempts to address the search process have not warranted improvements in the empirical estimation of location choice models compared to the traditional random sampling models (Zolfaghari et al. 2012). Further examination of the phenomenon is necessary, which should address the process orientation of the location search and location choice.

Some studies have taken life-course perspective to examine how changes along the life-time influences location choice. For example, Habib and Miller (2009) developed a reference dependent mixed logit model to investigate the role of status quo and response towards gains and losses during making location decisions. Chen and Lin (2011) investigated the effects of historical deposition on location decisions and argued that the choice of prior locations has an influence on the choice of the subsequent locations. Strom (2010) revealed that birth of the first child is associated with the choice of larger-sized dwelling with a higher number of rooms. Kim et al. (2005) argued that households with young children prefer to reside in locations on the basis of educational opportunities, residential facilities, and open spaces. The study also argued that households start to value job accessibility as children grow older. Recently, few studies have examined the effects of timing of life-cycle events on vehicle ownership level (Oakil et al. 2014), vehicle transaction (Fatmi and Habib 2016a), and mode transition decisions (Oakil et al. 2011, Fatmi and Habib 2016b). It is critical to address the timing of an event, since households require adjustment period to adapt prior or after an event in the life-course. Oakil et al. (2014) conducted a panel analysis to investigate the effects of life-cycle events on vehicle disposal and acquisition decisions. They revealed that households require adjustment period before and after a life-cycle event. For example, households were found to purchase a vehicle in anticipation of child birth and dispose of a vehicle after changing job. The modeling paradigm of residential location choice also needs to examine whether there is any adjustment period required before or after a change in the life-stage. It is also necessary to evaluate how the adjustment period affects the relationship. Hence, a life history-oriented approach is required to further examine the lead and lagged effects of the life-cycle events and multi-domain decisions during modeling location choice process.

Based on the needs and gaps in the literature, this study will contribute in two ways: (1) by developing empirical location models that explicitly demonstrate the process orientation, and (2) by examining how location choice interacts with life-cycle events at different life-domains as lead and lag events. This study addresses the process orientation of location decisions by modeling the phenomenon as a two-tier process of location search and location choice. The continuously evolving nature of the process over households' life-time is addressed by undertaking a panel modeling approach. The search model conceptualizes on the theory of residential stress. Residential stress is assumed to be induced by life-cycle events and decisions at different life-domains (also known as a reason for a relocation decision). The search model is developed following a fuzzy logic modeling method. The push and pull factors are mapped within the process of the fuzzy logic method to generate a pool of location alternatives, which has the potential to minimize the stress. The location choice model is developed using the outcomes of the search model that generates a pool of alternative locations. The inter-dependencies between location choice and life-cycle events are explored by extensively testing a number of hypotheses. For example, how the plan to buy a car influences residential location choice? does acquisition of a car in the existing vehicle fleet and first time vehicle purchase have the same influence? how change in job affects residential location choice? and does change in job and addition of a job have the same influence? To explore the influence of timing of critical events, the effect of adjustment period required to adapt prior or after an event is tested as lead and lagged effects. The major hypotheses regarding the effects of adjustment period includes, how the effects of an event in anticipation and an event on occurrence differs? and how the adjustment period varies for different events? In addition, the study examines whether the influence of life-cycle events varies by population segments or not? The variation in the effects of life-history attributes among different population segments is addressed within the modeling framework by adopting a latent segmentation-based logit (LSL) modeling technique. The LSL model captures unobserved heterogeneity by allocating households into discrete latent segments. The LSL model also accounts for the life-trajectory dynamics by assuming that the repeated choices made by the households along their life-course are correlated.

3. Data Description and Preparation

The retrospective Household Mobility and Travel Survey (HMTS) conducted from September 2012 to April 2013 in Halifax, Canada, is the primary source of data for this study. The HMTS collected information across the life-domains of the households. The survey asked respondents to provide details on their housing history, employment career, compositional change in the household and employment size, and vehicle ownership history, among others. The housing history component collected information regarding the three most recent residential episodes of the respondents. For each residential episode, respondents were asked to provide their location information, year and month of relocation, and corresponding socio-economic and demographic configuration, and dwelling characteristics. In addition, respondents identified their primary reasons for relocation for each residential episode. The reasons are thematically aggregated into the following four major categories: (1) to live in proximity to work and key activity locations, such as school, shopping center, entertainment, and transit stop; (2) to live in desirable neighborhood or dwelling; (3) due to life-cycle events such as change in household size and formation of a new household; and (4) other reasons. These reasons are the push factors. The pull factors are constructed in a way, which holds the potential to minimize the stress for the aforementioned reasons for move. The employment career component collected information of the three most recent employments, including employment location, employment type, employment starting and ending year and month. The compositional change in the household and employment size component asked the respondents to provide the year of household size change due to birth, death, member move out, and new member move in; and the year of employment size change due to addition of job, loss of job, retirement, withdrawal from labor force, and returning to school. The vehicle ownership component includes detail information up to four current and four previous vehicle ownerships.

The HMTS provided a total response from 475 households. Approximately 50% of respondents reside in urban areas and 38% reside in suburban areas. The survey sample has almost an equal ratio of male and female respondents. 31% of the respondents have an annual household income below \$50,000 CAD, and 33% above \$100,000 CAD. The sample characteristics of the HMTS was compared with the Statistics Canada Census by Salloum and Habib (2015). Majority of the stratums of household and individual characteristics were within a 3% variability of the Census information for Halifax Regional Municipality (HRM). Therefore, the HMTS can be considered a representative sample. This study considers home owners only for the purpose of modeling residential location choice. A total of 385 residential location choice observations of the home owners are derived from the HMTS.

Among the secondary data sources, Nova Scotia Property Database 2013 provides detail parcel attributes of all the parcels in Nova Scotia, including parcel location, size, and type. A total of 110,995 parcels in HRM are derived from the Nova Scotia Property Database. Additional data sources include location of different activity points, such as location of schools, central business district (CBD), transit stops, business parks, health services, park areas, and shopping centers; which are collected from the Desktop Mapping Technologies Inc. (DMTI). The location of activity points are utilized to determine the accessibility measures from each parcel. The accessibility measures are generated on the basis of the road network distances using the Network Analyst tool in ArcGIS. Moreover, land-use data at the dissemination area (DA) level are collected from the HRM. The land-use information measured on the ArcGIS platform are utilized to determine land-use indices, which follows the measures proposed in Bhat and Gossen (2004). Finally, 2011 Census information collected from the Statistics Canada provides neighborhood characteristics at the DA level.

4. Modeling Approach

Figure 1 presents a conceptual framework of the fuzzy logic-based location search model developed in this study. The first step in the stress-based fuzzy logic model is fuzzification that generates constraint sets for the push factors and opportunity sets for the pull factors. The constraint sets represent input sets and the opportunity sets represent output sets in the fuzzy logic modeling framework. Four major reasons for relocation derived from the HMTS data are considered as the push factors: to live in proximity to work/key activity locations (14.29%), to live in desirable neighborhood/dwelling (46.75%), due to life-cycle events (21.56%), and other reasons (17.40%). Since households' choices of residential locations are strongly influenced by their affordability, such as income (Guo and Bhat 2007) and average value of the property (Rashidi et al. 2012), this study makes *a priori* assumption that each push factor is constrained by these two parameters. Therefore, in the fuzzification stage, constraint sets in relation to household income and average value of the property for each push factor are generated.

The pull factors are the characteristics of locations that attract households to consider a location to relocate. This study conceptualizes that an inter-dependent relationship exists between the push and pull factors. For example, households relocating to live closer to work locations are expected to search for locations that are closer to their work place on the basis of their income and average value of the property. Hence, the push factor "to live in proximity to work/key activity locations" is assumed to correspond to the pull factor "distance to work location". In the case of households relocating to live in a desirable neighborhood/dwelling, households are assumed to search for locations that have a higher percentage of non-movers in the neighborhood. Generally, desirable neighborhoods refer to the neighborhoods with reputed schools and open spaces (i.e. park areas) in close proximity, and lower crime rates, among others (Latkin and Curry 2003, Guo and Bhat 2002). Population residing in such quality neighborhoods are expected to move less frequently. Hence, the push factor "to live in desirable neighborhood/dwelling" is assumed to correspond to the pull factor "percentages of non-movers in the neighborhood". Households relocating due to life-cycle events are assumed to search for locations based on the distance from CBD. Life-cycle events such as household formation (i.e. marriage, living common-law) and change in household size (i.e. birth of a child, death of a member, move-in and -out of members) influence households' decisions to live in urban or suburban/rural neighborhoods. For example, households with children prefer suburban and rural areas, since they value accessing open space, cleaner air and water (Cummins and Jackson 2001). On the other hand, households without

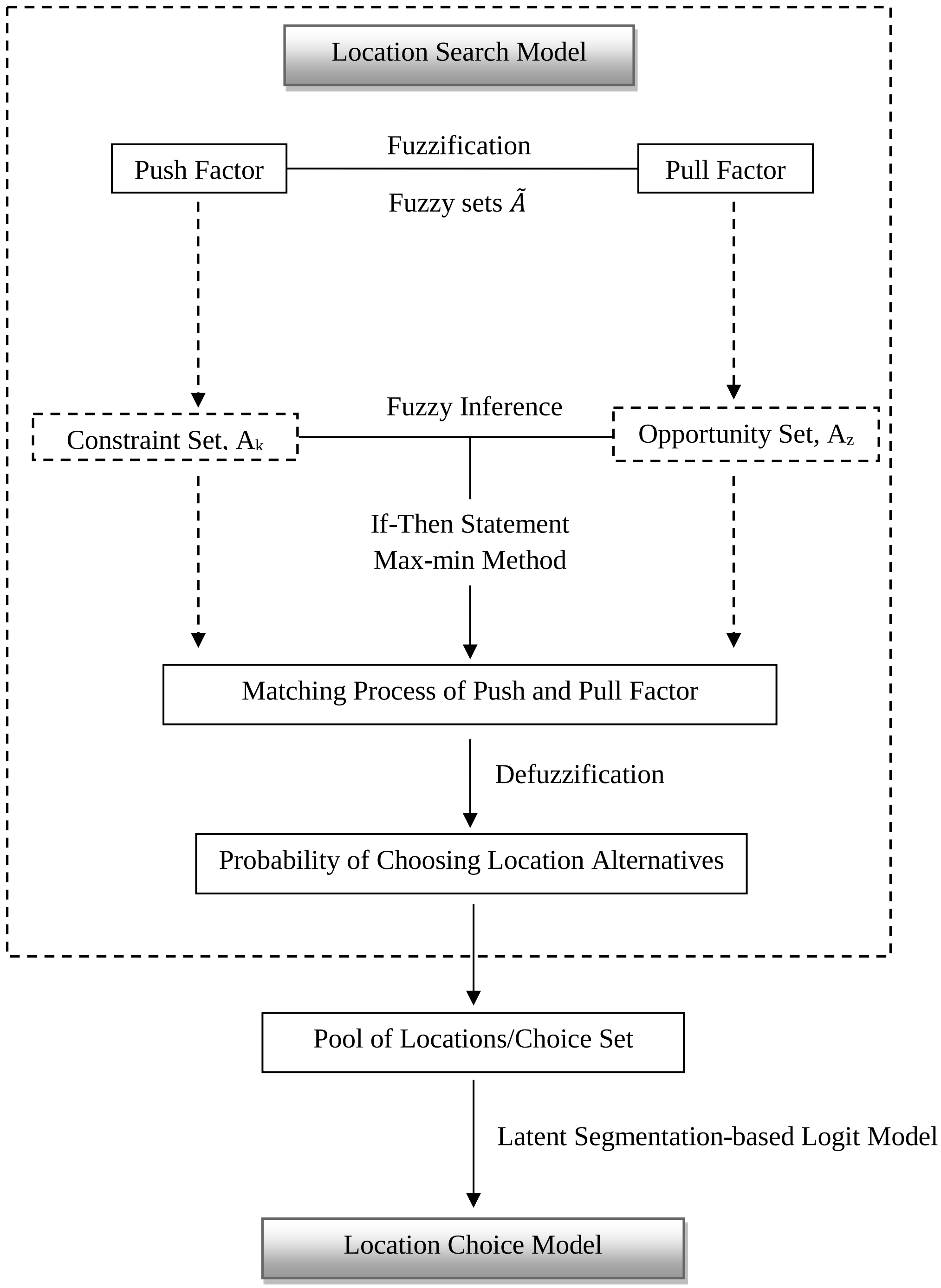

Figure 1: Conceptual Framework of the Fuzzy Logic-based Location Choice Model

children prefer urban areas, as they prioritize commuting and convenient access to different amenities (Van Ommeren et al. 1999). In general, one of the most common proxies used to represent urban and suburban/rural neighborhoods is distance to the CBD (Habib and Miller 2008). Therefore, the push factor "due to life-cycle events" is assumed to correspond to the pull factor "distance to CBD". In the case of households with "other reasons", detailed behavioral information regarding their reason for relocation is not available. Hence, their location alternatives are generated using traditional method of random sampling. Since pull factors are the attractors of a location, the fuzzy sets generated for each of the three pull factors are termed as the opportunity sets in this study.

In the second stage, fuzzy inference, a matching process of the push and pull factors is performed on the basis of "If-Then" statements. The most commonly used methods to conduct fuzzy inferences are max-min and sugeno methods (Guney and Sarikaya 2009). Sugeno method is popular in optimization problems. In contrast, max-min is widely used for decision support modeling due to its intuitive and interpretable nature. Moreover, max-min method offers the flexibility of validating the scales of fuzzy membership functions using known fuzzy rules (Teodorovic 1999, Verkuilen 2005). Therefore, this study uses max-min method for fuzzy inferences. The third stage is defuzzification, where the household-specific probability of choosing a parcel is determined by using the center of gravity method. The next step generates a pool of alternative locations for each household. Below is a brief description of the fuzzy logic-based search model developed in this study.

Let's assume, P to be the universe of discourse and $\tilde{A}$ is the fuzzy set of P, where $\mu_A(x)$ is the membership function of the fuzzy set $\tilde{A}$ and $\mu_A \epsilon [0,1]$. Fuzzy sets are represented by intervals and the crisp input is denoted as x. The α-cuts of a fuzzy set $\tilde{A}$ are defined as (Mockor 2013):

$$A_\propto = x \epsilon P | \mu_A(x) \geq \alpha = [\min\{x \epsilon P | \mu_A(x) \geq \alpha\}, \max\{x \epsilon P | \mu_A(x) \geq \alpha\}] \tag{1}$$

Where, $\alpha \in [0,1]$. Fuzzy set $\tilde{A}$ representing both constraint sets (input sets) and opportunity sets (output sets) are classified into fuzzy groups. The expression below represents the membership function for the constraint sets, which gives the association between the crisp input and the fuzzy groups in correspondence to the membership value:

$$\mu_{A_k}(x) = \begin{cases} low & x \leq x_1 \\ low/medium & x_1 \leq x \leq x_2 \\ medium/high & x_2 \leq x \leq x_3 \\ high & x \geq x_3 \end{cases} \tag{2}$$

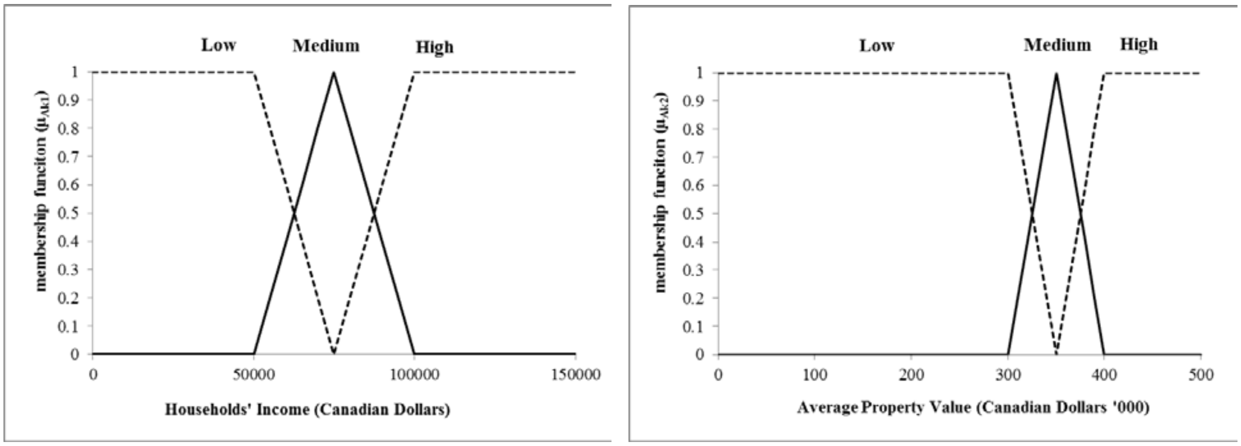

Figure 2: Fuzzy Membership Functions for the Constraint Sets Considered in this Study

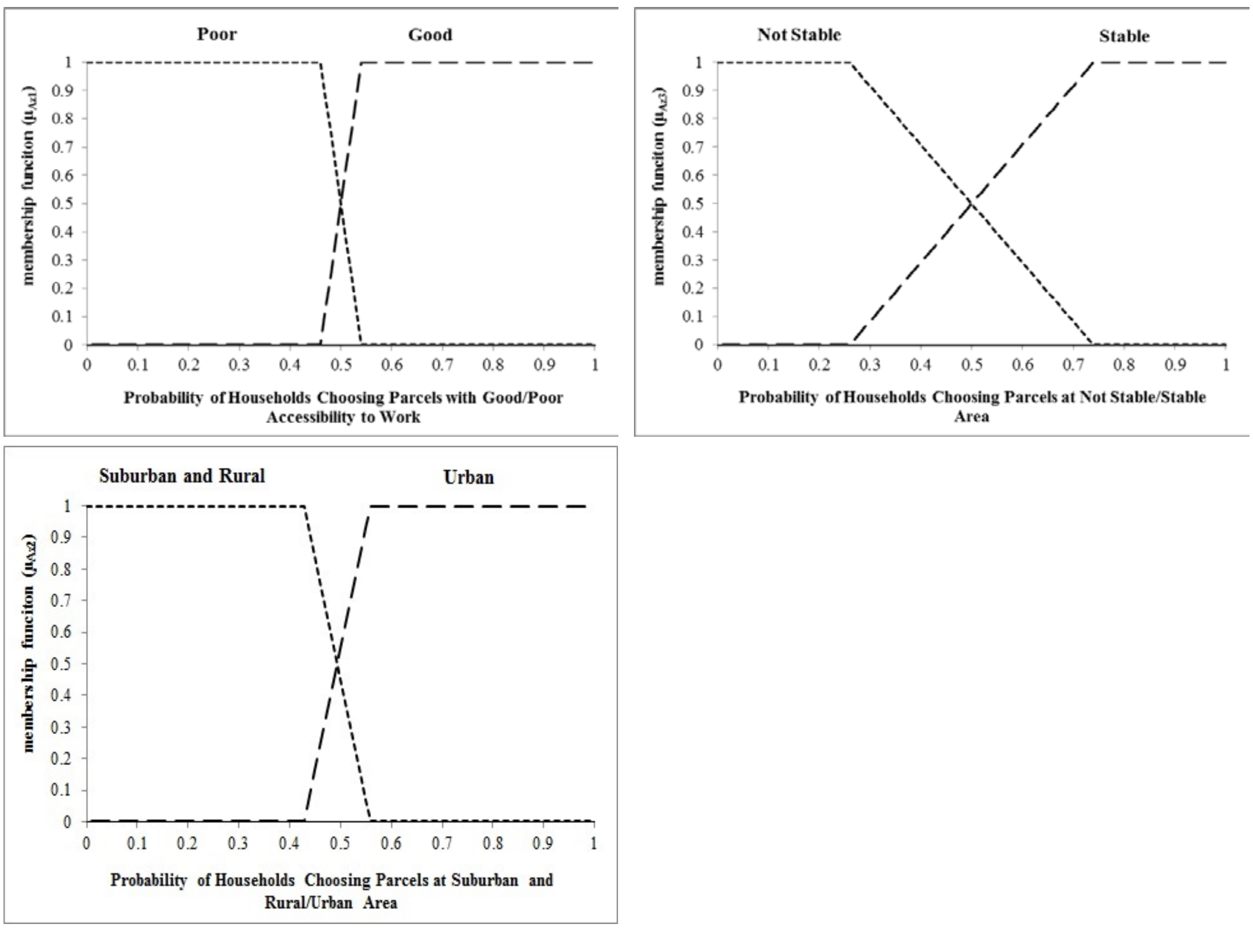

Figure 3: Fuzzy Membership Functions for the Opportunity Sets Considered in this Study

Here, A_k denotes constraint sets, where K can take values of 1 and 2 representing household income and average property value respectively. Figure 2 illustrates the two constraint sets developed for each push factor. A triangular shape is adopted for the membership functions following Postorino and Versaci (2008). Both the constraint sets are classified into three fuzzy groups: low, medium and high. For the constraint set regarding households' income, the threshold for low income is assumed to be ≤ 50,000 CAD[1], and high income threshold is assumed to be ≥ 100,000 CAD[2]. For the constraint set regarding average property value, the lower price threshold is assumed to be ≤ 300,000 CAD, and higher price threshold is assumed to be ≥ 400,000 CAD[3].

Assuming A_z as the opportunity set and $\mu_{A_{kz}}(x)$ as the corresponding membership function. Here, z can take values of 1, 2, and 3; which represent distance to work location, percentages of non-movers in the neighborhood, and distance to CBD respectively. The value of z is conditional on the push factor. For the push factor "to live in proximity to work/key activity locations", an example of the expression for the opportunity set "distance to work" can be given as:

$$\mu_{A_{k1}}(x) = \begin{cases} good & x \le 0.45 \\ good/poor & 0.45 \le x \le 0.54 \\ poor & x \ge 0.54 \end{cases} \tag{3}$$

Similar expressions are constructed for the opportunity sets "distance to CBD", and "percentages of non-movers in the neighborhood". Figure 3 shows the opportunity sets of the pull factors. Similar to the constraint sets, a triangular shape is adopted. Each of the opportunity sets are classified into two fuzzy groups. Opportunity set, "distance to work location" is categorized into "good" (< 10km from the work location) and "poor" (≥ 10km from the work location) accessibility to work place[4]. "Percentages of non-movers in the neighborhood" is classified into "not stable" (< 50% non-movers in the neighborhood) and "stable" (≥ 50% non-movers in the neighborhood)[5] neighborhoods. "Distance to CBD" is categorized into "urban" (< 10km from the CBD) and "suburban and rural" (≥ 10km from the CBD) areas[6]. Following the fuzzification stage, the matching process between a push factor and the corresponding pull factor

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[1]Low income threshold is determined on the basis of the low income cut-off for Canada, which is estimated to be $47,878 CAD before tax (Statistics Canada 2015). Low income cut-off refers to an income threshold where a household is likely to spend a higher proportion of its income on food, shelter and clothing than the average household, leaving less income available for other expenses.

[2]High income threshold is determined following the assumption in Prouse et al. (2014), which suggests that households with an income greater than 120% of the average household income ($76,210 CAD) in the HRM are considered as high income households.

[3] The lower and higher property price threshold is assumed according to the Canada Mortgage and Housing Corporation (2015 and 2016). The average and median price of house in Halifax was $282,951 CAD and $387,500 CAD respectively. The higher median value compared to the average value reveals a left skewed distribution of the prices, which means majority of the prices are above the average price. Hence, the lower threshold is assumed to be around the average price. On the other hand, the higher threshold is assumed to be around the median price.

[4] The threshold for the distance between work place and home is assumed to be 10km, since the average commute distance in Halifax is 10.50km (Tang 2011).

[5] The threshold for the percentage of non-movers in the neighborhood is considered at the 50% point. This study assumes a neighborhood to be stable if it has more non-movers than movers' population. On the other hand, if a neighborhood has more movers than non-movers, it is considered as a not stable neighborhood.

[6] In the context of Halifax, neighborhoods within 10km (approximately) from the CBD that encompasses peninsula Halifax and Dartmouth, are collectively known as "regional center" in the Regional Planning Strategy (Halifax Regional Municipality, 2014). Hence, 10km distance from the CBD is considered as the threshold.

is conducted in the fuzzy inference stage. Particularly, fuzzy inferences handle the degree of match between the constraint set (If) and the opportunity set (Then) by using "If-Then" logic statements (Andrade et al. 2006). The logic statements are derived from observing the general trend of the data. A total of twelve logic statements are developed for the "push-pull" combination of "to live in proximity to work/key activity locations - distance to work location". A typical format of the logic statements is as follows:

IF household's income is [HIGH] and average value of the property is [HIGH], **THEN** the household chooses residential location with [GOOD] accessibility to work place

A total of twelve and ten logic statements are developed for the "push-pull" combinations of "to live in desirable neighborhood/dwelling - percentages of non-movers in the neighborhood" and "due to life-cycle events - distance to CBD" respectively. The logic statements developed for the "push-pull" combinations are presented in Table 1.

In the fuzzy inference stage, the constraint set determines the boundaries of the search process which results in the probability of the selection of a parcel in the pool of alternative locations. As indicated earlier, the max-min method is used to conduct the inferences, which can be expressed as the following equation,

$$\mu_A(x) = max\{min[\mu_1(x), \mu_2(x), \dots \dots \mu_n(x)]\} \quad (4)$$

For the defuzzification stage, the center of gravity method is adopted to determine a crisp output (Ceder et al. 2013). The center of gravity method is expressed as,

$$y^* = \frac{\int \mu(y) y \, dy}{\int \mu(y) dy} \quad (5)$$

Here, y^* is the crisp output estimated using the center of gravity method, which represents household-specific probability of choosing a parcel. For example, in the case of a household with push factor "to live in proximity to work/key activity locations", if the crisp output derived from the opportunity set is $y^* \geq 0.50$, which falls under the area of parcels with good accessibility to the work place (parcels < 10km from the work location), such household considers parcels within 10km from the work location compared to those parcels that are ≥ 10km from the work location. Therefore, the potential alternatives for that household will include those parcels, which are within 10km from the work location. For $y^* < 0.50$, the potential alternatives include the parcels ≥ 10km from the work location. Similarly, potential location alternatives for the households with the other two push-pull combinations are developed. Note that the number of potential alternative parcels varies for each household, which ranges from 1,500 to 84,000. To reduce the computational complexities of the location choice model in the second tier, a feasible pool of parcel alternatives for each household is developed by randomly selecting a sub-set from the large number of household-specific potential parcels. The pool of alternatives for each household includes a total of ten parcels including the chosen parcel.

Table 1. "IF-Then" Logic Statements of the Fuzzy Logic Model

	IF		THEN
"Push-Pull" Combinations of "To Live in Proximity to Work/Key Activity Locations - Distance to Work Location"			
Rule No.	**Household Income**	**Avg. Value of Property**	**Accessibility to Work Place**
1	Low	Low	Good
2	Low	Medium	Good
3	Medium	High	Good
4	Medium	Medium	Good
5	High	Low	Good
6	High	Medium	Good
7	High	High	Good
8	Low	Low	Poor
9	Medium	Low	Poor
10	Medium	Medium	Poor
11	High	Low	Poor
12	High	Medium	Poor
"Push-Pull" Combinations of "To Live in Desirable Neighborhood/Dwelling - Percentages of Non-movers in the Neighborhood"			
Rule No.	**Household Income**	**Avg. Value of Property**	**Neighborhood Type**
1	Low	Low	Not Stable
2	Low	Medium	Not Stable
3	Medium	Low	Not Stable
4	Medium	Medium	Not Stable
5	High	Low	Not Stable
6	High	Medium	Not Stable
7	Low	Medium	Stable
8	Medium	Medium	Stable
9	Medium	High	Stable
10	High	Medium	Stable
11	High	Low	Stable
12	High	High	Stable
"Push-Pull" Combinations of "Due to Life-cycle Events - Distance to CBD"			
Rule No.	**Household Income**	**Avg. Value of Property**	**Neighborhood Type**
1	Low	Medium	Urban
2	Medium	Medium	Urban
3	Medium	High	Urban
4	High	Medium	Urban
5	High	High	Urban
6	Low	Low	Suburban
7	Medium	Low	Suburban
8	Medium	Medium	Suburban
9	High	Low	Suburban
10	High	Medium	Suburban

The next step develops a location choice model utilizing the pool of alternatives generated in the search model. The location choice model is developed following a latent segmentation-based logit (LSL) modeling technique. The LSL model captures unobserved heterogeneity by allocating households into discrete latent segments using a segment allocation component. The segment allocation component can be fixed across the segments if the segments are not defined with observed attributes (Fatmi and Habib 2014). This study formulates a flexible segment allocation model within the LSL framework and defines the segments using observed socio-demographic and neighborhood characteristics (Sobhani et al. 2013, Fatmi and Habib 2016a, Fatmi et al. 2014). Assuming that household i is allocated to segment s, the segment allocation model can be expressed in the following multinomial logit form:

$$\Phi_{is} = \frac{e^{\omega_s + \theta_s Z_i}}{\sum_{s=1}^{S} e^{\omega_s + \theta_s Z_i}} \tag{6}$$

Here, Z is the observed attributes of the households, ω is the segment membership constant, and θ is the segment membership vector parameter. For the identification purpose of the model, one segment is assumed to be the reference segment, considering ω and θ to be fixed for that segment.

Since, this study utilizes the restrospective HMTS data, correlated sequence of choices exists due to the repeated choices of locations made by the same households during their housing career. To accommodate such correlated sequence of choices, the repeated choice probability is estimated by deriving the joint probability of the choice sequence. Assuming that household i allocated to segment s chooses alternative location j at t choice situation, the joint choice probability can be expressed as:

$$P_{ij}(i \in s) = \prod_{t=1}^{T} \frac{e^{X_{ic_{it}t}\beta_s}}{\sum_{j=1}^{J} e^{X_{ijt}\beta_s}} \tag{7}$$

Here, X is the observed vector parameter, β is the segment specific vector parameter, and c is the location chosen by household i at t choice situation from a sequence of location choices $c = c_{i1}, c_{i2}, \ldots\ldots\ldots c_{iT}$. The likelihood of household i choosing an alternative location j can be written as:

$$P_i(j) = \sum_{s=1}^{S} \Phi_{is} P_{ij} (i \in s) \tag{8}$$

The model estimates parameters by maximizing the likelihood function using an expectation-maximization (EM) algorithm. The analytic second derivative matrix of the likelihood function is inverted to calculate the asymptotic covariance matrix for the full set of parameter estimators. The likelihood function can be written as:

$$LL_{\max} = \sum_{n=1}^{N} \ln P_i(j)^{\gamma_{ij}} \tag{9}$$

Here, N is the total number of observations, and γ is a dummy variable. γ takes a value of 1 while household i chooses location j and 0 otherwise. The model estimates segment specific parameter vector β for S segments, and segment membership parameter vector ω and θ for $S-1$ segments. The model is evaluated on the basis of the model fit measures of adjusted pseudo rho-square and Bayesian Information Criterion (BIC).

5. Independent Variables

This study extensively examines the effects of the multi-domain changes along the life-course on residential location decisions. To explore the *priori* hypotheses regarding the interactions between multi-domain changes and location choice, the effects of a wide array of life-cycle events are tested. Life-cycle events include, birth of a child, death of a member, move-in of a member, move-out of a member, addition of a job, loss of a job, job change, retirement, and vehicle transaction, among others. Vehicle transaction decision includes the decision of vehicle acquisition and purchase of the first vehicle. “Vehicle acquisition” refers to addition of a vehicle to the existing vehicle fleet of the household. “Purchase of the first vehicle” refers to the purchase of the first vehicle in the life-time of the household. The adjustment period of the life-cycle events is accommodated within the model by considering the events as lead and lag events. Lead events refer to the effects of an event on occurrence, and lag events refer to the effects of an event in anticipation. Hence, a lead event indicates to a lagged effect of the event, and a lag event indicates to a lead effect of the event. The model considers lead and lag events for the following periods: same year, one-year lead, two-year lead, three-year lead, one-year lag, two-year lag, and three-year lag. “Same-year” refers that an event and residential relocation occurred in the same calendar year. “1 year lead” refers that an event occurred one to two calendar years before the relocation decision. Two-year lead and three-year lead can be described similarly. “One-year lag” indicates that an event occurred one to two calendar years after the relocation. Similarly, two-year lag and three-year lag can be described. In addition, the study examines location preferences on the basis of parcel characteristics, accessibility to different activity points, and neighborhood characteristics. A detail description of the variables retained in the final model along with their summary statistics is presented in Table 2.

Table 2. Summary Statistics of Explanatory Variables used in the Residential Location Choice Model

Variables	Description	Mean/ Proportion	Std. Dev.
Socio-demographic Characteristics			
Age	Age of the head of the household	31.77	23.81
Income above 100K (Dummy Variable)	Household income above $100,000 CAD	48.05%	-
Life-cycle Events			
Birth of a Child_1Year Lag (Dummy Variable)	Birth of a child one year after residential relocation	3.6%	-
New Job_Same Year (Dummy Variable)	Addition of a job occurring in the same year of residential relocation	24.67%	-
Job Change_1 Year Lead (Dummy Variable)	Change of a job occurring one year prior to residential relocation	13.24%	-
First Vehicle_2 Year Lead (Dummy Variable)	Purchase of the first vehicle in the life-time of the household occurring two years prior to residential relocation	1%	-
Vehicle Acquisition _1 Year Lead (Dummy Variable)	Addition of a vehicle to the exiting vehicle fleet of the household occurring one year prior to residential relocation	7.01%	-
Vehicle Acquisition _2 Year Lead (Dummy Variable)	Addition of a vehicle to the exiting vehicle fleet of the household occurring two years prior to residential relocation	5.19%	-
Children (Dummy Variable)	Household with children	53.24%	-
No Vehicle Ownership (Dummy Variable)	Household not owning vehicle in the life-time	3.5%	-
Accessibility Characteristics			
Dist to Work	Distance from home to the work place in km	25.45	28.29
Dist to nearest School	Distance from home to the nearest school in km	2.98	5.45
Dist to nearest Transit Stop	Distance from home to the nearest transit stop in km	11.17	24.75
Dist to nearest Business Center	Distance from home to the nearest regional business center in km	11.56	10.33
Dist to CBD	Distance from home to the Central Business District (CBD) in km	24.40	27.67
Dist to nearest Health Service	Distance from home to the nearest health service in km	4.49	7.62
Dist to nearest Park Area	Distance from home to the nearest park area in km	2.06	4.50
Parcel and Neighborhood Characteristics			
Lot Size	Parcel lot size in acre	0.64	5.02
Population Density	Population per acre area in the home dissemination area	1530	2258
% of Owned Dwelling	Percentage of owned dwelling in the home dissemination area	80.01%	22.74%
Avg. Property Value	Average property value (CAD X 1000) in the home dissemination area	266.92	102.91
% of HH's Share of Shelter Cost to Income less than 30%	Percentage of households spending less than 30% of their household income on shelter cost in the home dissemination area	80.90%	12.37%

% of Non-movers	Percentage of non-movers in the last five years in the home dissemination area	66.74%	16.82%

6. Model Results

6.1. Goodness-of-fit Measures

This study determines the appropriate number of segments on the basis of the Bayesian Information Criterion (BIC) measures (Table 3). The results suggest that the BIC measure is minimum for the model with two segments. Therefore, the final model is assumed to have two latent segments.

Table 3 – Number of Segment Determination

Goodness-of-fit Measures	Latent Segmentation-based Logit Model		
	No. of Segments 1	*No. of Segments 2*	*No. of Segments 3*
Log-likelihood (at convergence)	-797.09	-682.57	-651.80
Log-likelihood (constant)	-886.50	-886.50	-886.50
No. of Parameters	21	43	65
No. of total Observation	385	385	385
BIC	1719.20	1621.13	1690.56

For comparison purposes, in addition to the proposed fuzzy logic-based location choice model, another location choice model is developed using choice set generated from the traditional random sampling method. For consistency in comparison and model specification, the final models of both the methods retain the same variables (as presented in Table 2). The models are compared on the basis of the predictive adjusted likelihood ratio index and average probability of correct prediction, which are used by Zolfaghari et al. (2012) to evaluate several choice set generation techniques. To compute the goodness-of-fit measures, 75% of the data are used to estimate the models and the remaining 25% of the data are used for validation purposes. The results suggest that the proposed fuzzy logic-based model improves model fit with a higher predictive adjusted likelihood ratio index and average probability of correct prediction values than that of the traditional model (Table 4). Moreover, the proposed model exhibits a higher adjusted pseudo rho-square value (0.23) than that of the traditional model (0.19). Therefore, it can be concluded that the proposed fuzzy logic-based location choice model outperforms the traditional random sampling-based model in terms of goodness-of-fit measures. This study considers the fuzzy logic-based model as the final model for further discussion on the parameter estimation results.

Table 4 – Goodness-of-fit Measures of the Proposed and Traditional Models

Goodness-of-fit Measures	Proposed Fuzzy Logic-based Location Choice Model	Traditional Random Sampling-based Location Choice Model
Predicted Log-likelihood (at convergence)*	-464.47	-452.46
Predicted Log-likelihood (constant)*	-644.72	-591.76
Predictive Adjusted Likelihood Ratio Index**	0.27	0.23
Average Probability of Correct Prediction***	0.29	0.24

**Predicted Log-likelihood is the log-likelihood value of the validation sample, which is computed by maximizing the likelihood function during the estimation of the validation sample*

***Predictive Adjusted Likelihood Ratio Index is computed using the predicted log-likelihood values (at convergence and constant)*

****Average Probability of Correct Prediction =* $(\sum_i \sum_j y_{ij} p_{ij})/N$*, where* y_{ij} *indicates that whether household* i *actually resides in parcel* j*,* p_{ij} *indicates the predictive probability of household* i *resides in parcel* j*, and* N *is the total number of observation in the validation sample*

6.2. Discussion of Model Results

6.2.1. Characterization of the Latent Segment Allocation Component

The results of the latent segment allocation component are reported in Table 5. The model is estimated considering segment two as the reference segment. The model results suggest a negative sign for the variable representing household income above $100,000 CAD, which indicates a lower likelihood of such households to be allocated to segment one. The positive sign of the variable representing age of the head of the household reveals that older head households are more likely to be allocated in segment one. Among the neighborhood characteristics, the negative sign of the variables representing percentage of owned dwellings in the neighborhood, and distance from home to the CBD in segment one indicate that urban dwellers have a higher likelihood to be included in segment one. In summary, segment one has a higher propensity to include urban dwellers with lower household income and older head. Presumably, segment one can be identified as a segment for “urbanite households”. On the other hand, segment two can be identified as a segment for “suburbanite households”.

6.2.2. Discussion of the Latent Segmentation-based Logit Model Results

Parameter estimation results of the latent segmentation-based logit model are reported in Table 5.

6.2.2.1. Parcel Characteristics and Interaction with Life-cycle Events

The model results suggest that location choice is significantly influenced by parcel characteristics. For instance, the variable representing lot size reveals a positive relationship in segment two. Segment two is identified to include suburbanite households who are higher income suburban dwellers. Essentially, suburbanite households prefer larger dwellings (i.e. parcel size), potentially in the suburban areas. In contrast, urbanite households in segment one show a negative relationship. Interestingly, while a life-cycle event represented by birth of a child is interacted with the lot size, a positive relationship is found for urbanite and suburbanite households in both segments. An increase in the household size due to birth of a child might trigger the requirement of a larger dwelling. Therefore, households prefer larger-sized lots, which is consistent with the findings in Strom (2010). The model confirms a one-year lead effect of this life-cycle event. Life-cycle event represented by job change shows a heterogeneous behavior as evident in parametric values in the two segments. Households in segment two exhibit a positive relationship. Suburbanite households in segment two belong to the high-income group and arguably a change in job might be associated with further increase in income. Thus, such households reveal preference for larger dwellings following a job change. In the case of addition of a job, urbanite and suburbanite households reveal a higher likelihood for larger-sized lots. Addition of a job refers to increased affordability as discussed in Fatmi and Habib (2016b), which is expected to positively influence the choice of larger dwellings. The model confirms a longer adjustment period for job change (one-year lagged effect) compared to addition of a new job (same year effect). The increased

Table 5. Results of the Proposed Fuzzy Logic-based Residential Location Choice Model

Results of the Latent Segment Allocation Component		
	Latent Segment 1	**Latent Segment 2**
Segment Membership Probabilities	0.51	0.49
Constant	2.2529 (3.22)	-
Socio-demographic Characteristics		
Income above 100K (Dummy Variable)	-0.8002 (-2.219)	-
Age	0.0124 (1.63)	-
Neighborhood Characteristics		
% of Owned Dwelling	-0.0259 (-3.16)	-
Dist to CBD	-0.0181 (-1.60)	-

Parameter Estimation Results		
Variables	**Latent Segmentation-based Logit Model**	
	Latent Segment 1	**Latent Segment 2**
	co-efficient (t-stat)	***co-efficient (t-stat)***
Parcel Characteristics and Interaction with Life-cycle Events		
Lot Size	-0.1134 (-1.03)	0.1605 (2.13)
Lot Size × Birth of a Child_1Year Lag	1.2932 (1.00)	1.4578 (1.34)
Lot Size × Job Change_1 Year Lead	-4.6300 (-1.00)	2.3653 (2.49)
Lot Size × New Job_Same Year	0.0979 (0.3)	0.3033 (2.10)
Accessibility Characteristics and Interaction with Life-cycle Events		
Dist to Work	-0.0462 (-3.23)	-0.0462 (-3.23)
Dist to Work × Vehicle Acquisition_1 Year Lead	0.0049 (0.20)	0.0263 (0.44)
Dist to Work × First Vehicle_2 Year Lead	0.0953 (1.35)	0.0953 (1.35)
Dist to Work × Children	0.0331 (1.93)	-0.4197 (-8.21)
Dist to nearest School	0.4117 (2.72)	-0.291 (-0.23)
Dist to nearest School × Children	-0.4296 (-2.28)	0.3026 (1.86)
Dist to nearest Transit Stop	-0.0081 (-0.60)	-0.0081 (-0.60)
Dist to nearest Transit Stop × No Car Ownership	-3.8791 (-1.60)	-3.8791 (-1.60)
Dist to nearest Business Center	0.0230 (1.00)	0.0403 (2.08)
Dist to nearest Business Center × Vehicle Acquisition_2 Year Lead	0.0215 (0.23)	0.1221 (1.00)
Dist to nearest Health Service	-0.0485 (-1.00)	-0.4231 (-4.83)
Dist to nearest Park Area	-0.3763 (-2.08)	0.2815 (1.78)
Dist to nearest Park Area × Children	0.3331 (1.40)	-0.6954 (-2.20)
Neighborhood Characteristics		
Population Density	0.0001 (1.94)	0.0001 (4.77)
Avg. Property Value	0.0022 (2.18)	0.0018 (2.82)
% of HH's Share of Shelter Cost to Income less than 30%	0.0130 (1.32)	0.0219 (3.41)
% of Non-movers	0.1065 (10.41)	-0.0266 (-4.89)

affordability associated with addition of a job might influence households to relocate to larger-sized lots within a much shorter time from the occurrence of the event.

6.2.2.2. Accessibility Characteristics and Interaction with Life-cycle Events

In general, households are found to be more likely to reside closer to their work place, which reflect their preferences for shorter commute distance. To examine how vehicle transaction decisions influence location choice, the following two variables are interacted with commute distance: vehicle acquisition, and purchase of the first vehicle. Urbanite and suburbanite households reveal a positive relationship for both the variables. Interestingly, a longer adjustment period is observed for the first time vehicle purchase (two-year lagged effect) compared to vehicle acquisition (one-year lagged effect). First time vehicle purchase is a key event in the life-time of the household. Due to the limitation in time and money budgets, a longer adjustment period is expected between two large investments of purchasing a house and first car. When the presence of children is interacted with commute distance, a variation in relationship is found in two segments. Suburbanite households (i.e. segment two) who have children show a higher likelihood to reside closer to work place, which might offer them the flexibility of trip chaining to day care centers or schools on the way to and from work. On the other hand, urbanite households with low income (i.e. segment one) show a higher probability to compromise with the longer commute. Locations closer to work place might be expensive and they might be trading off longer commute with the opportunity to reside in proximity to other potential amenities for their children. One such amenity might be distance to school, as argued in Kim et al. (2005). Furthermore, when the presence of children in the household is interacted with distance to the closest school, urbanite households show a higher likelihood to reside closer to school.

Distance to the closest transit stop reveals a negative relationship. Interestingly, when this variable is interacted with a dummy variable representing households not owning a vehicle in their life-time, the negative effect substantially increases. This reflects the fact that households prefer to live closer to transit stop; however, the propensity to reside closer to transit stop increases for households without vehicle ownership. Distance to the nearest regional business center shows a positive relationship. Since, households prefer locations farther away from regional business centers, which is characterized as big-box retails in the case of Halifax. A similar positive relationship is found while distance to the nearest regional business center is interacted with vehicle acquisition. This result reflects that addition of a vehicle might offer added freedom and convenience for longer trips. Households exhibit a higher probability to choose locations closer to the health care services, since locations closer to health services offer easier access to daily and periodic medical services. Distance to the closest park area exhibits heterogeneous relationship in the two segments. Urbanite households are found to be extremely sensitive to distance to the nearest park area and prefer to live closer to park areas. Locations closer to park areas are preferable due to the convenient access to open space, which can serve as a regular recreational place for the household members. In contrast, households in segment two reveal a positive relationship. Interestingly, while distance to the closest park area is interacted with presence of children in the household, suburbanite households exhibit a strong preference for locations closer to park areas. In summary, the model results reflect that the effects of accessibility characteristics in choosing home locations are substantially dictated by life-cycle events.

6.2.2.3. Neighborhood Characteristics

Regarding the neighborhood characteristics, households have a higher probability to live in neighborhoods with higher population density. Average property value in the neighborhood shows a positive relationship, since higher average property value indicates high income neighborhoods with better housing and access to diversified amenities (Guo and Bhat 2002), which are expected to be desirable. The variable representing percentage of households with a shelter cost to income share of less than 30% reflects high income neighborhoods with more disposable income after housing related payments. This variable exhibits a strong positive relationship, which extends the fact that locations with more disposable income are more attractive. Interestingly, stable neighborhoods represented by percentage of non-movers show significant variations between the two segments. Urbanite households prefer stable neighborhoods and suburbanite households show affinity to evolving neighborhoods in Halifax. This result is a deviation from an earlier Toronto study (Habib and Miller 2009), in which households generally preferred stable neighborhoods. This may reflect a unique continual growth of new subdivisions in Halifax, which has become an interesting feature of the city as documented in Brewer and Grant (2015).

The final model retains a number of variables with statistical significance below 95% confidence interval. These variables reveal key insights towards location choice behavior and have important policy implications. Therefore, these variables are retained in the final model with an assumption that they might reveal statistical significance if a larger data set were available. In addition to the above discussed variables, the model tests a number of variables such as, death of a member, member move out, loss of a job, distance to the nearest shopping center, average household income, percentage of employment rate, percentage of immigrant, and land-use indices. These variables could not be included in the final model due to discrepancies in the hypothesis confirmation along with reasonable statistical significance. The model also could not confirm statistically significant effects of how neighborhood characteristics varies by life-cycle events. One of the possible attributing factors might be the unavailability of historical records for changes in urban form.

7. Conclusion

This study follows life-course perspective to investigate households' residential location decisions as a two-tier process of location search and location choice. The location choice process is modeled at the most fine-grained parcel-level. The continuously evolving nature of the process over households' life-time is addressed by utilizing retrospective survey data and panel modeling approach. In the first tier, a location search model is developed assuming that households continuously search for locations on the basis of residential stress generated by changes at different life-domains, a reason why households are making the relocation decisions. The search model adopts a fuzzy logic-based modeling method to accommodate the inter-dependencies between the stress-driven push and pull factors. The push factors correspond to households' stress and the pull factors are the characteristics of the locations that assist in releasing the residential stress. The search model generates specific pool of alternative locations for each household on the basis of constraint and opportunity sets identified in the fuzzy logic-based search model.

In the second tier, a location choice model is developed utilizing the pool of alternative locations generated in the first tier. The model adopts a latent segmentation-based logit modeling technique to accommodate the correlated sequence of repeated choices of the households'. The model accommodates the lead and lagged effects of the life-cycle events occurring at different life-domains. The model captures latent heterogeneity by allocating households into discrete latent segments. The model results of the segment allocation component suggest that segment one can be identified as urbanite households' segment which includes low income older head urban dwellers. On the other hand, segment two can be identified as suburbanite households' segment which includes high income younger head suburban dwellers.

The goodness-of-fit measures suggest that the proposed fuzzy logic-based model outperforms the traditional random sampling-based model. The model results suggest that life-cycle events, parcel characteristics, and accessibility measures significantly influence the choice of residential locations. For instance, most households prefer larger lots. Households in general are found to prefer locations closer to work place, transit stop, and health service. The effects of life-cycle events are found to significantly affect location preferences. For instance, birth of a child magnifies the need of larger lots. Vehicle transaction represented by vehicle acquisition, and purchase of the first vehicle in the life-time of the household show a higher propensity to choose locations farther away from work place. The adjustment period is found to be longer for first time vehicle purchase compared to vehicle acquisition. The model results suggest considerable variation in location choice behavior by life-cycle events in the two latent segments. For example, suburbanite households (i.e. segment two) show a higher likelihood to choose larger lots following the life-cycle event of job change. On the other hand, urbanite households in segment one show a negative relationship. Interestingly, addition of a new job positively influence urbanite and suburbanite households to choose larger lots. The adjustment period for job change is found to be longer than that of addition of a new job. Suburbanite households with children prefer to reside closer to work place. Urbanite households with children are more likely to live closer to school. Households without ownership of car in their life-time have a higher likelihood to choose locations closer to the transit stops.

This study has certain limitations. For instance, this study could not capture the effects of the historical evolution of land-use and urban form due to the unavailability of such information. Moreover, this study could not consider the historical evolution of the transportation system measures, which includes travel time, travel cost, and transit level of service (LOS), among others. Further GIS database needs to be built to maintain historical record of urban form and transportation system measures.

Nevertheless, the proposed modeling framework significantly contributes in dynamic modelling of location choice processes. It explicitly implements the stress-based search process. The model captures the interactions of life-cycle events at different life-domains, including lead and lagged effects. Such life history-oriented approach offers important behavioral insights towards understanding what triggers households' relocation decisions, which is critical for transportation and urban planning. One of the immediate future extension of this work includes implementing the location choice model within a micro simulation-based integrated Transport, Land Use, and Energy Modeling System (iTLE) for Halifax, Canada. The implementation of the proposed model within the iTLE will add capacity to evaluate how people's location choice behavior evolves at different life-stages, which will be useful for inter-generational planning approaches.

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